Steel bridge structural damage detection using Ground-Based Radar Interferometry vibration measurements and deep learning Convolutional Neural Networks

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Key words: *bridge structural health monitoring*; *ground based radar interferometry; bailey type steel bridge; continuous wavelet transform; deep learning convolutional neural networks*

ABSTRACT

This paper introduces a new, data-driven, vibration-based, damage detection strategy realized on an on-purpose built, *Bailey* type, steel bridge model (6.12 m x 1.80 m, scale 1:2.5) as part of the research work undertaken in the School of Rural, Surveying and Geoinformatics Engineering, NTUA, Greece. Vibrations of the bridge model in a "healthy" and damaged condition were recorded using a Ground-Based Radar Interferometer (GBRI). Structural damage was deliberately induced on the bridge model by removing a number of carefully selected structural parts, whilst bridge excitation was achieved using a vibration generation apparatus. This system employs an in-house built in trolley system capable of realizing preset dynamic load scenarios. The damage detection approach developed relies on the transformation of GBRI vibration measurements to Continuous Wavelet Transform (CWT) scalogram images. The latter are then used to apply alternate pattern recognition techniques; particularly, a class of pre-trained Deep Learning Convolutional Neural Networks (CNNs) through the application of Transfer Learning technique. The classification results of the bridge health status reach an accuracy of the order of 90%, suggesting the effectiveness and the high potential of the proposed approach.

I. INTRODUCTION

Non-Destructive Structural Health Monitoring (ND-SHM) methods measure the response of a bridge structure against static or dynamic loads of a controlled or an arbitrary character. In recent years, they have attracted a great deal of attention, as a result of the non-invasiveness and constantly evolving technology in the field. In contrast to static loading excitation, methods that rely on the measured response of structures under dynamic loading are much easier to implement, as they do not require the operational shutdown of the bridge, making them widely used in the last decade. Their principle of operation relies on the assumption that a structural damage of any kind induces changes in the structural parameters, (*i.e.*, stiffness, mass or energy damping), which, in turn, alter the dynamic response of the structure (Farrar and Worden, 2013). ND-SHM methods are classified into parametric ones, which are based on Finite Element Models (FEM) (Model-based); and non-parametric ones that rely only on response-measurements of a structure (Data-based). The latter, are also known as vibration-based inspection methods that rely in the measurement of the response (displacement, speed, acceleration, elongation, etc.) of a structure during its oscillation, using appropriate sensors. However, as there are no sensors that can directly measure structural damage, it is necessary to transform raw oscillation measurements into suitable features/indicators, which in turn, are sensitive to structural damage. These features are compared against the corresponding features extracted from Finite Element analytical Models (FEM) or against features produced from oscillation measurements previously obtained, and if the comparison yields a statistically significant difference, the presence of a structural defect might be possible. Otherwise, the structure is considered to be in a "healthy" structural condition.

The transformation of raw measured oscillation data to meaningful, damage-sensitive features is a hard task that requires a great deal of user intervention, along with specialized user skills. However, in the last decade, new methods emerged; for instance, techniques of Deep Learning Neural Networks that seem to overcome such prerequisites and pave the way towards the automation of Structural Health Monitoring data analysis techniques.

Deep Learning Neural Networks or Deep Neural Networks (DNNs) allow the automatic extraction of appropriate features directly from data, without user intervention. The name of the Artificial Deep Learning Neural Networks is a consequence of their complex architecture, which is based on multiple layers of non-linear transformations. Neural networks of this class, in order to model a high degree of data abstraction, (Provos, 2015), build up complex, high-level, abstract representations of primary data, resulting from a series of increasingly simpler representations of this data, with each representation corresponding to their different feature characteristics (Helm *et al.*, 2020). In effect, moving from the simplest to the most complex layer of representation, an increase in the understanding of the underlying problem characteristics is progressively achieved. In this way, deep neural networks allow computers to "learn" from empirical knowledge and perceive the world, based on a hierarchical structure of concepts, with each concept being defined by its relation to a number of simpler concepts. The types of Deep Neural Networks widely used are Convolutional Neural Networks (CNNs) and Recurrent Deep Neural Networks (RNNs).

In the present study, taking advantage of the Transfer Learning technique, pretrained Convolutional Neural Networks (CNNs), which have shown excellent results in the field of pattern recognition in images (Jarret *et al.*, 2009; Krizhevsky *et al.*, 2012) are used. Prior to implementation, these models were adjusted suitably to accommodate the characteristics of the Bailey type steel bridge used in this study.

