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Composite Panel Damage Classification Based on Guided Waves and Machine Learning: An Experimental Approach

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Abstract: Ultrasonic guided waves (UGW) are widely used in structural health monitoring (SHM) systems due to the sensitivity of their propagation mechanisms to local material changes, i.e., those induced by damage. Post-processing of the signals gathered by piezoelectric sensors, typically used for both the excitation and the sensing of UGW, is a fundamental step to extract all the peculiar features that can be related to both damage location and severity. This research probes the efficacy of machine learning (ML) models in discerning damage location (R-Classification) and size (S-Classification). Seven supervised ML classifiers were examined: Ensemble-Subspace K-Nearest Neighbors (KNN), Ensemble-Bagged Trees, KNN-Fine, Ensemble-Boosted Trees, Support Vector Machine (SVM), Linear Discriminant, and SVM-Quadratic. The experimental dataset comprised measurements from varied reversible damage configurations on a composite panel, represented by wooden cuboids of single and three different sizes. Signal noise was minimized by performing a low-pass filter, and sequence forward selection-aided feature selection. The optimized ensemble classifier proved to be the most precise for R-Classification (95.83% accuracy), while Ensemble-Subspace KNN excelled in S-Classification (98.1% accuracy). This method offers accurate, efficient damage diagnosis and classification in composite structures, promising potential applications in aerospace, automotive, and civil engineering sectors.

Keywords: ultrasonic guided wave; PZT transducers; machine learning; damage detection and classification; experiments



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1. Introduction

Damage diagnosis and analysis play a pivotal role within the broader field of structural engineering. This process is instrumental in averting catastrophic failures. Damage diagnosis mainly consists of three steps: detection, isolation, and identification. While an anomaly can be investigated during the detection stage, efforts are focused on pinpointing the types of the fault (locations and severity included) along with the damaged component in the isolation and identification phases, respectively [1]. Following these steps, the remaining useful life of a structure can be estimated. Damage diagnosis is particularly valuable when applied to large, complex and costly engineering structures, especially those made of fiber-reinforced (FRP) composites as they exhibit heightened sensitivity to Low-Velocity Impacts (LVIs) [2,3]. LVIs could induce Barely Visible Damages (BVD) such as delamination, as well as fiber failures, and matrix cracking that can significantly diminish the residual strength of the structure [4–6]. Notably, LVI damage typically found its maximum extension at the surface opposite to the impacted one; this aspect complicates the malfunction identification process with various challenges. Furthermore, structural changes could also result from the environmental and operational conditions (EOCs), naturally affecting the components during their life cycle: factors such as temperature [7] and load variations [8] can lead to fatigue crack onset and propagation [9,10].

The pressing need to enhance safety and reliability while simultaneously reducing design and maintenance costs is driving advancements in data collection, processing methods, and computing power.

One of the promising remedies to the issue is structural health monitoring (SHM). SHM facilitates the establishment of a detection and tracking strategy for damage progression to estimate the structural residual life span. This, in turn, enables the implementation of condition-based maintenance policies by collecting, interpreting, and analyzing data gathered by opportunely distributed sensors embedded or attached to the structures [11,12].

Within the domain of SHM, a range of methods can be employed to enhance the continuous monitoring of structural health. These methods encompass eddy current, vibration analysis, acoustic emission analysis, electrical resistance measurements, impedance analysis, infrared thermography, and damping assessment [10]. Moreover, the choice of the appropriate sensor type is a contentious issue. Various sensors, including the acoustic emission (AE) sensors, Eddy-current transducers, accelerometers, laser interferometers, fiber-optic sensors, and piezoelectric lead zirconate titanate (PZT) elements, have demonstrated their utility in structural health monitoring. Notably, many of these sensors operate in a passive manner. However, PZT sensors can be used as active actuators as well, in terms of dual piezoelectric effect. Compact size, low weight, minimal power consumption, and the ability to generate the wave signal with the desired amplitude, frequency, and waveform are the main advantages offered by PZT elements, making them a preferred choice for SHM.

Beyond all these merits, SHM based on ultrasonic guided waves (UGW) stands out as one of the most accurate techniques that can be used in a variety of plate-like structures, spanning from airplanes to medical composites, for malfunction diagnosis [13], because of their powerful capability of long-distance propagation with high speed and little loss of energy. UGWs are dependent on the properties and thickness of the medium they propagate through. Cost-effectiveness, ability to monitor large areas (guided waves can propagate with little attenuation in thin-walled structures), and high sensitivity to detect small damages are all benefits of SHM based on UGW and PZT elements [14]. UGWs signals are generated and received by the PZTs across the monitored area, so variations in the signals are then analyzed to diagnose damage in the structure [15]. The anomaly detection is mostly carried out according to the supervised paradigm, based on observation of relative changes in the inspected part: signals recorded in a current state are compared to a dataset gathered in the pristine state of the structure (i.e., reference or benchmark), serving as the baseline. Deviations, resulting from baseline measurements, may be treated as an indication of damage [13]. Health indicators, damage-imaging approaches, as well as machine learning tools can be used for the damage-related features extraction.

In recent decades, significant efforts have been dedicated to the development of UGW-based damage detection algorithms by combining several techniques, including damage index (DI), time of flight, time reversal (TR) technique, and probability-based diagnostic imaging, in order to extract features from the captured signal that can be connected to damage at various states. For instance, the time of flight algorithm relies on the time lag between the incident wave that the sensor first captures and the wave scattered by damage that the same sensor subsequently captures [4,5,7,16]. The time reversal technique consists of identifying the presence of damage in the vicinity of a path between two sensors by verifying the similarity between the reconstructed signal and the original incident signal [17]. Probability-based diagnostic imaging describes a damage event using a color-scale image to represent the likelihood of a damage occurrence at a specific location of the structure [8]. Damage index-based techniques entail calculating the ratio between a structure's initial and diminished impedance capability, which can then be used to determine the severity and location of the damage [18].

Recently, a procedure introduced by Falcatelli et al. [19] utilized the TR method and a Frequencies Compensation Transfer Function (FCTF) approach to reconstruct both Narrow-Band and actual Broad-Band AE signals. A variety of sensor layouts and materials

were used in the study's experimental testing; two different AE sources were also employed: (1) a Numerically Built Broadband (NBB) signal, and (2) a Pencil Lead Break (PLB). Abaqus®/CAETM was applied to numerically verify the findings while implementing absorbing boundaries to reduce edge reflections. After that, the suggested method was employed to detect damage in an aluminum flat plate.

Furthermore, investigation concerning damage diagnosis methods of components manufactured by FRP composite materials is witnessing increasing attention [11,20]. Perfetto et al. [8] used experimental and numerical techniques to inquire about guided wave propagation in the composite winglet structure at various actuation frequencies. They developed a damage detection technique based on their investigation of the guided wave propagation's dispersion property. In the same work, the authors used a composing procedure consisting of Probability Ellipse (PE) and the guided ultrasonic wave propagation technique to investigate the location of a malfunction throughout a composite winglet when subjected to a LVI damage; the sensitivity analysis regarding the location of the actuating PZT was performed, jointly to an analysis on the effects of the load on the PE field value. The presence of a spar stiffener on the dispersion and scattering/reflection phenomena of guided waves were evaluated as well by means of the finite element method.

Parallel with a sharp increase in the computational power, modern techniques such as artificial intelligence (AI) have proved their potential. This technology offers several critical benefits that make it an excellent tool for solving a vast majority of complex human problems, making faster decisions, being constantly available, and reducing human error. AI encompasses various methods, including artificial neural networks (ANN), machine learning (ML), and deep learning (DL) algorithms, which are all well suited for SHM and monitoring tasks. These techniques, thanks to their robust information fusion and pattern analysis abilities, enable the classification or regression-based diagnosis of damages [21,22]. ML techniques for SHM are entirely data driven; and for this reason, a large set of data must be provided to describe the structural state comprehensively [23].

Rai and Mitra [24] presented a hybrid physics-aided multi-layer feed-forward neural network to improve damage detection under Lamb wave responses in a numerically modelled aluminum thin panel. To localize damage positions around an aluminum flat plate, Perfetto et al. [25] combined the finite element method and ANN. In this study, the damage index calculated on the 0-order symmetric UGW propagating mode demonstrated its usefulness in differentiating between different damage regions.

Zhang et al. [26] used ML to recognize the size and shape of damages in a simulated aluminum beam with 17 different damage configurations by the classification of selected features. Kumar and Mitra [27] tested an Orthogonal Matching Pursuit process combined with a ML algorithm to automate the damage detection process, offering an efficient technique tested on a numerically modelled aluminum panel.

Melville et al. [28] used a DL Lamb waves-based algorithm for rapid, accurate, and automated damage position detection by comparing the full wavefield images of a pristine and a damaged state of two identical aluminum plates. Sampath et al. [29] proposed a hybrid method that incorporated a DL model with higher order spectral analysis in order to detect fatigue cracks in an aluminum specimen. Gao and Hua [30] explored a broadband Lamb wave DL algorithm for damage localization and quantification on a corroded aluminum plate.

Lee et al. [31] presented an automated technique through ultrasonic wave pattern using a deep autoencoder (DAE) for the damage detection and classification through automatic feature extraction with unsupervised clustering.

Chiachío et al. [32] proposed a multilevel Bayesian procedure for the damage assessment in layered composites using through-transmission ultrasonic data; the method was first validated on synthetically generated data (damage hypothesis was, however, based on the uniform reduction in the Young's modulus of several layers at specific area), and then evaluated on real signals from post-impact damage experiments.

Dipietrangelo et al. [33] proposed a ML application for impact localization on an isotropic plate. The authors compared polynomial regression and shallow neural network results, confirming the effectiveness of the ML procedure in detecting and localizing damages under different combinations of training/test sets.

A state-of-the-art review of the different data-driven solutions for SHM and damage detection is provided in [34]. Several works dealing with ML can be found in literature also for composites.

He et al. [35] discussed the use of vibration-based monitoring and machine learning algorithms (MLAs) for anticipating delamination damage in FRP composites. To create a database for the MLAs' training, the authors used a theoretical model of a FRP beam with delamination under vibration. Support Vector Machines (SVM) demonstrated the best prediction performance for both discrete and continuous parameters of delamination location and size among the MLAs tested: Back Propagation Neural Network (BPNN), Extreme Learning Machine (ELM), and SVM. The study demonstrated the potential to enhance the prediction capability of MLAs in assessing delamination damage and provided evidence for the applicability of SVM for structural health monitoring of delamination damage in FRP composites.

Viotti and Gomes [36] presented an innovative technique for identifying delamination in sandwich composite structures utilizing ML. The method employed sensor data to train an ML network to categorize the damage location and estimate its size. The technique exhibited promising results, achieving an average accuracy of 85% in pinpointing damage location. However, accurately estimating the extent of the damage solely from modal datasets remains challenging.

