CONVOLUTIONAL NEURAL NETWORKS ALGORITHMS FOR STRUCTURAL HEALTH MONITORING OF AIRCRAFTS COMPOSITES PANELS

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Abstract

Composite materials replaced metals even in aircrafts primary structures but they can be affected by hidden damages hardly detectable. An SHM system based on sensorised structures and deep neural networks signal analysis methodologies is presented in this paper with the scope of detect and localise delaminations into composites plates.

Keywords: Structural Health Monitoring, composites structures, Convolutional Neural Networks, Finite elements modelling, guided waves propagation

1. Introduction

The latest developments push the modern aerospace industry towards improving manufacturing, automation, and flight efficiency, leading to a significant increment in the usage of composite materials. One reason is their potential in strength-to-weight ratio and automatized production processes. They allow lower weights and obtain easily more complex shapes, but due to their peculiar composition and fabrication methods, they are affected by delaminations and defects. So, every aircraft component is subject to time-scheduled maintenance sessions even when there is no clear evidence of repairs. It becomes an expensive and time-consuming process.

In this field, the availability of SHM systems [1,2,3,4], based on networks of distributed sensors embedded or secondary bonded throughout the whole structure under investigation, could be conveniently used for real-time health monitoring and/or as a data acquisition tool. Structural data, however, may constitute an enormous amount of information that, in most cases, is difficult to classify. Furthermore, since time is an essential factor, the automation of the analysis process could be a significant advantage in this field. From this point of view, intelligent algorithms that can autonomously reduce human participation, like Deep Neural Networks (DNNs), may be helpful in overcoming this impasse.

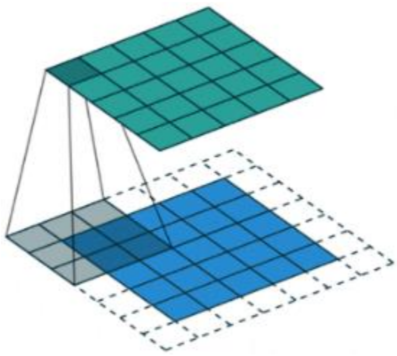
Structural data can be analyzed with specific DNNs designed and trained to classify and identify significant parameters [5,6,7,8]. The DNNs, based on strategic engineering criteria, may represent an effective and efficient analysis tool to promote faster data analysis and classification. In the field of aircraft maintenance, this approach may lead, for example, to a faster awareness of a component's health situation or predict failures. Neural Networks typically require a relevant amount of data to be trained and to acquire the necessary reliability in classifying and recognizing the occurrence of the selected event. However, once trained, they can be extremely effective and low time-consuming in analyzing every single scenario to be classified. Deep-learning networks can automatically extract high-level features from signals and capture differences in waveforms without the requirement of any prior knowledge. As a consequence, deep-learning networks have been often used in combination with guided waves for intelligent damage detection, including artificial neural networks, deep neural networks, recurrent neural networks, autoencoder networks and convolutional neural networks (CNN). In this work, the potentialities of deep learning with high-frequency Lamb waves propagation-based SHM methodologies are investigated, also employing explicit finite element simulations to augment numerical propagation signals due to impact damages on a composite plate [6].

This work will concentrate on the approaches developed by the authors within the framework of convolutional neural networks aimed at supervised learning methodologies for damage detection and localisation in composite aerospace structural components. Unsupervised learning approaches present the undoubtful advantage of permitting to train the networks only by pristine (or healthy) configuration signals, being that the networks themselves can detect anomalies in test signals when acquired on a perturbed structural scenario (with a certain threshold of uncertainty); this methodology, as cons, cannot permit to classify the typology, severity or location of the damage. These latter features can be in principles categorized by a supervised learning approach, where a network able to classify signals coming from many damage scenarios can be trained, provided that enough data (and their experimental variability) can be available for each class to be recognized; it is clear how this requirement implies the availability of data from many damaged structural items both "physical" or "virtual" (i.e., simulated by a mathematical model previously validated by experiments); lately many works on how to employ machine learning techniques for generating “synthetic training data” for ultrasonic NDE have been published demonstrating that ML can also be employed to enrich propagation signals data-bases [6] . The paper will present examples of CNN employ for supervised structural damage detection; the presented results are based on strain-guided waves analysis and represent the latest achievements after some years of previous works in which the authors developed, collaborating with other international research groups, different machine learning based approach for structural health monitoring.