A. *Convolutional Neural Networks (CNNs) – Transfer Learning technique*

The name Convolutional Neural Networks (CNNs) stems from the mathematical operation of convolution, which takes place at one layer of their structure, at least. The purpose of CNNs is to learn abstract features of input data that usually refer to images. Their structure is based on the sequence of convolutional layers (which also use a non-linear activation function, usually RELU) and pooling layers. The last network layers consist of neural networks of the classic "shallow" form of Multi-Layer Perceptrons (MLPs), in which the classification process takes place. A convolutional neural network (CNN) is a type of artificial neural network primarily designed and used in image recognition to process pixel data.

Transfer Learning is a machine learning technique, which is based on the generalization of experience (Zhuang *et al.*, 2021). It allows the re-use of knowledge acquired during the solution of a problem, known as the "source domain", to solve a different but similar problem, the field of which is called the "target domain" (Azimi and Pekcan, 2019) (Figure 1). In practice, this operation asks for an appropriate adjustment of the most recently computed classification layers whilst the latter still retains the same layer architecture. A taxonomy of the alternative approaches of this technique are given in Zhuang *et al.* (2021).

The great asset of the Transfer Learning technique resides in the ability to face situations of excessive lack of training data (Pan and Yang, 2010). Specifically, the size of neural networks and the amount of training data proved to share an almost linear relationship (Tan *et al.,* 2018). In addition, if a set of predetermined parameters are used (layer weights, etc), the time periods required for network training are significantly shorter than the corresponding time required for the training of Neural Networks developed from scratch. Finally, the Transfer Learning technique makes possible for new users of Neural Networks to successfully use existing networks of award-winning architectures.

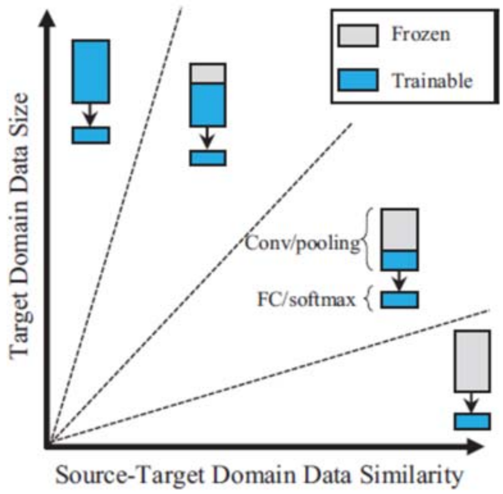

Figure 1. Different Transfer Learning Strategies (Azimi and Pekcan, 2019).

B. *Related work – CNNs in Structural Health Monitoring (SHM)*

It has been only since 2017 that Deep Learning Neural Networks are in use in SHM vibration inspection studies aiming at detecting, locating and determining the type of a damage in civil engineering structures. The work by Azimi *et al.* (2020) offers a thorough review on the use of Deep Learning Neural Networks in SHM applications. It provides a taxonomy of research findings concerned with the use of Deep Neural Networks: (i) in vibration based inspection methods, and (ii) in visual inspection methods which are further categorized in crack detection applications and structural components identification / change detection.

From this analysis it is apparent that the majority of the research effort resides on the use of oscillation measurements obtained from acceleration sensors. The most common type of structures examined in the literature are bridges of different types. In all SHM studies, the use of alternative Deep Learning Neural Network architectures is proposed. Only three research studies rely on oscillation measurements that pertain to physical models of real structures, which have been constructed according to regulations (Khodabandehlou *et al.,* 2018; Zhang and Wang, 2019). In the remaining studies, oscillation measurements have been used obtained in laboratory constructions that resemble real structures; however, they do not comply with any design standard or with the similitude law.

II. The Proposed Approach

A. *Research objective*

The aim of this study is to investigate the potential of damage detection in bridge structures using oscillation measurements from a Real Aperture – Ground Based Radar Interferometer (RAR-GBRI) sensor; in particular, the IBIS-S radar system produced by the Italian company IDS (Ingeneria Dei Systemi). In this regard, a set of experimental trials were undertaken in a laboratory conditions, subject to controlled excitation on a bridge model, both in intact condition and under intentionally induced structural damages. The type of structure chosen was the *Bailey* bridge type, which is widely used in Greece, both for normal connection needs and after emergencies as a result of natural disasters.