Given the extensive range of structures operating under variable environmental conditions, such as fluctuating temperature and humidity, the adoption of resilient learning models, domain-adaptation algorithms, and transfer learning models holds potential advantages. In the realm of non-destructive tests, where boundaries between classes are not distinctly defined, fuzzy classifiers have demonstrated remarkable capabilities [37,38].

To date, the damage classification using UGW procedure reported in literature mainly deals with isotropic components and simulated (numerical) dataset. The next logical step, in line with current research trends, involves working with more complex specimens made of anisotropic composite materials, and employing more advanced techniques, such as ML. Therefore, this study proposes a combined approach that integrates guided wave propagation with ML for the detection and classification of damage in flat FRP composite plates.

The remainder of this paper is structured as follows. Section 2 provides details on the case study, the testing process, the noise reduction methodology, the signal pre-processing, as well as both features extraction and selection phases. After that, the considered ML algorithms and the classification stage along with the provided results are discussed in Section 3. Finally, the Section 5 summarizes the entire procedure.

2. Materials and Methods

The present study employed the UGW propagation method in conjunction with a ML algorithm for the purpose of damage diagnosis, encompassing both damage identification and localization, within a composite panel. The ML algorithm underwent training and validation phases, utilizing an experimental dataset opportunely built as elaborated in Section 2. Notably, an element of novelty introduced in this work lies in the usage of the experimental dataset to design the ML algorithm in the condition that the number of sample tests is restricted. It is noteworthy that conventional practice in the literature involves the training and verification of ML algorithms against numerical simulations, that typically yield "clean" measurements that are far from the reality. This approach is favored because it facilitates the physical comprehension and interpretation of the data, while mitigating the drawbacks associated to the use of such a UGW-based SHM method. However, in contrast to numerical simulations, where a sizable number of samples can be

generated, in this experimental investigation, only 180 samples were produced for each class, for a total of 540 samples. The steps required to prepare the data for the classification phase are described in the following sections.

2.1. Testing Procedure

The case study consists of a CFRP (Carbon Fiber-Reinforced Polymer) laminated square panel with dimensions of side length $L = 300$ mm and thickness $t = 1.5$ mm, as depicted in Figure 1. The panel is made of 8 unidirectional laminae with the stacking sequence of $[0]_8$ aligned along the x -axis of Figure 1b. This stacking sequence was intentionally defined so as not to exclude from the investigations the slowness phenomenon (i.e., the dependency of the signal group velocity on the measurement angle). This phenomenon can influence UGW propagation mechanisms and consequently impact damage classification. In contrast, quasi-isotropic laminates tend to mitigate this effect. The transducers network encompasses 5 surface-bonded circular PI Ceramics PIC255: one placed at the center of the plate (S-C) and four (S2, S3, S4, and S5) located at a distance $h = 79.29$ mm from the plate edges, as shown in Figure 1b, covering the corner positions of a square 140 mm $\times$ 140 mm sized. The diameter of the transducers is $d_{PZT} = 10$ mm, and the thickness is $t_{PZT} = 0.25$ mm. Table 1 lists the mechanical properties of both the plate and the transducers.

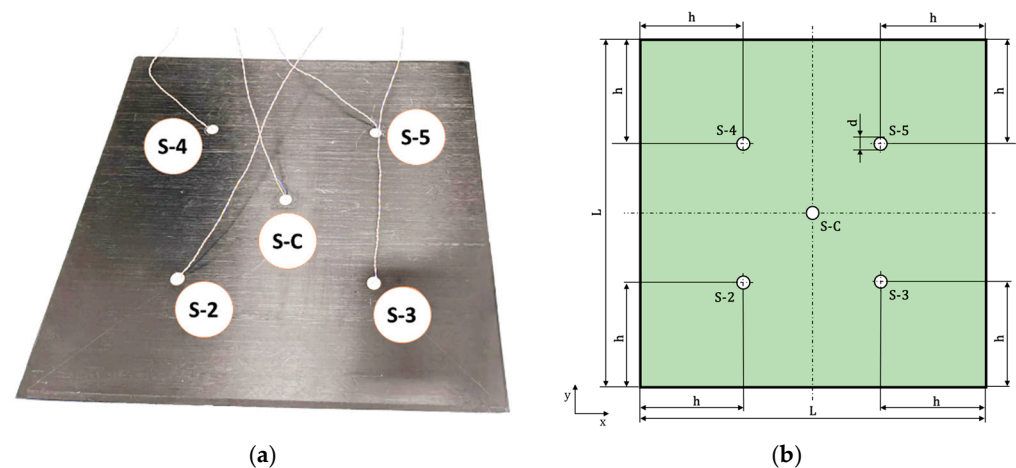


Figure 1. (a) Case study; (b) schematic of the considered plate companion with the number of sensors, their locations, and the regions (R classes).

Table 1. Material mechanical properties of CFRP composite lamina and PIC255 sensors.

Material Property	Symbol	Units	CFRP Lamina	PZT
Mass density	ρ	$[\text{kg m}^{-3}]$	1534	7800
Longitudinal Young's modulus	E_{11}	$[\text{GPa}]$	123.182	62.1
Transversal Young's modulus	E_{22}	$[\text{GPa}]$	7.700	62.1
Transversal Young's modulus	E_{33}	$[\text{GPa}]$	7.700	48.3
Shear modulus	G_{12}	$[\text{GPa}]$	3.60	23.5
Shear modulus	G_{13}	$[\text{GPa}]$	3.60	21
Shear modulus	G_{23}	$[\text{GPa}]$	2.70	21
Poisson's ratio	ν_{12}	—	0.360	0.32
Poisson's ratio	ν_{13}	—	0.360	0.44
Poisson's ratio	ν_{23}	—	0.4	0.44

Figures 2 and 3 illustrate the significant influence of the propagation direction on the group velocities (C_g) of both S_0 and A_0 modes, with higher values along the fiber's direction (0° measurement angle). Specifically, the values of the group velocities were extracted by means of a proprietary code developed in MATLAB[®] that enabled the identification of the time of flight of the diagnostic signal for each actuator-sensor path (pitch-catch approach) by reference to its energetic center defined by the Hilbert Transform (HT). According to the arrangement of the sensors on the panel, measurements were taken at 0° , 45° , -45° , 90° measurement angles, and the C_g extracted values (indicated by markers in Figure 2) were subsequently interpolated, as previously demonstrated in [7,8], to define the dispersive behavior of UGW (solid lines in Figures 2 and 3). The interpolation allows the characterization of the dispersive behavior of the UGW, demonstrating the dependency of the C_g on the excitation frequency, given the plate thickness.

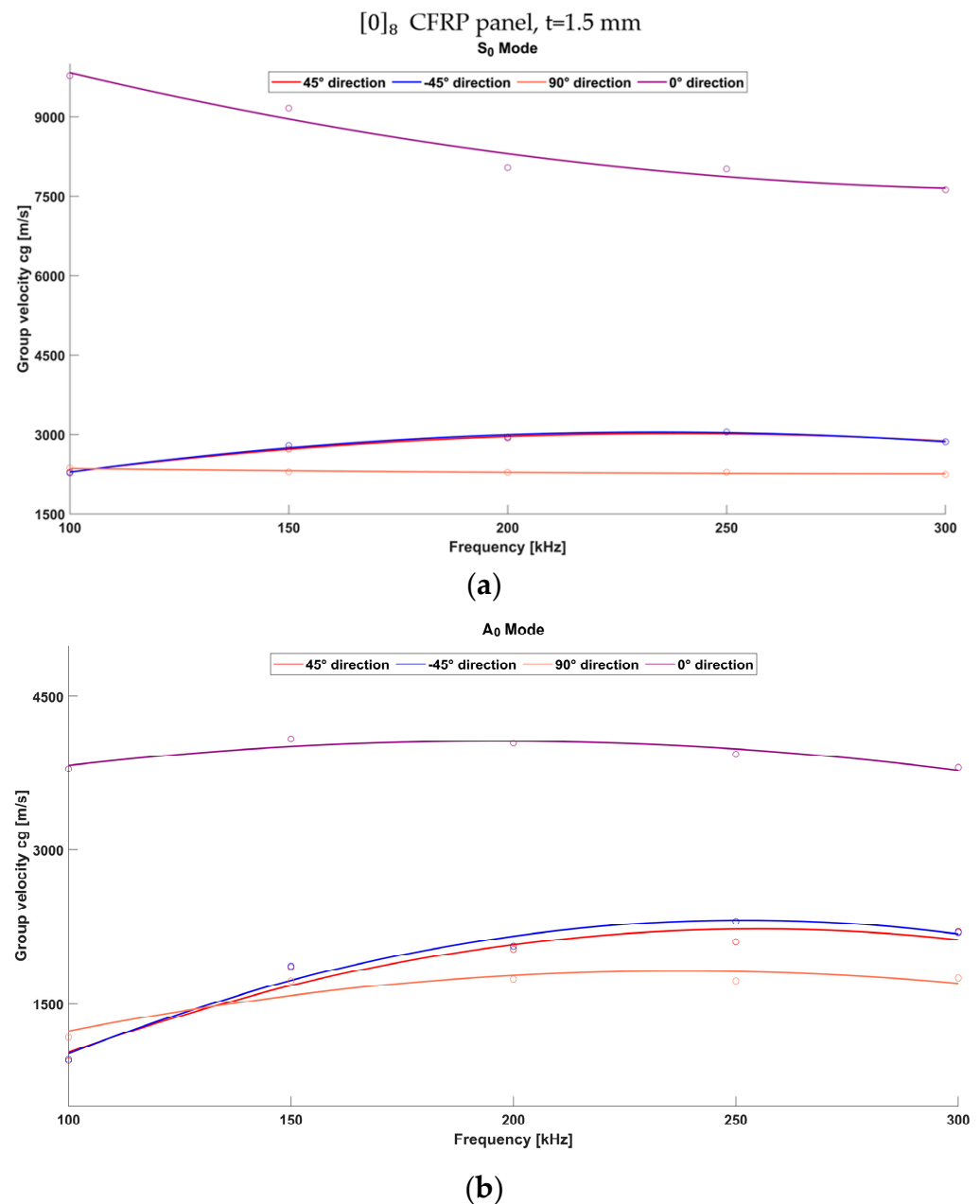
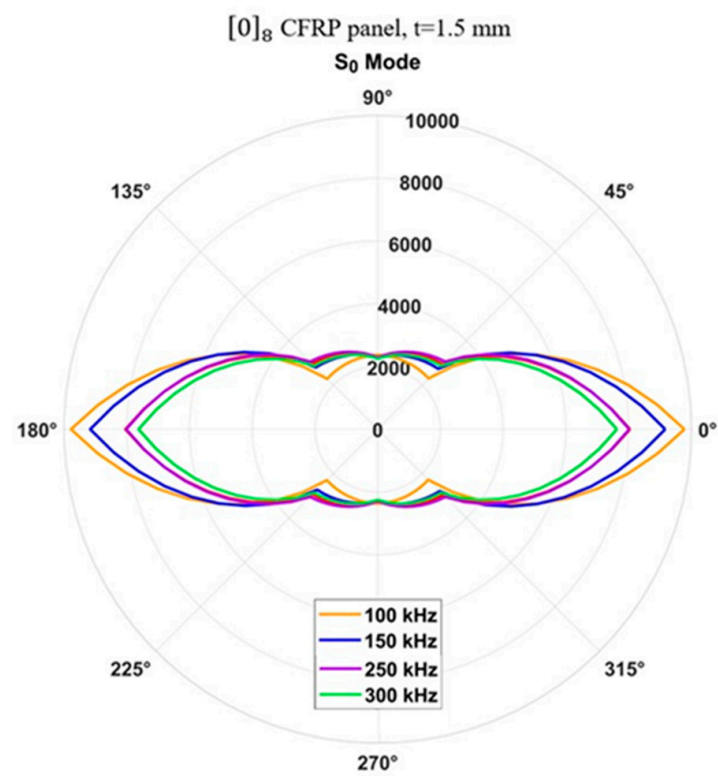
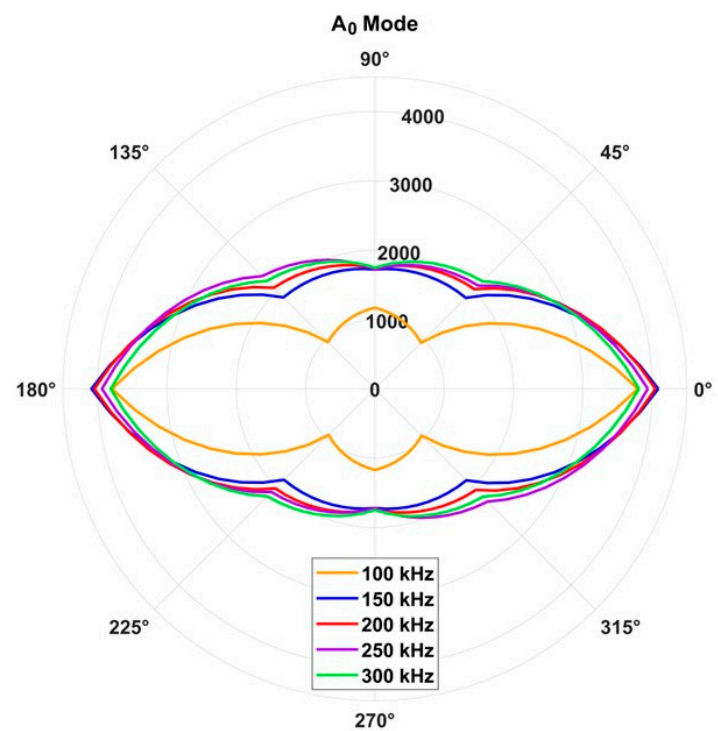