2. Description of methodologies

2.1 Convolutional Neural Networks

The Convolutional Neural Networks (CNN) represent a group of highly successful deep neural network architectures adopted in computer vision applications and in applications that process media such as audio and video. The most popular application of convolutional neural network is to identify, by a computer and with a certain probability, what an image represents. Such networks are built to analyze images included within certain datasets and classify objects in the images within them. The basic structure of a convolutional neural network consists of a convolutional layer, a nonlinear activation function, a pooling layer, and a fully connected layer. A convolutional process applied to an image is equivalent to applying a filter to that image. Convolution is defined by an array called the kernel, which is generally smaller than the image, and is applied by translating the kernel to it. The result of the convolutional filter depends on the numerical content of the kernel matrix. Varying the convolutional kernels, it is possible to obtain an infinity of filters, which can highlight some characteristics of the image and hide others. Generally, a convolutional layer manages several kernels that are all applied to the same input image, so that it is possible to have many different filters.



Example of convolution

Convolution layer filters provide denser information, highlighting some features and eliminating others that would constitute noise. So, a pooling operation is applied to decrease the size of the input image, maintaining the main characteristics of the same.

The input image is scanned with the pooling matrix obtaining a submatrix containing the maximum value (Max pooling) and the average value (Average pooling) of all input elements. The result is not a simple resizing of the image because the maximum or average information is maintained.

SHM algorithm implementation

The goal of the work is to develop a neural network capable of detecting damage and its position in a composite panel exploiting Lamb waves. For this purpose, a numerical model was used to simulate the propagation of Lamb waves in a flat composite panel in order to enrich the experimental data available. Then, a Matlab algorithm has been created to transform the detected signals into images that the adopted neural network classifies as damaged or intact.

2.2 Numerical model and signal analysis

The composite panel considered consists of 12 plies of three different pre-preg types oriented according to multiple directions. Plies material characteristics are summarized in Table 1.

Material	ρ	E_1	E_2	E_3	$G_{12} = G_{23} = G_{31}$
5harness	$1.77\, g\, cm^{-3}$	$65\,000\, MPa$	$65\,000\, MPa$	$8800\, MPa$	$3600\, MPa$
Biaxial	$1.79\, g\, cm^{-3}$	$81\,000\, MPa$	$81\,000\, MPa$	$8800\, MPa$	$4100\, MPa$
Uniaxial	$1.79\, g\, cm^{-3}$	$152\,000\, MPa$	$8800\, MPa$	$8800\, MPa$	$4100\, MPa$

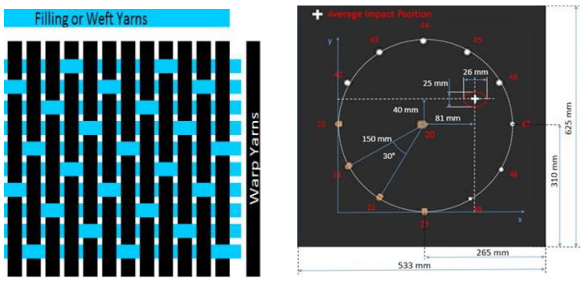
Table 1 – material properties

The lamination sequence can be written as:

$$[5H(0°/90°), B(+45°/-45°), U(0°/90°), U(0°/90°), B(+45°/-45°), B(0°/90°)]s$$

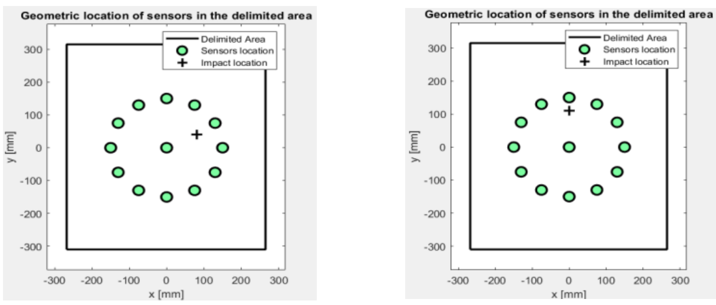
Where 5H ("5harness") is a particular biaxial fabric characterized by the overlapping of one warp thread every five weft (Fig. 1), “B” stands for biaxial, “U” for uniaxial. The PZT sensors, utilized for lamb waves generation and acquisition, are applied on the panel according to the geometry in Fig. 1b.