The main reason for choosing a laboratory space for testing was in order to avoid the influence of external environmental conditions; especially, temperature variations. Clearly, temperature changes have an extremely large effect on structural behavior, which can mask the corresponding effect of a structural damage.

For a successful outcome of the trials, special attention is required for the artificial stimulation of the laboratory structure, so that it resembles bridge operational stimuli, *e.g*. the scenario of a passing vehicle. In addition, due to the use of indoor space and taking into account the mode of radar operation, it was necessary to take precautions to limit the multipath effect of its signals.

Regarding the conditions that the damage detection methodology should meet, the use of Deep Learning Neural Networks was decided, so that the extraction of classification features, which would be further used in pattern recognition, was conducted automatically, without user intervention.

B. *Design and construction of a scaled Bailey type steel bridge*

In order to meet the needs of this study, a physical model of a single-truss / single-storey (one truss made of five panels and one storey at each girder) *Bailey* type steel bridge (American M2 type) was designed by the PhD Candidate Mr. Vassilios Papavassiliou, Lab. of Metal Constructions, NTUA School of Civil Engineering and manufactured (Figure 2) by him and the first author. The model structure corresponds to a 50-foot *Bailey* bridge in a scale @ (1:2.5), with dimensions 6.125 m x 1.815 m. The design was performed using Finite Element Modeling (FEM) in SAP2000 software.

The design and setting up of the bridge model fully adheres the similitude theory, and therefore, it is possible to generalize the results of this research to real *Bailey* type bridges. Consequently, a constant ratio (1: 2.5) was maintained in the dimensions and cross-sections of the model, in relation to a corresponding real size 50-foot opening bridge. In addition, in order to achieve a mass correspondence factor, and therefore, similarity in the developed accelerations, sandbags were placed on the deck of the model, thus appropriately changing its weight (ballast). The construction of the bridge model was followed by experimental measurements of its oscillation, which were compared with the numerical results from the Finite Element Model (FEM). The results of the comparisons indicated further changes in the structure. Thus, the sway braces, which were originally implemented by wires, were finally replaced by steel bars, whereas the way of attaching the transoms to the lower parts of the girder panels was also changed.

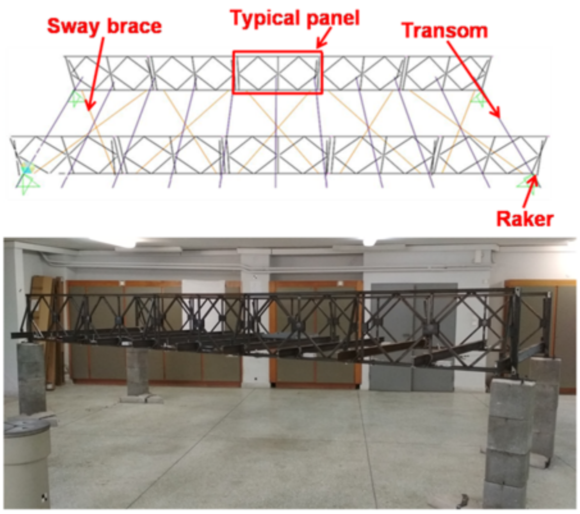

Figure 2. Bailey bridge FEM (up) and constructed model (down).

C. *Measurement environment and experimental equipment The*

The physical model of the *Bailey* bridge was placed in the metrology sector, in the basement of the School of Rural and Surveying Engineering of NTUA. This room ensures stable temperature conditions, especially in summer months. During the experiments the temperature was constant, of a value of 24^{o} Celsius. In order to reduce multipath reflections of the radar signal, a special barrier surface (Figure 3), was constructed using suitable tiles that absorb reflected electromagnetic signals.

Figure 3. Special barrier surface for the absorption of reflected electromagnetic signals.

This barrier surface was placed perpendicular to the Line of Sight (LOS) of the radar sensor.

The apparatus used for the excitation of the bridge model consists of two parts; namely, the electrodynamic power generator (excitation unit) Modal 110 exciter (MB Dynamics Inc®) and the amplifier unit that accompanies it. The electrodynamic power generator has a frequency output range from DC up to 5000 Hz, a maximum oscillation range of ±1.9 cm, a maximum power output of 500 Newtons and weighs 25 kg. The amp unit is responsible for the amplification of the incoming electrical signal and for supplying the excitation unit with the appropriate electrical power. The unit's moving part range of motion is controlled by thoroughly adjusting its power supply through the amplifier.