Figure 2. Group velocities at different carrier frequencies for (a) S_0 and (b) A_0 modes in the investigated CFRP panel—classical representation.



(a)



(b)

Figure 3. Group velocities (units in [m/s]) at different carrier frequencies for (a) S_0 and (b) A_0 modes in the investigated CFRP panel—polar representation.

The UGW actuation was performed by exciting the central sensor (S-C) with a five-cycle Hanning windowed tone burst signal having a central frequency of 200 kHz and a peak-to-peak amplitude equals to 12 V, as illustrated in Figure 4.

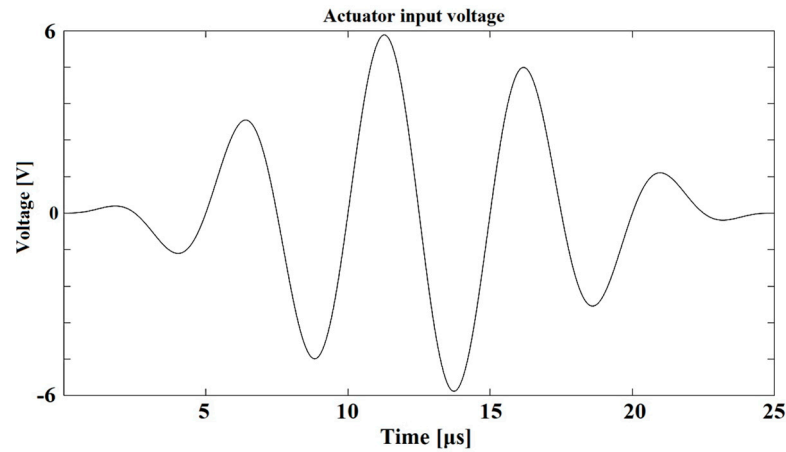


Figure 4. Actuator input voltage applied to the central PZT transducer.

Two two-channel TiePie oscilloscopes (Handyscope HS5) were used for both UGW actuation and reception; the sampling frequency is of 200 MHz, the duration is 200 μ s for a total of 40,000 sample points, and the resolution is of 12 bits. Each acquisition, encompassing both actuation and measurement of the released wave signals, was repeated 64 times; the average of the 64 final raw signals gathered by each sensor is calculated to prevent potential errors during the test, including those induced by environmental noise. Figure 5 represents the test rig along with the wave propagation measurement instruments.

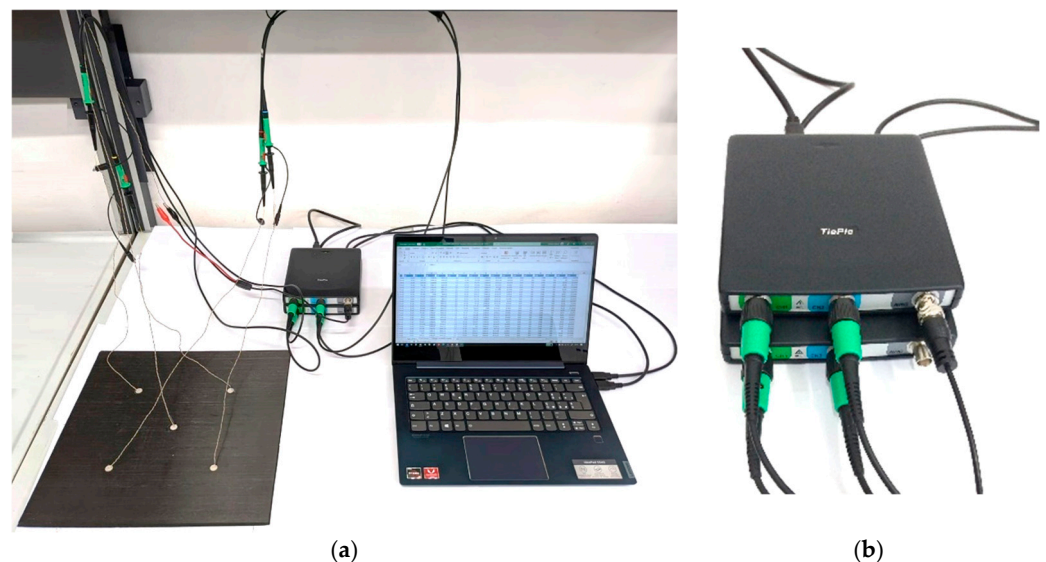


Figure 5. Test rig (a) and wave measurement (b) instruments.

The current research tackled two distinct issues: damage localization (R-Class) and damage severity detection (S-Class). For each of these categories, a unique dataset was generated using UGW test. The initial hypothesis involved 160 sample tests, whereas the second scenario incorporated 540 observations. Upon data collection, three procedures were implemented: noise reduction, feature extraction, and feature selection. The features identified through these stages were then inputted into machine learning classifiers. All the aforementioned steps are detailed for each of the two classification issues in the subsequent sections. Figure 6 illustrates the workflow of the research process.

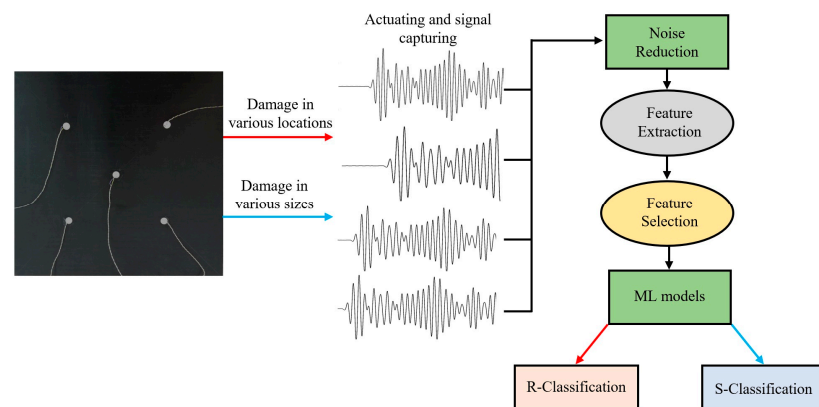


Figure 6. Flowchart of the stages proposed in this work.

2.2. Damaged Region Classification (R-Class)

Damage identification is the first fundamental step that the UGW-based SHM must undertake. In this context, the ML was first used here to ascertain the presence of damage within a given plate and to discern the specific “region” of structural damage, if it exists. Subsequently, the system endeavors to estimate the extent and severity of the damage, along with its precise spatial localization within the structure.

To experimentally reproduce several different damage configurations without necessarily increasing the samples number, the effect of a BVD can be simulated through an added mass (reversible damage) placed on the surface of the plate. To accomplish this, a wooden cube with in-plane dimensions of 20 mm × 25 mm and a thickness of 10 mm was used for the experiments (Figure 7a). A mass of 0.3 kg was applied to the cube to ensure contact with the plate. The structure was thus partitioned into four equal-sized regions denoted as R_i , with $i = 1, 2, 3, 4$, as illustrated in Figure 7b. The experiment was run 40 times in each region using a randomly chosen fault location on each occasion. Specifically, “R-Class i ” refers to the damaged region R_i . The remaining 4 sensors ($S-i$, $i = 2-5$, located in the diagonal directions) captured the signals while the sensor $S-C$ (located in the center) activated the plate. Only the signals related to the damaged conditions were examined for the feature extraction process. The entire length of the received signals was considered, and two sensor pairings—comprising sensors 2 and 3, and 4 and 5, respectively—were investigated. The primary objective of the research was to determine whether or not damage localization could be demonstrated using only two sensors on the assumption that the number of observations is limited. The machine learning algorithm was used for this purpose.