The "pitch-catch" technique has been adopted for signals acquisition and damage detection, that is, a transducer behaves as an actuator, while the remaining sensors detect the signal that has been released inside the panel. Four different positions were considered for impact damage simulation (Fig. 2 and Fig. 3).



(a) **(b)**

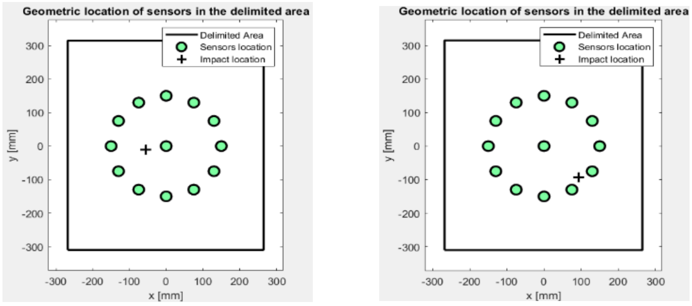
Fig. 1. a) 5-Harness Satin Weave Layer; b) composite panel sensors configuration



(a) **(b)**

Fig. 2. a) damage position 1; b) damage position 2

The signals obtained will be affected by the influence of damage every time it is present. Of course, since wave propagation in composites is a complex mechanism, it is more convenient to compare the signals acquired with the ones from the undamaged model (Fig. 4).



(a) **(b)**

Fig. 3. a) damage position 3; b) damage position 4

A key point is the data analysis from rough signals to get a proper identification system. Features (time of flight, group velocity, signal transmission factor, wave energy) are extracted with an appropriate signal processing technique obtaining a diagnosis that presents location and/or severity of the damage.

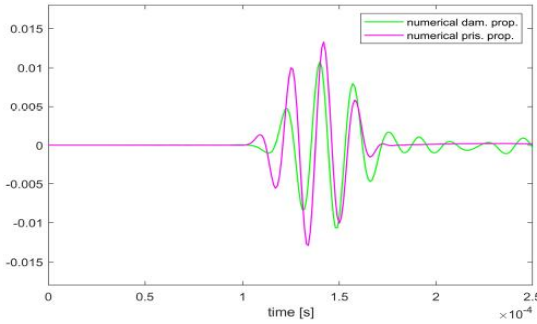


Fig. 4. Signals comparison between pristine and damaged model (path 20_46)

So, if “f“ is the particular propagation feature considered, it is possible to define a damage index according to the following formulation:

$$\mathrm{DI} = \frac{(f_d - f_b)\cdot(f_d - f_b)}{f_b \cdot f_b}$$

Where f_d is the value obtained by the signal of the panel as it is at the analysis time, while f_b is the one extracted by the baseline propagation. This approach is called "multi-path analysis".

2.3 RGB images generation

To implement the convolutional approach, the acquired signals are transformed into RGB images exploiting a MATLAB code [10]. RGB (Red Green Blue) is an additive color model, that is, an abstract mathematical model that allows to represent colors in numerical form, using the red, green, and blue color components. These colors together determine a color space that can be defined as a cube aligned with the Cartesian axes of a three-dimensional space, where the amount of red color is represented along the X-axis, the amount of green along the Y-axis, and the amount of blue along the Z-axis.

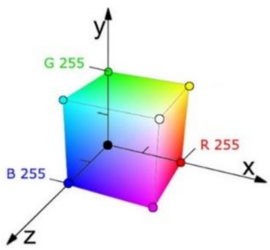


Fig. 5. RGB model

Each image obtained concerns a specific actuator-sensor path and consists of the overlap between the signal detected in the intact panel and that detected in the damaged panel. Going from top to bottom, the signals overlap consists, for this first part of the presented analyses, of 10 intact signals, 10 signals in which a damaged and an intact alternate, and finally 10 damaged signals. Once the image of the aligned signals has been obtained, the absolute maximum “M” is calculated. Then the RGB components (Red, Green, Blue) are calculated, making sure to associate with M the maximum intensity of white if positive or the maximum intensity of black if negative, while all the other values are obtained linearly from these two (Fig. 6). The result is an array in which each value is between 0 and 1. In this way, each pixel corresponds to a trio of (x, y, z) values, to which a specific color is associated, according to the position assumed in the color space of the RGB model. So, a total of 624 images have been obtained (156 for each damage), each one characterized by its own DI.

a) b)

Fig. 6. RGB transformed signal: a) healthy path – b) damaged path.