A dedicated set of software routines were developed in LabVIEW graphical programming environment to control the excitation unit's movement, while a National Instruments® 6211-USB data acquisition card was used to connect and "drive" the unit from a PC system. In order to excite the bridge model in the most possible realistic manner, the excitation unit was forced to a controlled motion with a "white noise" signal, due to its resemblance with standard functional bridge excitation, such as vehicle crossings.

An iron mass, weighing 2.5 kgr, was placed on top of the excitation unit, so as to create sufficient excitation on the bridge, taking advantage of the inertia effect. In addition, with the aim of realizing the diversity of the bridge excitation, a suitable electric vehicle was constructed, on which the excitation unit was placed, while iron rails were distributed on the bridge deck, for forcing the movement of the vehicle along them (Figure 4).

Figure 4. The electric vehicle with the excitation unit placed on it. Its movement was forced along the iron rails shown.

Using this excitation configuration it was possible to load the bridge in two modes; firstly, through holding the vehicle stationary at many different predefined locations in the bridge deck, with the excitation unit in operation at each one of them. Secondly, with continuous vehicle bridge deck crossings, while the excitation unit was inactive. Unfortunately, vehicle bridge deck crossings affected GBRI displacement data, making them impossible to be further processed.

D. *Experimental setup and observational scenarios*

Experimental planning involves measuring the oscillation of individual points along the bridge deck, using the GBRI unit for a number of predefined scenarios with the bridge in "healthy" state/condition, as well as with the bridge artificially damaged. On the north side of the bridge deck, three passive GBRI targets (metal cones) were properly fixed. Subsequently, the GBRI was placed under the bridge, as shown in Figure 5, while the absorbing barrier surface was placed in the background to reduce multipath effects (Figure 5).

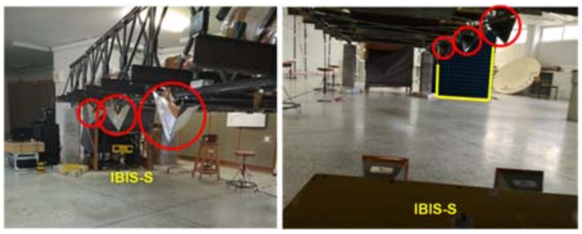

Figure 5. Experimental setup.

The radar system was put into operation at a sampling frequency of 200 Hz and acquired oscillation data for a 10 min period for each trial and for each one of the following bridge conditions (Figure 6): (i) bridge in "healthy" state condition, (ii) bridge with a raker element removal, and (iii) bridge with a sway brace element removal.

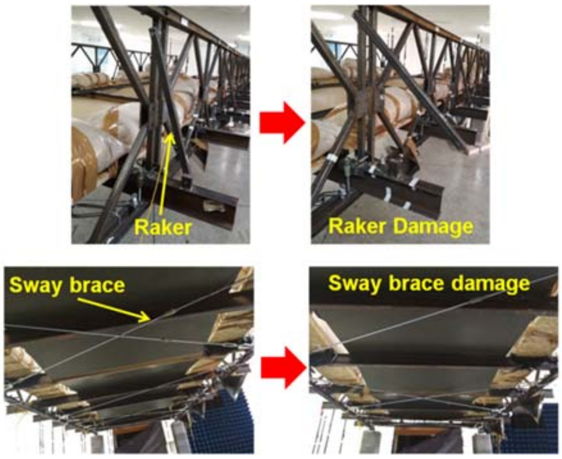

Figure 6. Artificial damages induced to the Bailey type bridge.

In total, 33 trials were performed for each of the three bridge structural states. In every test trial the excitation unit featured white noise characteristics to resemble an excitation pattern of passing vehicles.

It is pointed out that in order to avoid biases in the data, the order of the experimental scenarios was mixed and the position of the oscillation generator, as well as the intensity of the excitation itself, varied from scenario to scenario. In addition, all experimental scenarios for structural state (ii) and (iii) were applied deliberately at various locations along the bridge deck. In the sequel, the GBRI measurements were processed using the dedicated IBIS DV software and finally the vertical displacement time series of each reflective cone were computed for each of the experimental scenarios. Thus, a total of: 33 (experimental scenarios) x 3 (structural states) x 3 (reflective cones) have resulted in 297 displacement cases, lasting 10 minutes each.