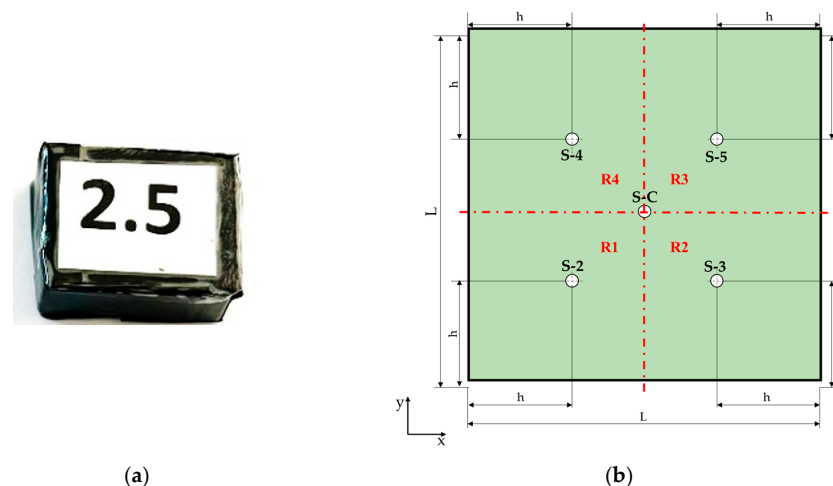


Figure 7. (a) Wooden cuboid (simulated damage); (b) schematic of the considered regions on the plate (R-Classes).

2.3. Damage Size Classification (S-Class)

Damage localization and sizing is then the next fundamental step that the UGW-based SHM must accomplish. The SHM system is expected to provide reliable and consistent information concerning the location of the damage on the structure and, potentially, information about its severity (in-plane dimensions, e.g., size). This information is pivotal in enhancing the awareness of the maintenance/repair operation to be performed. Again, a ML approach was used. In order to experimentally replicate a few damage configurations without increasing material costs and waste, damages were simulated through an added mass placed on the surface of the plate. Three wooden cuboids, representing three distinct classes, were considered for the experiments: 20 mm × 25 mm, 20 mm × 35 mm, and 20 mm × 45 mm sized (Figure 8a), hereinafter referred to as S-Class 1, S-Class 2, and S-Class 3, respectively. The cuboids have a thickness of 10 mm, and, prior to testing, a mass of 0.3 kg was applied on each cuboid to guarantee contact with the plate.

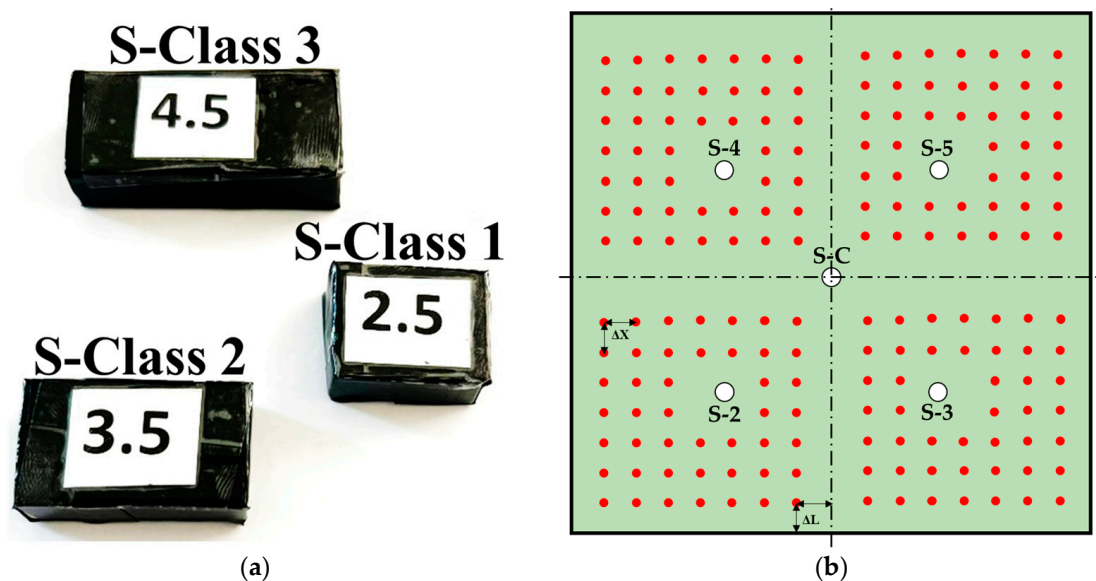


Figure 8. (a) Wooden cuboids (simulated damages) in the three sizes (S-Classes); (b) investigated fault positions.

For each cuboid, 180 tests were performed, varying its position over the plate. Each test consisted of two phases: excitation of the S-C PZT and acquisition of the signals from the remaining 4 sensors (S-i, $i = 2, 3, 4, 5$). More specifically, the plate is assumed to be divided into the four equal zones previously studied, according to the R-classification delineated in Figure 7b. Within each zone, 45 equally spaced damage locations were analyzed. As shown in Figure 8b, the investigated flaw spots were uniformly distributed: the external damages of each region were positioned at a distance $\Delta L = 25$ mm from the region boundaries (both external boundary of the plate and internal borderline), for a total of 24 distinct damage positions, while consecutive spots were arranged at a mutual distance of $\Delta x = 16.67$ mm. The total squared area covered by the damage spots is 100 mm × 100 mm, whereas the areas around the sensors were avoided to prevent the wooden blocks from interacting with the sensors. Hence, 540 tests were performed.

3. ML Algorithm Steps

Various ML algorithms were examined for damage classification, as widely detailed in the following, exploiting the sensitivity of the signals dataset to the damage severity. In a general definition, an ML algorithm consists of several sequential phases: signal pre-processing, signal processing, feature extraction, feature selection, and classification. In the following sections, each of these phases is thoroughly explained.

3.1. Signal Pre-Processing (Denoising)

In this initial phase, collected data undergoes pre-processing for both classification procedures in order to prepare it for the next steps. Concretely, as a result of the experimental acquisitions, signals may contain noises that can threaten the effectiveness of the ML procedure, thus necessitating dedicated attention. Noise can be broadly categorized into two fundamental types: random noise and coherent noise [39]. While the period and, therefore, the frequency, can be precisely measured in coherent (purely periodic) noise, in random (non-periodic) noise the frequency can only be roughly determined, for example between a frequency band. As a result, based on the frequency of the original captured signal, random noise can be categorized as either high-frequency or low-frequency. A significant diversity of high-frequency noise originates from electronics, leading to the potential inclusion of noise generated by sources such as wires and electronic boards in the recorded signal if an analog filter is not present in the data acquisition system.

Therefore, noise reduction plays a fundamental role in almost all experimental works in the field of signal processing. An inadequate management of the noise can adversely affect the feature extraction and machine learning steps. As a matter of fact, high-frequency noise was found to affect the recorded signals in the present investigations. The absence of an analogic filter in oscilloscopes causes this particular type of noise, which has an electrical origin. It can stream from the oscilloscopes' circuits, nearby cables or conductors [40], and can be eliminated or at the very least diminished at the first stage of the signal processing step by using a suitable digital noise reduction technique.

In this paper, different noise-reduction methods were investigated, including the Wavelet Transform (WT), a combination of Savitzky–Golay and Baseline filters (S-G and Baseline), and the Butterworth filter. It was found that the low-pass Butterworth filter [41] provided the most favorable results in terms of noise reduction, while retaining damage-related information. It is worth noting that in this process the filter is in order 4, and the cut-off corner frequency is equal to 0.01 Hz (the optimized parameters were obtained through an iterative process). Figure 9a showcases the raw noisy signals from an undamaged plate, along with its noise-reduced versions produced by the WT (Figure 9b), S-G and Baseline (Figure 9c), and Butterworth filters (Figure 9d).

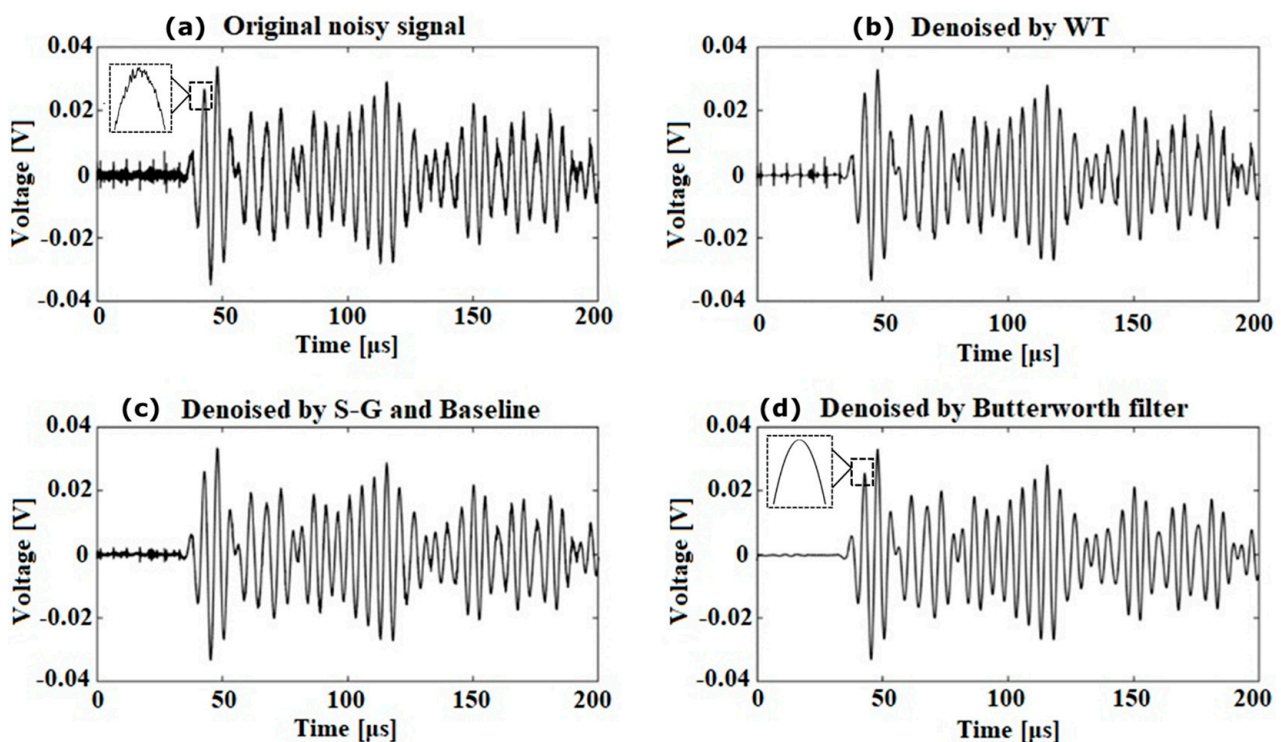


Figure 9. Comparison of various noise-reduction techniques for the undamaged plate signal.