2.4 Image analysis

Convolutional Neural Networks (CNNs) are Deep Neural Networks (DNNs) made by heterogeneous layers originally designed to process data in the form of multiple arrays. The architecture of a classical CNN consists of three main layers typologies: input layer, hidden layers and output layer (Figure 1). In detail, the hidden layers structure is what characterise the CNNs from many other classical feed forward networks, since it is characterized by two main sublayers called convolution and pooling. In the convolutional layer, data are re-arranged in metrics maps whose elements are the result of a local weighted sum. Each of them is connected to local patches in the feature maps of the previous layer through a set of weights called filter (or kernel) bank. There is one filter for each feature map, and so, different feature maps have a different filter. A bias matrix is then summed to the feature map and then followed by a nonlinear operation, such as the popular ReLU. Thus, the role of the convolutional layer is of extracting high-level features and, simultaneously, of reducing the dimensionality of the provided input into a form that is easier to be further processed by the following layers. Similarly to the convolutional layer, the pooling layer is responsible for reducing the spatial size of the convolved data. The weights value in each filter bank is the result of the training process allowing the CNN to learn the input–output relationship. As training methodologies the most commonly used is back-propagating gradient through the CNN, resulting as simple as for a regular deep network. Many effective CNN architectures have been created during the last years with different purposes (image recognition, object detection, characters recognition), like, for example, GoogleNet, AlexNet or VGG.

For images analysis within this work the Google Net neural network [12], already present in MATLAB, was used. It is a deep convolutional neural network architecture codenamed Inception that achieves the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14); is a convolutional network consisting of 144 layers, which requires an image as input and returns its classification in output (Fig. 7).

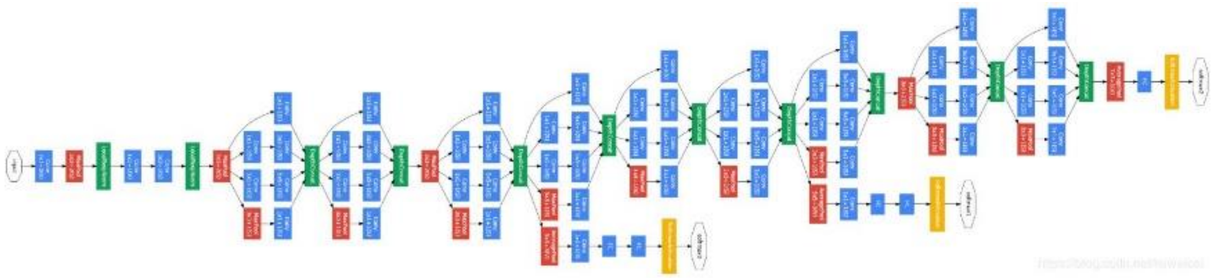


Fig. 7. Google Net CNN

The network training phase was carried out using MATLAB's Deep Network Designer, a tool that allows to graphically train a neural network, entering the appropriate training parameters such as learning speed, validation frequency and number of epochs.

3. Confusion matrix and results

The confusion matrix allows the evaluation of the quality of a classification method comparing the "correct" result with the "predicted" one. Every cell of the matrix is associated to a real and to a calculated classification and reports the number or the percentage of instances in which the same situation repeats. Usually, rows and columns are ordered in such a way, that cells for which the two values coincide are on the diagonal. In the case of the classification matrices presented in this work, the top left cell reports the number of well-recognized undamaged signals, the bottom right one indicates the instances of damaged propagations correctly classified; on the top-right space it is indicated the number of times that a "pristine signal" is predicted to be damaged (false alarms), while in the bottom left one the instances of damaged propagations classified as "pristine".

The network was first trained and tested only using numerical signals, obtaining very promising results as shown in Fig. 8

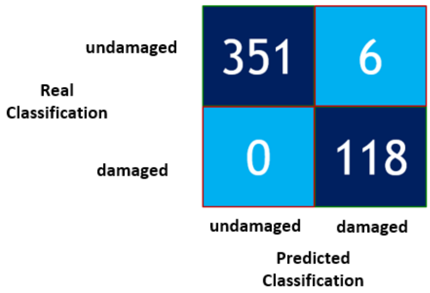


Fig. 8. Confusion matrix of images with calibrated DI threshold values

Once the effectiveness in signal classification was proofed for the chosen network, the real intent of the work was to verify the possibility of training the net by a hybrid combination of experimental and numerical data to classify experimental signals. In this case the numerical data would permit to "expand" the experimental data set, for example including more damage locations than the experimental damage scenario available (avoiding the damaging of more test articles in many locations). For these purposes the experimental signals data base presented in [6] has been combined to the previous numerical one: they both referred to the same test article sensorised with the same sensors networks. In detail the numerical wave propagation signals where obtained after validating and correlating the numerical model with the experimental data (See the activities presented in [6] for more details).