E. *Data pre-processing and transformation*

Prior to processing the GBRI displacement data via the pre-trained Deep Learning Neural Network strategy discussed previously, the raw data have undergone through a number of pre-processing and transformation steps. For this purpose a dedicated set of software routines was developed in Matlab® programming language to implement the following steps (Figure 7):

- Signal noise removal (filtering): In order to remove the unwanted displacement signal noise, a band pass, 8^{th} class Butterworth digital filter was applied using a frequency band from 1 Hertz to 40 Hertz (Hz). These cut-off frequencies have been selected based on the FEM analysis of the model structure, according to which its modal frequencies lie in the frequency band from 5 to 30 Hz.
- Outlier detection: Detection of outliers and replacement using linear interpolation on their neighboring values. The criterion for locating outliers was defined as: 3 x mean absolute deviation (Median Absolute Deviation).
- Data standardization: Subtraction of the data average value and division by their standard error.
- Data normalization: The standardized data were normalized in the range of 0 to 1 using the formula (Eq. 1):

$$\bar{d}(t) = \frac{d(t) - \min(d)}{\max(d) - \min(d)} \tag{1}$$

  where, $\bar{d}(t)$ is the normalized displacement value, d(t) is the corresponding standardized displacement value, min(d) refers to the minimum standardized displacement value and, max(d) is the maximum standardized displacement value.
- Conversion of the pre-processed displacement signal to images using the Continuous Wavelet Transform (CWT): Following extensive investigation of the alternative techniques used for converting a time series dataset to an image representation, we concluded on the CWT technique as it suits for the study and analysis of signals with abrupt changes. By virtue of the CWT technique characteristics, the pre-processed time series data were represented simultaneously in the time and frequency domain, using the Morse (3, 60) analytical wavelet. The 2D plots generated correspond to the time and frequency values of a point displacement respectively. In these plots, the frequency intensity is depicted using a color scale. These images constituted the input data of the pre-trained GoogleNet, ResNet-18 and ResNet-50 type Deep Neural Networks.

In order to determine the most efficient representation of a signal time series into an image formulation, the pre-processed datasets were converted into scalogram images of Continuous Waveform Transform images for periods of 10, 15, 20, 30, 60 seconds and 10 minutes. Analysis revealed that the optimal time for building a scalogram was 15 sec. Therefore, 40 Continuous Wavelet Transform images were generated for every 10-min test trial scenario; namely, 3960 images (= 40 images x 33 scenarios x 3 targets) for each one of the *Bailey* bridge model structural states (*i.e.*, "healthy", raker damage, sway brace damage), equals to a total of 11880 images. The constructed images have a resolution of 656 x 875 pixels, which was then changed to 224 x 224 pixels, so that they could be successfully inputted into the pre-trained Deep Neural Networks.

III. DAMAGE DETECTION THROUGH SUPERVISED LEARNING

Following the pre-processing of the raw displacement signal and its conversion into RGB images, the latter were fed into the pre-trained Deep Learning Neural Networks; specifically, the *GoogleNet*, ResNet-18 and ResNet-50. These Networks rely on award winning layer architectures, since they have won the first place in the annual ImageNet Large Scale Visual Recognition Challenge (ILS).

The aforementioned Networks were used without any change in their layer structure, except from the last layers. More specifically, the last output layer contains three neurons that correspond to the three categories of the bridge structural state adopted in this study (*i.e.*, the "healthy" state, raker damage state and the sway brace damage state). The learning rate was set to 0.001, so that the change of layer weights was not "aggressive". Following a random separation of the data, 80% of the data volume was used for training the networks, while the remaining 20% was used for testing. The accuracy achieved was 87.1% for *ResNet-18* and 91.4% for *GoogleNet,* respectively. In addition, in order to investigate the effect of the existence of more layers in the Deep Learning Neural Networks architecture on their performance, the *ResNet-50* Deep Neural Network was used. The latter consists of 50 layers, so its performance could be directly compared with the performance of ResNet-18, bearing 18 layers. The average accuracy of the *ResNet-50* network proved to be the highest one, reaching a percentage of 92.3%, for the same input data used in *GoogleNet* and *ResNet-18*. Comparing to the performance of the *ResNet-18* it can be concluded that through adding 32 convolutional layers, an increase of about 5% in the classification accuracy was achieved. Table 1 depicts the classification performance metrics *i.e*. the accuracy (A), precision (P), sensitivity or Recall (Sen.), specifity (Spec.) and F-score (F), for each one of the Deep NNs, in percentages (%).