As can be observed from Figure 9, it is clear that the high-frequency noise in the signal was stringently eliminated by the Butterworth filter, whereas the low-frequency components are preserved for the feature extraction step. Figure 10 reveals a comparison between the signal obtained from a pristine configuration (solid line) and the signals collected by receiver S2 in a specific damage configuration (e.g., a specific region of the plate) for each cuboid size (dotted lines). At first glance, all signals appear largely, with no discernible differences. However, by thoroughly analyzing the data (zoomed area in the black circle), some discrepancies can be qualitatively observed: the different damage sizes determine different effects on the signals in terms of both signal amplitude and phase with respect to the pristine one. A first, expedient method for quantitatively discerning damage-related attributes is to extract the damage indices. The DIs set permits the straightforward identification of the most critical path, i.e., the path closest to the possible identified damage. For the example reported in Figure 10, the obtained values along the actuator S-C—receiver S2 path are 0.102, 0.105 and 0.109 for S-Class 1, 2, and 3, respectively. As a result, due to the close resemblance of these signals, and to the very close DI values for each cuboid size, it follows that analyzing the sole signals trend and the DIs set is insufficient for the S-Classification of the damage (severity). Therefore, the utilization of more robust techniques, such as ML tools, is imperative.

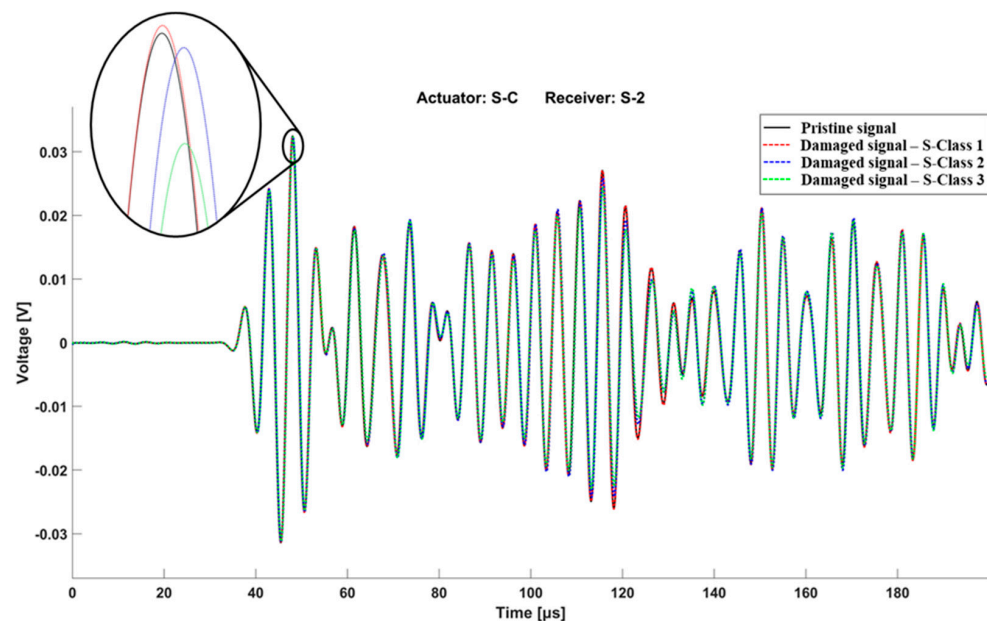


Figure 10. Comparison of the received pristine signal (solid line) and damaged signals (dotted lines) for all S-Classes.

3.2. Feature Extraction

The primary target of any feature extraction plan is the derivation of a suitable set of condition indicators in vector form from the original signal vector. These derived features are intended to be informative for the machine learning exercise [42]. The conventional feature extraction procedures can be divided into two main categories: statistical characteristics and syntactic descriptions; on the assumption of a transient signal, statistical features have proven their ability in revealing the latent discrepancies.

Since statistical formulas can reveal non-linear features and the captured waves in the present study are transient, several statistical features were extracted from each signal.

Statistical features can be extracted either directly from the original signal in the time domain or following a processing (transformation) step. The aforementioned processing can be performed using five well-known methods, including Fast Fourier transform (FFT), Wavelet Transform (WT), eigenvectors, time-frequency distributions, and autoregressive method [43].

The feature extraction process for use in deep neural networks or machine learning classifiers can be performed manually or automatically. Shaheen et al. [44] demonstrated that, if the parameters and features are extracted and selected correctly in a manual feature extraction and selection method, the final accuracy of the classification procedure can be even higher than the automatic process, despite the widespread belief that automatic feature extraction and selection, which is primarily used in deep neural networks, has superior performance.

There are two main ways to use an ML classifier in this context. On the one hand, the time-series signal can be directly fed into the classifier, and the most beneficial features can then be automatically extracted via a dimension reduction technique such as Principal Component Analysis (PCA), or Linear Discriminant Analysis (LDA) [45]. On the other hand, a feature vector can be manually extracted from each signal, whether in the time, frequency, or time-frequency domain, and then added to a classifier [46]. Although finding a suitable feature in the latter case is a specialized task and implies full knowledge about the nature of the signal, the required computational capacity after the feature extraction step is much lower than the mentioned dimension reduction methods. Features such as statistical, entropy, amplitude of frequency components, and wavelet coefficients can be extracted based on the nature of the signal [47].

Since the sampling frequency is 200 MHz, the dimension of each signal in the time domain is $1 \times 40,000$, so adding it to an ML classifier without extracting the suitable features can pose computational challenges.

In the pursuit of discerning the presence and location of the damage, i.e., the R-Classification, a dataset comprising 160 samples was built (40 different and random faults for each of the four regions “Ri” (Figure 7b)). For each sample test, 120 features were extracted in time, frequency, and time-frequency domain, i.e., 30 features for the signal of each of the 4 channels (sensors). The amplitudes of some of the features listed in Table 2 were found to be significantly higher than others. For example, the average value of the MDET1 vector for sensor 2 was -6.31×10^{-19} , while the mean value of the SFDR vector for sensor 3 was equal to 62.05. To ensure impartiality in the classification phase and prevent bias due to large magnitudes, it is necessary to scale the feature vectors. This entailed rescaling all 120 feature vectors to fall within the range [0, 1].

In order to get information on the size of the damage, i.e., the S-Classification, the same set of features as listed in Table 2 was extracted. In this case, for the feature extraction phase, the full length of the signals was selected.

3.3. Feature Selection

Conductive to prevent the classification algorithm from adapting to the observed data rather than learning the features, i.e., overfitting, the number of features that are intended to be used in the classification procedure should be proportional to the number of observations. A high number of features in the feature vector may improve the training stage, but the accuracy of the testing step can diminish sharply [48]. In fact, since there are non-informative features among the extracted items, they can confuse the network and detrimentally impact both the training and testing stages.

As a result, it is imperative to identify and prioritize the most salient and informative features. A variety of feature selection methods are available, ranging from metaheuristic techniques to more straightforward statistical tests such as the *t*-test [49].

On the one hand, as far as the R-Classification is concerned, it was accomplished using two different sensor configurations. Feature selection was executed independently for the S2–S3 and S4–S5 combinations, as will be demonstrated in the following: the features that proved suitable for the complex S2–S3 configuration did not exhibit the same efficacy for S4–S5.

Table 2. Extracted feature for each channel (sensor).

Number	Name of the Feature	Number	Name of the Feature
1	Shape factor	16	Maximum fractal length (MFL)
2	Kurtosis	17	Logarithmic representation of Teager-Kaiser energy operator (LTKEO)
3	Skewness	18	Spurious free dynamic range (SFDR)
4	Peak value	19	Band power
5	Crest factor	20	Amplitude of the first frequency harmonic (AFFH)
6	Impulse factor	21	Frequency of the first frequency harmonic (FFFH)
7	Clearance factor	22	Second root of the summation of the power values of persistence spectrum (SRPVPS)
8	Signal-to-noise ratio (SNR)	23	Mean value of the wavelet approximation coefficients in level 4 (MAPP4)
9	Total harmonic distortion (THD)	24	Mean value of the wavelet detail coefficients in level 1 (MDET1)
10	Signal to noise and distortion ratio (SINAD)	25	Shannon entropy
11	Difference absolute standard deviation value (DASDV)	26	Difference absolute mean value (DAMV)
12	Logarithmic representation of DASDV (LDASDV)	27	Waveform length
13	Variance	28	Teager-Kaiser energy operator (TKEO)
14	Standard deviation (SD)	29	Logarithm transformation of DAMV (LDAMV)
15	Mean absolute deviation (MAD)	30	Median

The feature selection phase was carried out using the Sequential Forward Selection (SFS) technique. This way, features are incrementally added to an empty feature vector until the rest features do not diminish the criteria. A custom criterion was identified with the intention of setting the maximum number of iterations to infinity, and the 5-fold cross-validation method was introduced as the validation procedure. Additionally, a relative objective function with a termination tolerance of 1×10^{-6} was established.

After the feature selection procedure, the selected feature vector for the combination of sensors S2–S3 contains 9 features as presented in Table 3.

Table 3. R-Classification: name of selected features for sensors pair S2–S3.

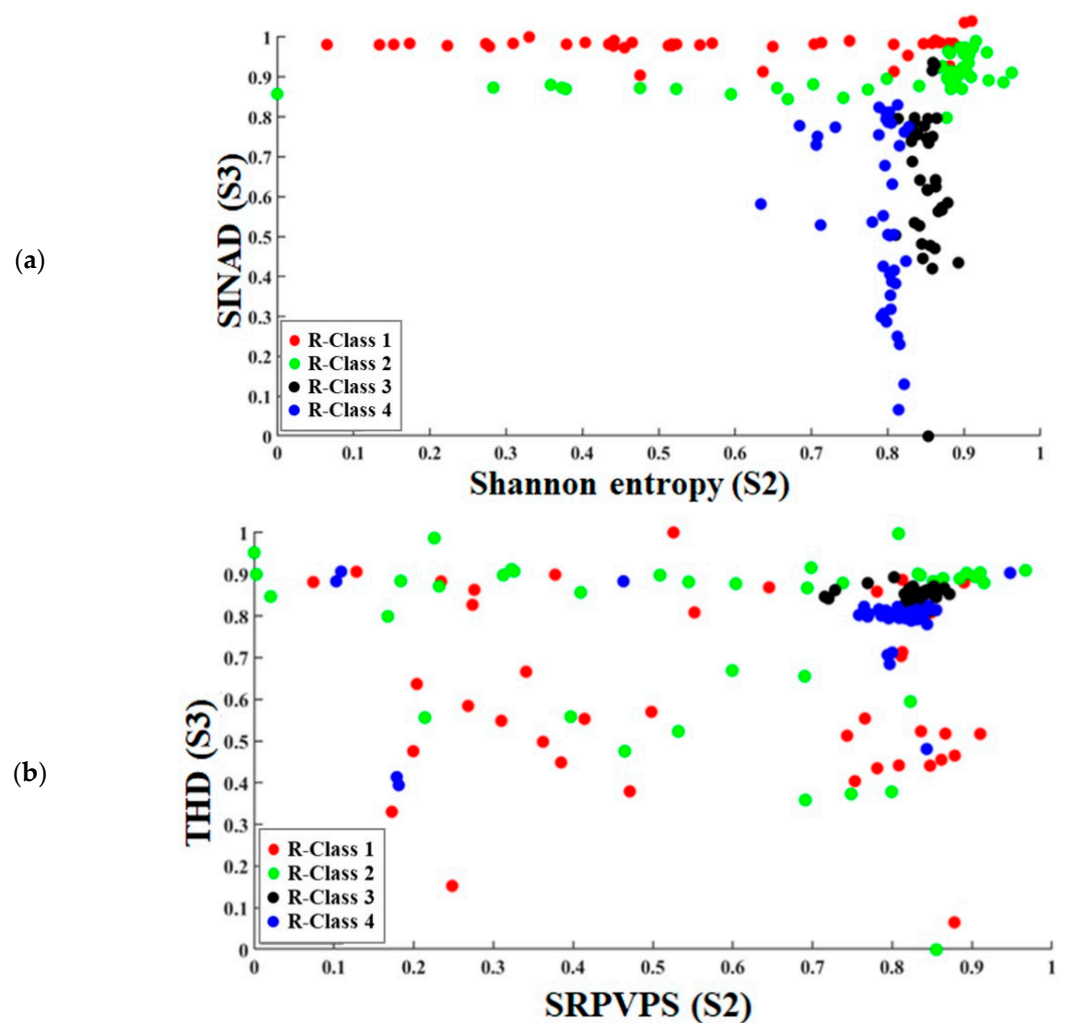
Number	Name of the Feature	Number of the Sensor
1	SNR	S2
2	SINAD	S2
3	DASDV	S2
4	Shannon entropy	S2
5	Crest factor	S3
6	Clearance factor	S3
7	SINAD	S3
8	SFDR	S3
9	Shannon entropy	S3