It was attempted the training of three different networks, one only by numerical signals, one only by experimental ones and finally a "hybrid" network that was trained by mixing numerical and experimental ones. Surprising results were provided by the hybrid network, trained with mixed signals. In fact, overall, it is the network that has shown a higher recognition rate. These results confirmed the high potential that characterizes the hybrid training obtained by combining validated experimental and numerical data.

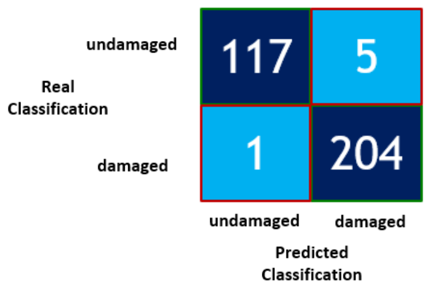


Fig. 9. Results obtained by the Net trained on "hybrid" results

3.1 Multi-class analysis aimed at localization of damages

Finally, the latest and newest results that will be presented in this work are related to an extension of the network for the classification of more classes, each one of them associated to a specific area of the investigated plate, in order to identify and locate simultaneously the imposed delamination. If the Google Net network has already proven to be very reliable for the binary classification of numerical signals into the "intact" and "damaged" categories, the localization of the damage using the same network deserves further investigation. First of all, it is necessary to clarify that the numerical simulations carried out on the panel in question constitute a problem of a linear nature, therefore Betti's reciprocity theorem applies, which states: "The deflection in a point J due to a load P applied in a point I is equal to the deflection that would occur at point I if the same load P were applied at J." We must therefore expect that both in the intact panel and in the damaged panel, for symmetric positions of the damage, the two signals obtained by alternately exchanging the actuator and sensor of the same path are practically indistinguishable (see Fig. 1b). Under these hypotheses, symmetries are created that work against us: if we imagined that the damage in position 1 was in a symmetrical position with respect to the horizontal axis of symmetry of the panel, by Betti's theorem we would obtain two signals (and therefore two images) identical, generating confusion during their classification. To overcome the symmetry problem, it was decided to divide the panel into 4 areas that are not perfectly rectangular so that each contains 3 transducers (Fig. 10) and to generate images that have different characteristics depending on the position of the receiving sensors inside the aforementioned areas. With this particular geometric division we will have transducers 21, 22 and 24 belonging to zone I, transducers 25, 42 and 43 belonging to zone II and so on up to zone IV.

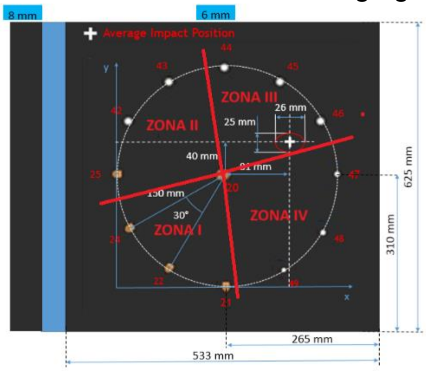


Fig. 10. Panel’s zones definitions

This approach should help differentiate the signals, eliminating any symmetries. At this point the final step is to locate the damage via the neural network. In this regard, a statistical approach was followed: all the damaged or intact images relating to a single simulation (e.g. damage in position 1) were provided to the network and it was asked to classify them; if the damage is localized near one of the four zones, it is reasonable to expect that the number of damaged actuator-sensor paths (and therefore images) will be higher in correspondence with the aforementioned zone; should the case arise of damage positioned on the boundary between two areas, the difference in the number of damaged images between the two areas is rather low.

The methodology to transform the wave propagation signals for each path into RGB images has also been modified for the scopes of damages localization: comparing to the approach described in paragraph 2.3, this time the band of alternating Damaged/Healthy signals has been shifted depending on the area of the panel where the sensors are located. Following pictures, from Fig.11 to Fig. 15, present examples of RGB images obtained for a healthy path (belonging to any of the four zones) as well as to damaged path acquired by sensors lying in one of the four zones. It can be easily noticed how the area in which damaged and healthy signals alternate is located at varying height in the pictures depending from the zone at which the receiving sensors belong.