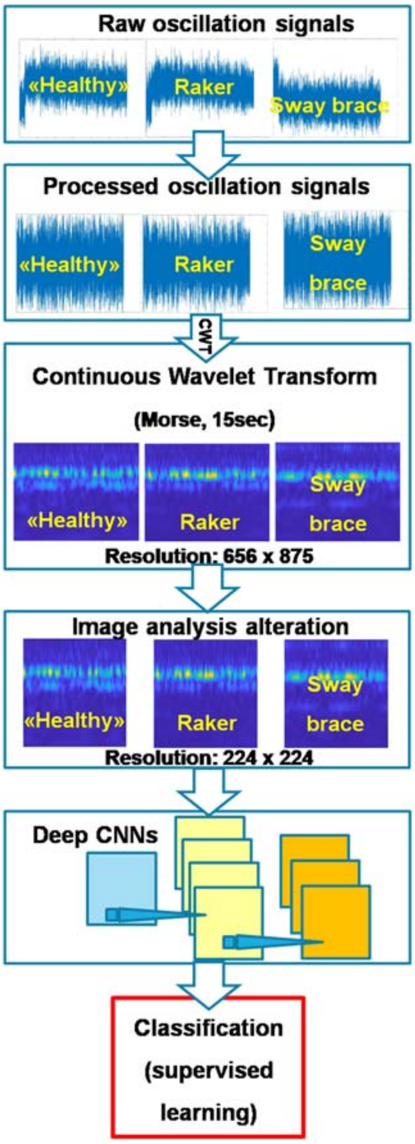

Figure 7. Methodological approach.

For all Deep Neural Networks used, the classification performance metrics are excellent, revealing their effectiveness for all bridge structural states, healthy and damaged.

In order to validate the results in the most affirmative way and to avoid over-fitting phenomena, in addition to the random division of data to training (80%) and testing (20%) images we enforced the k-fold cross validation method. Using this method, the data are randomly divided into k-sections (k-folds) and then, the algorithm is trained considering k-1 sections. In total, k neural network trainings are performed, omitting a different part of data each time, and finally the average of the accuracy results of the resulting k networks is calculated (Azimi and Pekcan, 2019). In the present study, the use of five-fold cross-validation was used, leading to an average classification accuracy of 90.4% for *ResNet-18*, 93.5% for *GoogleNet,* and 94.1% for *ResNet*-50, suggesting the suitability and effectiveness of the proposed method. Figure 8 shows the confusion matrices resulting for *ResNet-50* Deep Neural Network, when applying the five-fold cross-validation method.

IV. CONLUDING REMARKS AND FUTURE WORK

This paper introduces a new, data-driven, vibration-based, damage detection strategy applied on a laboratory *Bailey* type, steel bridge physical model (scale 1:2.5), built dedicatedly for fulfilling the goals of ongoing Structural Health Monitoring research work. Bridge oscillations were measured using a Ground Based Radar Interferometer (GBRI). Towards structural "health" condition identification the bridge physical model is excited using a "white noise" vibration generation apparatus, based on an on purpose built trolley, variously positioned on the bridge deck, to realize the monitoring scenarios, while structural damage is artificially induced by removing specifically selected structural parts, namely bridge rakers and sway braces.

The presented approach adopts state of the art pattern recognition techniques, namely Deep Learning Neural Networks (NNs) and particularly, the award-winning Deep NNs (*GoogleNet*, *ResNet*-18 and *ResNet*- 50), taking advantage of the Transfer Learning technique, after appropriately having transformed GBRI vibration measurements to Continuous Wavelet Transform (CWT) scalogram images.

The structural condition identification results demonstrate that the proposed strategy framework reaches an average identification accuracy of 94.1% (*ResNet*-50) when applying the five-fold cross-validation method, confirming its effectiveness and promising potential.