Similarly, the same process—the SFS—was carried out for the pairing S4–S5, with the exception that in this instance, 12 features were chosen using the same feature selection algorithm criteria. The features that were chosen for the S4–S5 combination are displayed in Table 4.

Table 4. R-Classification: name of selected features for sensors pair S4–S5.

Number	Name of the Feature	Number of the Sensor
1	Shape factor	S4
2	Kurtosis	S4
3	Crest factor	S4
4	SNR	S4
5	SINAD	S4
6	DASDV	S4
7	Kurtosis	S5
8	LDASDV	S5
9	Variance	S5
10	SD	S5
11	Band power	S5
12	Shannon entropy	S5

For each of the combinations S2–S3 and S4–S5, two selected and two unselected features are scattered in Figures 11 and 12, respectively, to provide a better visual representation of the importance of a feature selection procedure. There are many overlaps between the various classes on the “b” side of the plots, whereas on the “a” side the classes can be more clearly distinguished. The classification process will be more accurate thanks to this improved detection capability.

**Figure 11.** R-Classification: (a) two selected features; (b) two unselected features for sensors pair S2–S3.

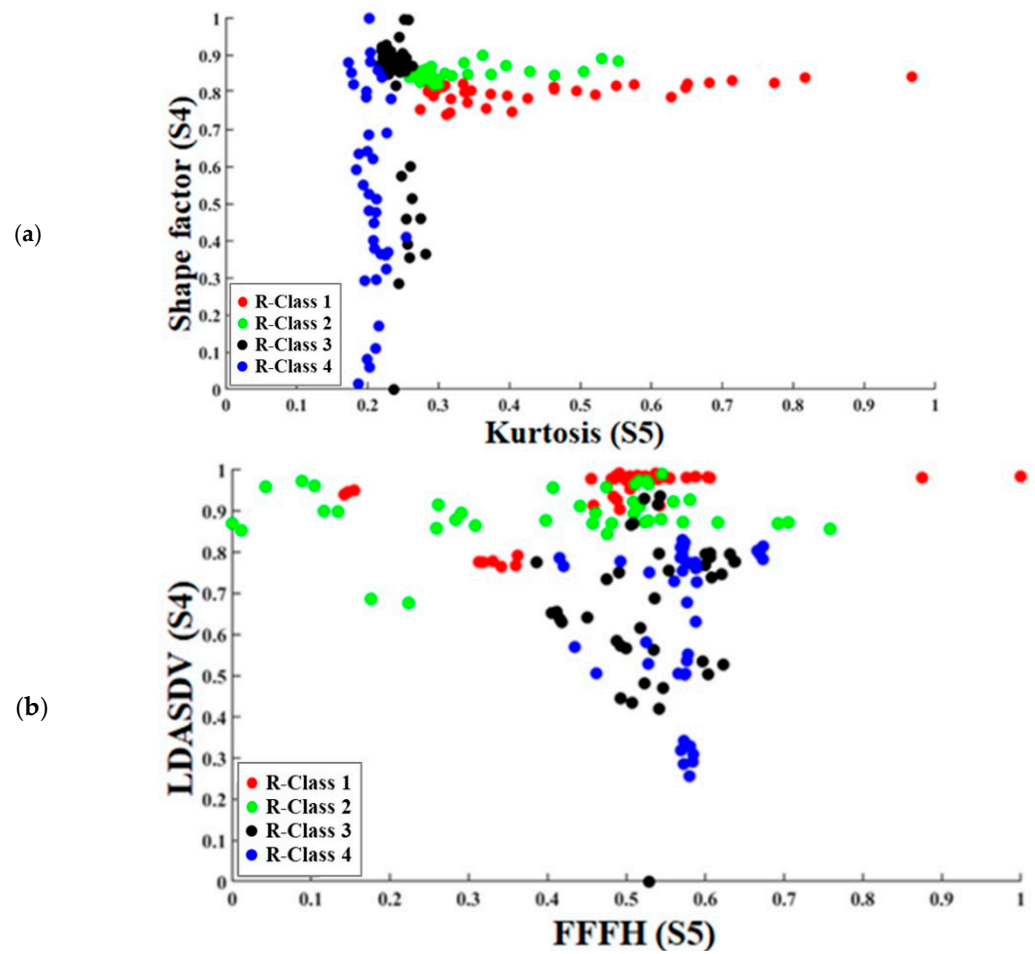


Figure 12. R-Classification: (a) two selected features; (b) two unselected features for sensors pair S4–S5.

For the S-Classification task, an analogous procedure employing SFS with the specified criteria led to the automatic selection of the most informative 13 features. The outcome of the S-Classification features selection process are presented in Table 5.

Table 5. S-Classification: name of selected features for all sensors.

Number	Name of the Feature	Number of the Sensor
1	DASDV	S2
2	DASDV	S3
3	Waveform length	S3
4	Waveform length	S4
5	Variance	S4
6	MAD	S3
7	MFL	S2
8	MFL	S5
9	TKEO	S3
10	TKEO	S4
11	LDAMV	S4
12	Median	S3
13	Median	S4

To improve the representation of the results, the scatter plot of waveform length S3 and LDAMV S4 was graphed in Figure 13a; the scatter plot for the same features and for sensors 2 and 3 was plotted in Figure 13b. Since there is more overlap between classes in Figure 13b compared with Figure 13a, these two features can result in wrong classification.

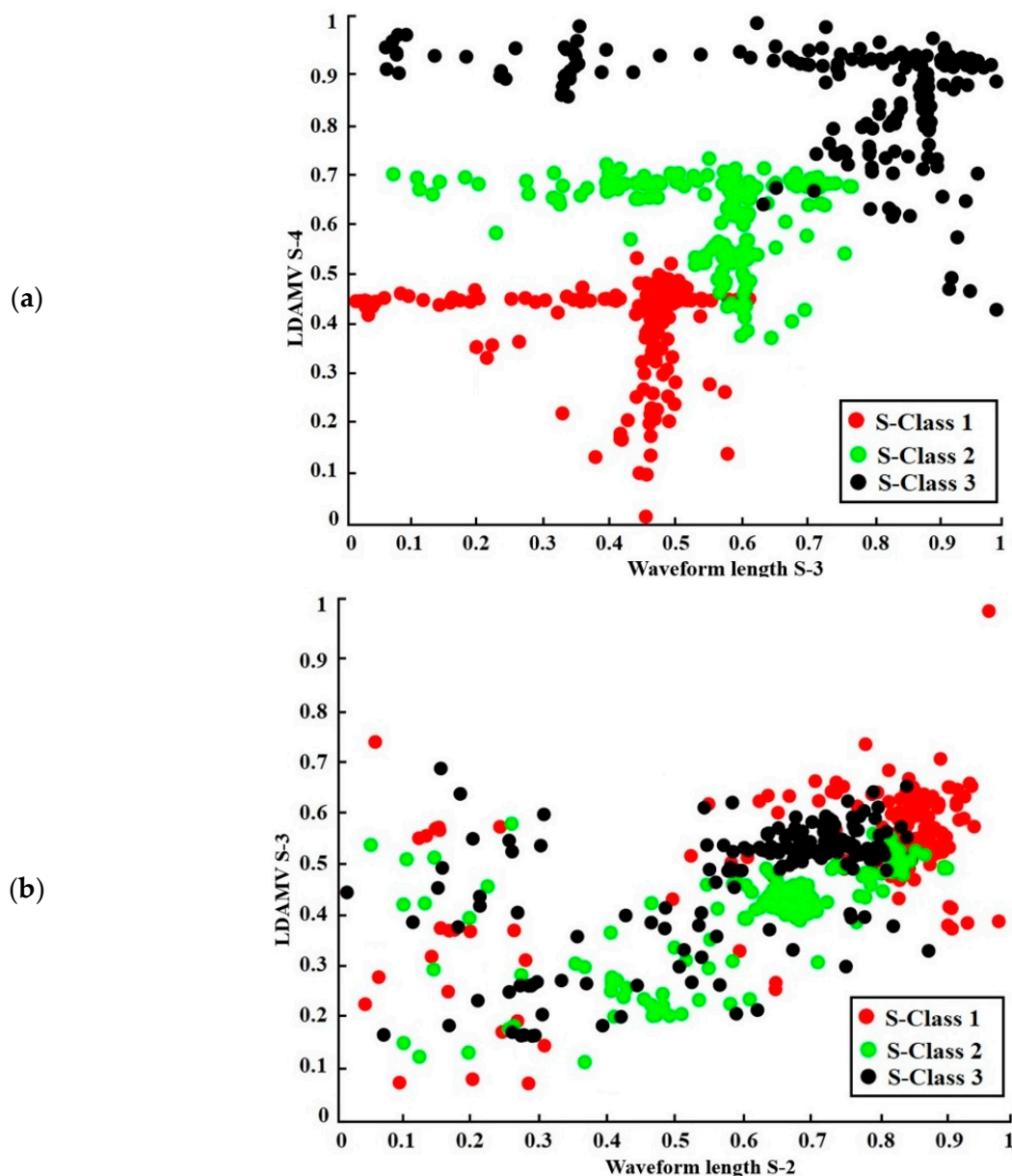


Figure 13. S-Classification: scatter plot of waveform length and LDAMV for (a) sensors 3 and 4, and for (b) sensors 2 and 4, respectively.