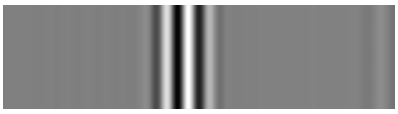


Fig. 11. RGB transformed signal: healthy path

Fig. 12. RGB transformed signal: damaged path – Zone 1

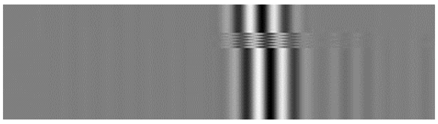


Fig. 13. RGB transformed signal: damaged path – Zone 2

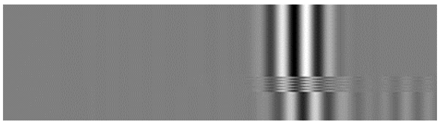


Fig. 14. RGB transformed signal: damaged path – Zone 3

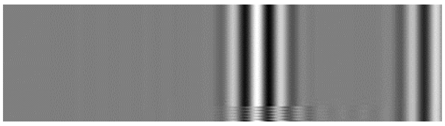


Fig. 15. RGB transformed signal: damaged path – Zone 4

The results, case by case, were illustrated through graphs. Each graph represents the geometry of the panel, the location of the damage and sensors, and the four zones. The areas were colored differently depending on the quantity of damaged routes detected within them, the color hierarchy is as follows: no. damaged routes red zone > no. damaged routes orange zone > no. damaged routes yellow zone > no. damaged paths green area. An example of the obtained results is shown below.

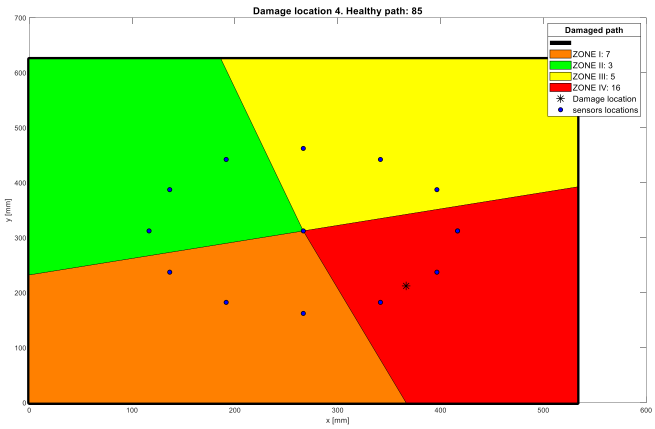


Fig. 16. Example of damaged area classification

4. Conclusions

The present work is part of a research project under development and participated by the authors in collaboration with other research groups aimed at implementing innovative Structural Health Monitoring approaches based on machine learning in general and on CNN for wave propagation signals more in detail [12]. The authors are not expert in machine learning algorithms development but their scope is to implement SHM approaches based on algorithms already available within the increasing number of libraries of ML algorithms available in almost all the main coding languages. The choice in this case was to test the capabilities of a well known CNN (the GoogleNet) typically employed for image recognition and analysis in classifying propagation signals obtained both experimentally and numerically for a healthy and damaged carbon-fiber reinforced plate. Opinion of the authors, in fact, is that duty of the structural engineers should be the choice of the best pre-processing of signals to feed the chosen CNN algorithms in order to permit the networks to carry on the desired classification, as well as the preliminary design of the classes number and typology and finally the choice of the best training strategy in order to achieve the best possible results with the available data. The presented work goes in this direction and the effectiveness of a well-known and tested network has been proved for the scopes of identification of delamination damages into the selected composite plates as well as the localisation of the delaminated area. The results have been encouraging both using experimental as well as hybrid (numerica/experimental) propagation signals. Further activities will consist in comparing other signal pre-processing approaches as well as other typologies of networks capabilities, even combining CNN with Autoencoders to accomplish the necessary compensation of environmental influences on propagation signals typical of real world applications. Furthermore the opportunity to obtain more information about the influence of each networks parameter on the classification results will be investigated by the use of Explainable Neural Networks in order to permit a better selection of the data sets.

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6. Copyright Statement

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