Table 1. Classification performance metrics in percentages (%) for each one of the Deep NNs used

	GoogleNet					ResNet-18					ResNet-50				
	A	P	Sen.	Spec.	F	A	P	Sen.	Spec.	F	A	P	Sen.	Spec.	F
Healthy	94.1	91.2	91.3	95.6	91.2	91.3	87.8	85.7	94.1	89.5	95.5	94.5	91.9	97.3	93.2
Raker damage	94.6	91.2	92.7	95.5	91.9	91.0	85.2	88.3	92.4	86.7	94.3	89.5	93.9	94.5	91.6
Sway brace damage	94.0	91.8	90.2	96.0	90.7	91.9	88.3	87.2	94.2	87.7	94.8	93.2	91.2	96.7	92.2

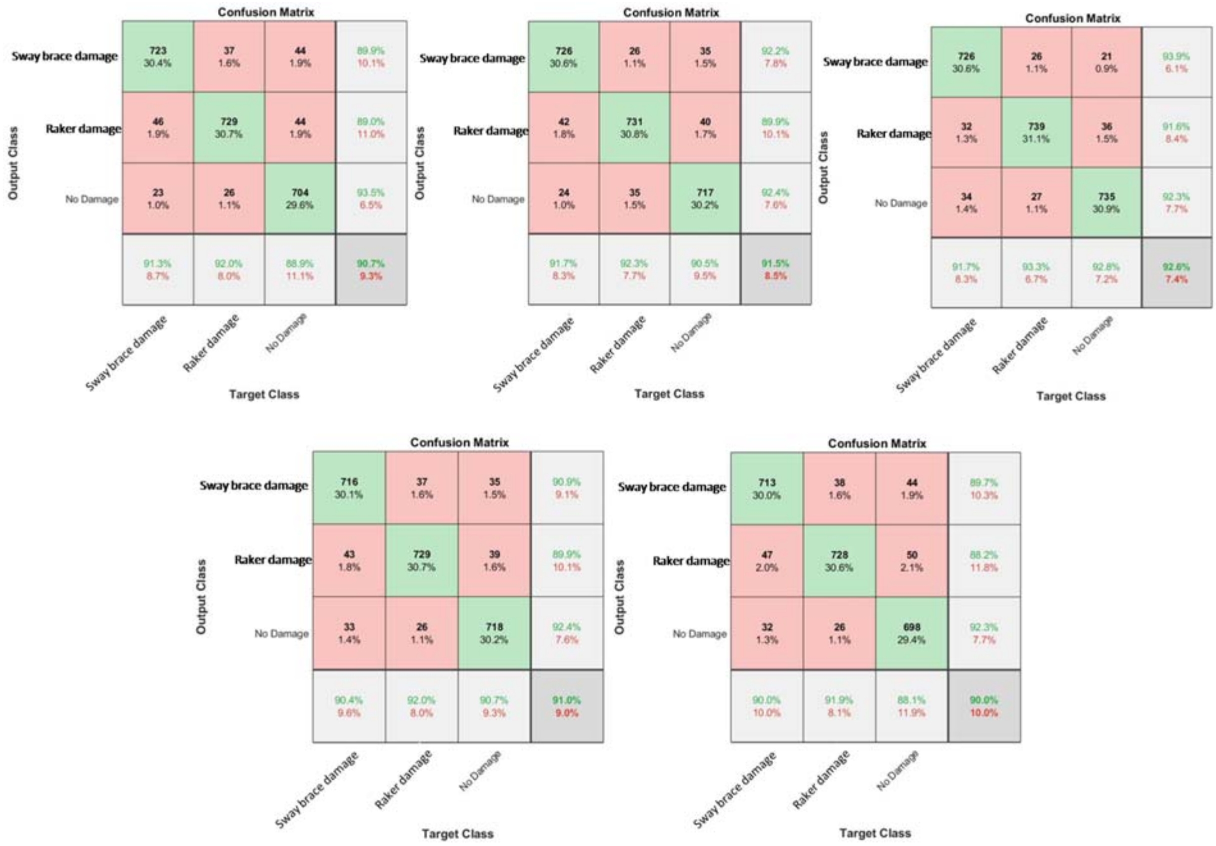

Figure 8. Confusion matrices resulting from the application of the five-fold cross-validation method for *ResNet-50* Deep Neural Network.

In the future, the focus will be placed in detecting and locating potential damages on the structure. Also, the authors will focus on the implementation of Deep Neural Networks in an unsupervised learning frame, so as to apply them on real structures, in which data from damaged structural conditions are unavailable.

V. Acknowledgements

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