Although there is some overlap in the graph, from Figure 13a it can be well appreciated that each S-Class covers a distinguishable area of the plot; moreover, a few numbers of outliers can be seen. It is worth noting that the presence of outliers in the dataset is acknowledged and retained, as their occurrence is inherent in real-world scenarios. Overall, this level of distinguishability is deemed acceptable for an experimental work where the environmental noise, potential human errors, and instrument limitation can all influence the outcome.

4. Classification and Results

In the realm of machine learning, three fundamental classification techniques exist: supervised, unsupervised, and reinforcement learning. While the output labels are not introduced in an unsupervised classification procedure such as clustering, they are pre-distinguished in supervised ML algorithms such as Support Vector Machine (SVM). On the other side, a reinforcement learning algorithm works in such a manner to maximize the cumulative rewards; in this process, the data type is not predefined [50,51].

The objective of the current study is to conduct a comparative evaluation of the accuracy of diverse supervised machine classifiers. For this purpose, labels (classes) are introduced along with the dataset.

4.1. R-Classification

In the present study, supervised machine learning algorithms were employed for detecting the damage location, i.e., the R-Classification. Two different feature vectors were evaluated, derived from selected features obtained from sensors 2 and 3, and features belonging to sensors 4 and 5 (refer to Tables 4 and 5, respectively). The Classification Learner application available in MATLAB® was used for this sake. The dataset was partitioned such that 85% was allocated to the training phase and the remaining 15% to the testing phase. Importantly, these two sets were randomly selected from the specified feature vectors before entering the application environment.

As a starting point, all available classification algorithms in the eight families, i.e., decision trees, discriminant analysis, Support Vector Machines, nearest neighbor, kernel approximation, ensemble, neural network, and Naive Bayes classifiers, were trained on the feature vector belonging to sensors 2 and 3. Upon comparing the validation accuracies, it was found that the “Bagged Trees” belonging to the ensemble family exhibited the highest performance, e.g., 92.9%.

The next step was to implement an optimization scheme for this family using “Bayesian optimization” as the optimizer, “expected improvement per second plus” as the acquisition function with 200 iterations, and “decision tree” as the learner type to find the tuned hyperparameters. Figure 14 shows the performance of the optimization procedure in terms of minimum classification error versus the number of optimizer iterations. The Best point hyperparameter (the red square in the figure) was reached after 33 iterations when the ensemble method was set to “Bag”. The observed minimum classification error, the number of learners, the maximum number of splits, and the number of predictors to sample were, in that order, 0.0368, 366, 134, and 3.

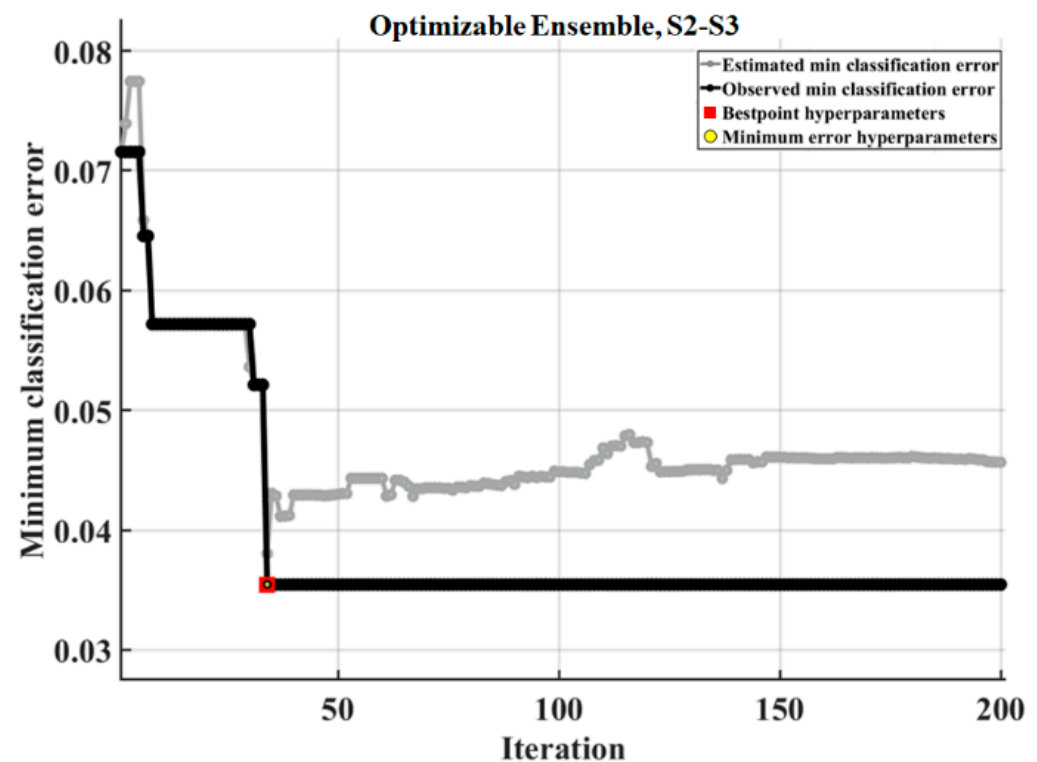


Figure 14. R-Classification: the optimization process for the tuned hyperparameters for the network in the case of S2–S3.

Figure 15a,b show the confusion matrices for the training and testing phases, respectively, using the optimized network on the assumption of the sensors pair S2–S3. In the confusion matrices, R-Class 1, R-Class 2, R-Class 3, and R-Class 4 are represented by numbers 0, 1, 2, and 3, respectively. The validation accuracy increased in this instance to 96.32%. Only 5 out of 136 samples were mistakenly classified. Furthermore, the observed accuracy in the testing stage was 95.83%. Additionally, the average F1-score and sensitivity of the testing phase are both 0.958.

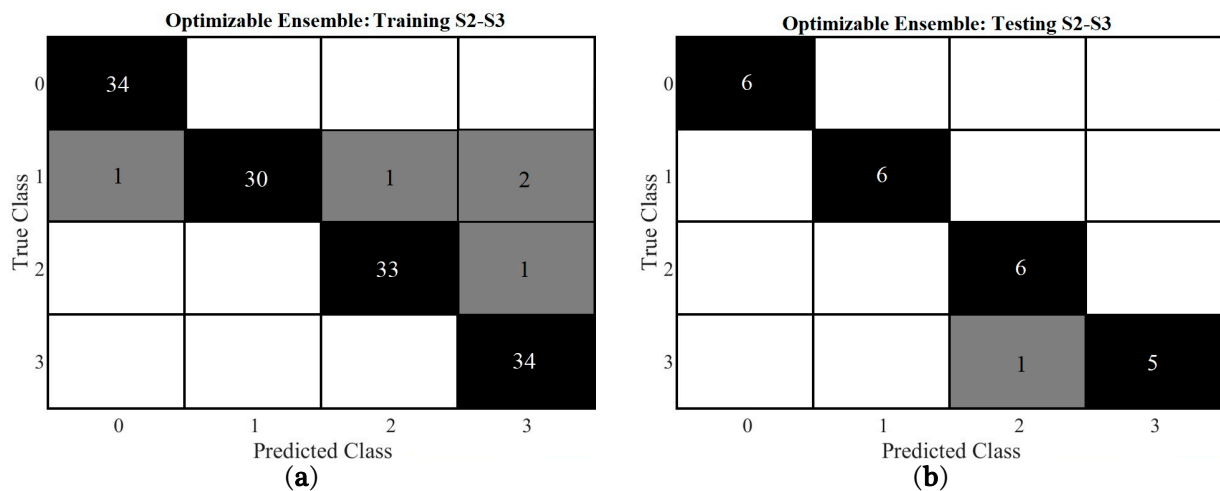


Figure 15. R-Classification: (a) confusion matrix for the training phase; (b) confusion matrix for the testing phase in the case S2–S3.

As depicted in the graphs of Figure 15, out of the 136 samples randomly assigned to the training phase, only 5 were misclassified. Specifically, 1 sample from R-Class 2 was classified as R-Class 1, 1 sample from R-Class 2 was classified as R-Class 3, 2 samples from R-Class 3 were classified as R-Class 4, and just 1 sample from R-Class 3 was classified as R-Class 4. During the testing phase, only 1 sample from R-Class 4 was incorrectly classified as R-Class 3.

The process previously outlined was then applied to the feature vector selected from sensors 4 and 5, as specified in Table 5. In the training phase, the initial accuracy was 92.71%, with the “Bag” ensemble method exhibiting superior performance. Using the same optimization settings as the previous case, the AdaBoost ensemble method with 488 learners, a learning rate of 0.86794, a maximum of 6 splits, and a minimum classification error of 0.028429 was determined through the tuning procedure. The optimization procedure based on the minimum classification error per number of iterations is illustrated in Figure 16. It is worth mentioning that after 144 iterations, the Best point hyperparameters were explored. The training and testing confusion matrices with accuracy values of 96.32% and 91.67%, respectively, are shown in Figure 17a,b. In the confusion matrices, R-Class 1, R-Class 2, R-Class 3, and R-Class 4 are represented by numbers 0, 1, 2, and 3, respectively. Furthermore, during the testing phase, the average F1-score and sensitivity stand at 0.935 and 0.958, respectively.

Comparatively, the accuracy during the training phase remained consistent at 96.32% for both feature vectors. However, the testing accuracy in the cases of sensors 4 and 5 was slightly lower than in the first case, i.e., 91.67% and 95.83%, respectively, despite a higher number of selected features (12 compared to 9 for sensors 2 and 3).

As depicted in the previous graphs of Figure 17, out of the 136 samples randomly assigned to the training phase, again only 5 were misclassified. Specifically, 2 samples from R-Class 3 were classified as R-Class 1, 1 sample from R-Class 3 was classified as R-Class 2, 1 sample from R-Class 3 was classified as R-Class 4, 1 sample from R-Class 4 was classified as R-Class 3. During the testing phase, only 1 sample from R-Class 1 was incorrectly

classified as R-Class 4, and only 1 sample from R-Class 2 was incorrectly classified as R-Class 3.

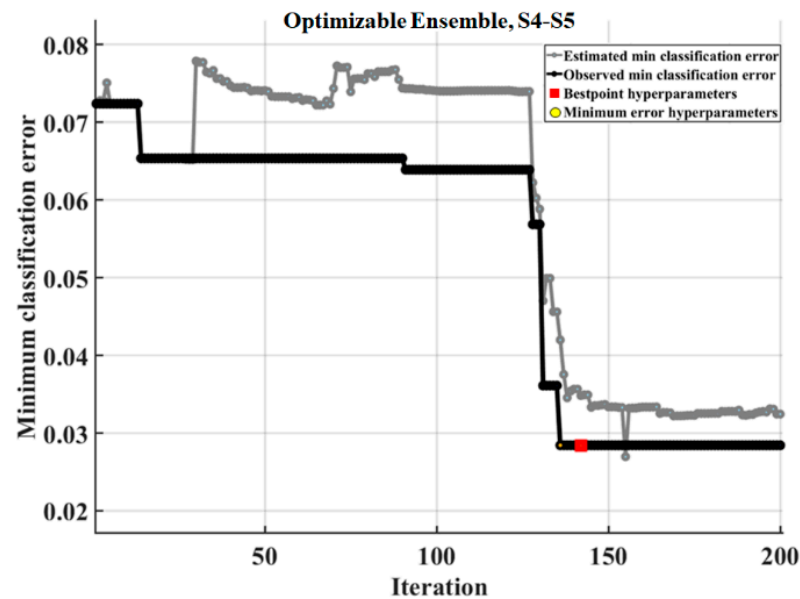


Figure 16. R-Classification: the optimization process for the tuned hyperparameters for the network in the case of S4–S5.

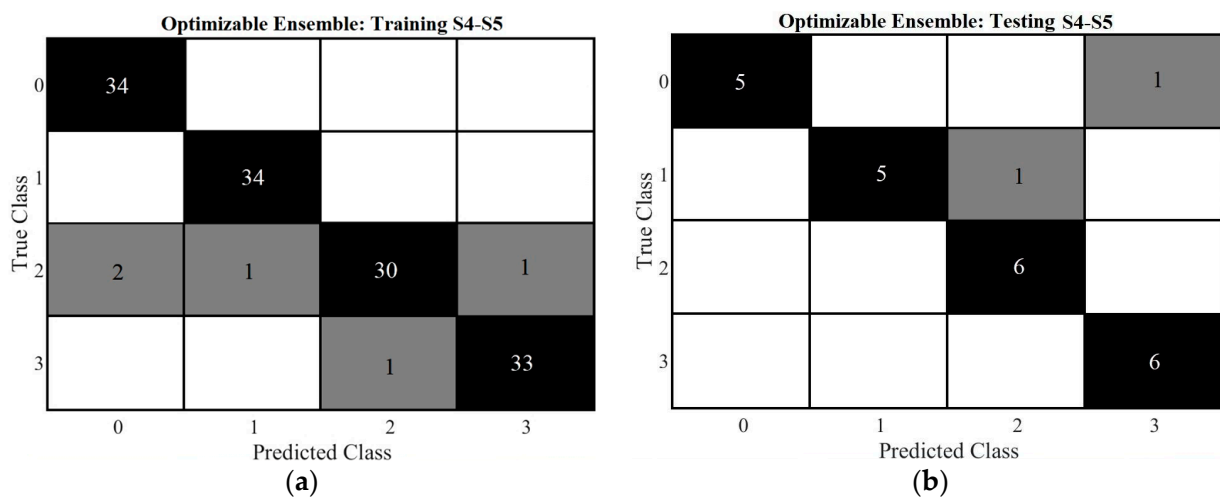


Figure 17. R-Classification: (a) confusion matrix for the training phase; (b) confusion matrix for the testing phase in the case S4–S5.

While the four receiving sensors were initially installed on the plate structure under consideration, the results of the training and testing phases on the two distinct conditions, i.e., sensors pair S2–S3 and S4–S5, suggest that analyzing the signals of only two sensors, either in the lower or upper part of the structure, can be sufficient to identify the occurrence of the damage and its location within the faulted region.

4.2. S-Classification

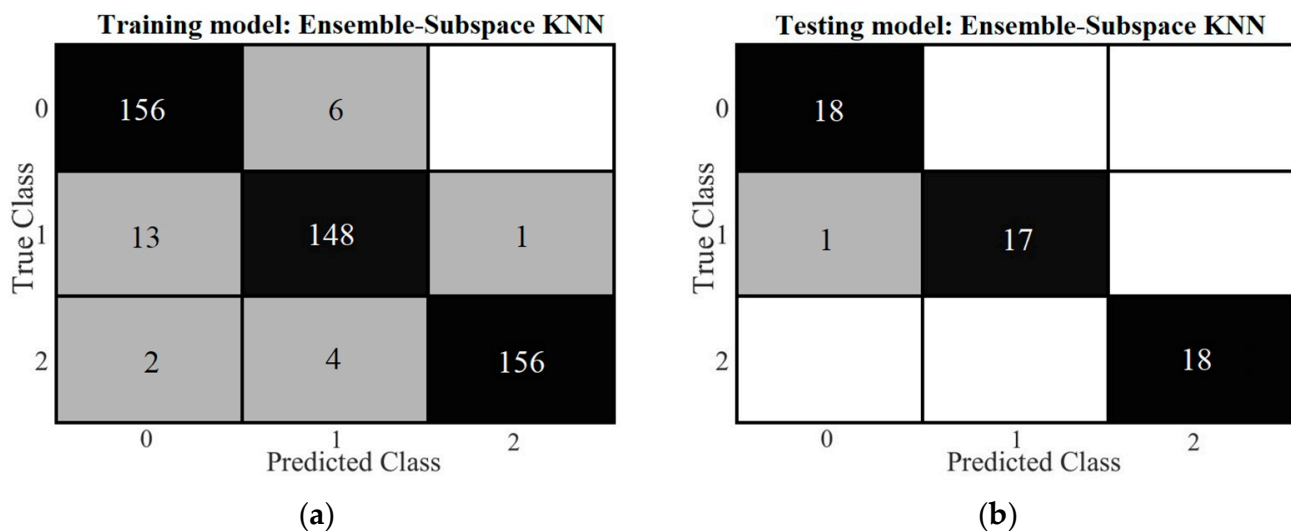
The feature matrix, consisting of 540 samples and 13 features, is utilized for size detection, specifically for the S-Classification. During the testing phase, 10% of the dataset was allocated for evaluation and the 5-folds cross-validation method was selected as the validation scheme. The best performing machine learning classifier models were determined by running various algorithms, and the results are summarized in Table 6.

Table 6. Accuracy of the S-Classification procedure with different algorithms.

Classification Algorithm	Validation Accuracy (%)	Testing Accuracy (%)
Ensemble-Subspace KNN	94.65	98.15
Ensemble-Bagged Trees	94.2	98.15
KNN-Fine KNN	93.6	96.3
Ensemble-Boosted Trees	93.4	98.15
Kernel-SVM Kernel	92.8	98.15
Linear Discriminant	92.4	94.4
SVM-Quadratic SVM	92.2	94.4

Table 6 showcases that the Ensemble-Subspace KNN algorithm boasts the highest validation accuracy of 94.65%. It is important to note that this algorithm uses the Subspace method for the ensemble and the nearest neighbors learning type, with a total of 30 learners. The Ensemble-Subspace KNN algorithm, alongside the Ensemble-Bagged Trees, Ensemble-Boosted Trees, and Kernel-SVM Kernel, achieved the highest accuracy in the testing phase, which was 98.15%. During the testing phase, the mean F1-score and sensitivity were recorded as 0.990 and 1, therefore. A higher accuracy in the testing phase compared to the validation accuracy suggests that the algorithm has not been overfitted during the training phase. Furthermore, since the accuracy in the testing phase is high enough, no optimization process was carried out to tune the hyperparameters.

The confusion matrices for the training and testing phases of the Ensemble-Subspace KNN algorithm are shown in the following graphs, Figure 18a,b. It should be emphasized that S-Class 1, S-Class 2, and S-Class 3 are represented by indices 0, 1, and 2, respectively.

**Figure 18.** S-Classification: confusion matrices for (a) training and (b) testing steps.

As depicted in the previous graph, out of the 486 samples randomly assigned to the training phase, 26 samples were misclassified. Specifically, 6 samples from S-Class 1 were classified as S-Class 2, 13 samples from S-Class 2 were classified as S-Class 1, 1 sample from S-Class 2 was classified as S-Class 3, 4 samples from S-Class 3 were classified as S-Class 2, and 2 samples from S-Class 3 were classified as S-Class 1. During the testing phase, only 1 sample from S-Class 2 was incorrectly classified as S-Class 1.

5. Conclusions

This research explored the application of machine learning (ML) classification techniques to classify damaged plates based on their failure location and size, e.g., R-Classification and S-Classification tasks.

In the initial phase of the experiment, a composite plate measuring 300 mm × 300 mm was used, with a cuboid of 20 mm × 25 mm placed on its surface to simulate various reversible damage configurations. Guided waves were propagated over the plate through a central piezoelectric sensor, and the resulting diagnostic waves were captured by four sensors placed in diametrically opposed directions. The plate was divided into four equal regions, and the experiment was repeated 40 times for each region, moving the damage position in each of the plate's four zones. After collecting 160 signals, high-frequency noises were filtered out using the Butterworth filter, and 30 features were extracted in the time, frequency, and time-frequency domains. The 120 extracted features were designated as the primary feature vector for each experiment. To examine the ability to localize damage using only two sensors, 9 features were selected for the combination of sensors 2 and 3, and 12 features were selected for the combination of sensors 4 and 5 using the sequential forward selection procedure. Several ML classifiers were then used to classify the labeled signals using MATLAB® Classification Learner App. As the primary accuracy was not satisfactory, an optimization process was employed to find optimized hyperparameters. The final accuracy in the training and testing phases was 96.32% and 95.83%, respectively, for the selected features from sensors 2 and 3. Meanwhile, the training accuracy remained consistent at 96.32%, but the testing accuracy decreased to 91.6% for the combination of sensors 4 and 5.

In the second section and to intelligently detect the damage size, three cuboids of 20 mm × 25 mm, 20 mm × 35 mm, and 20 mm × 45 mm were used to experimentally simulate various damage scenarios on the same plate as the previous part. For each damage size, the test was repeated 180 times, changing their positions across the plate. Once the 540 signals were collected by the four sensors, the same procedure involving noise reduction, feature extraction, and feature selection was employed with the difference that the data from all four receiving sensors is used in the feature extraction. In the classification stage the 13 selected features were fed into the existing classifiers models, the Ensemble-Subspace KNN emerges as the best performer, scoring 94.7% and 98.1% accuracy in the validation and testing phases, respectively.

The findings demonstrated the potential of this technique for the damage diagnosis in composite plate-like structures, whereas only two receivers can be employed for the automatic sake of localization and severity without losing accuracy.

Implementing the proposed methodology may present certain challenges, particularly due to potential uncertainties arising from varying environmental conditions. This is because piezoelectric sensors, which are integral to the methodology, are highly sensitive to temperature changes. This sensitivity could lead to shifts in the distribution of classes between the training (source) and testing (target) domains. A possible solution to mitigate these effects could involve the use of a domain-adaptation algorithm, which could be explored in future research.

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