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Innovative strategies to preserve the Italian engineering heritage: the historical tunnels.

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Abstract

Italy, a nerve center for Western culture, holds the largest number of artistic and cultural assets declared World Heritage by UNESCO. From the Romans to the present day, an ever-growing infrastructure system, rich in tunnels, bridges and viaducts, has been the expression of a high engineering expertise. For the management of the aforementioned complex infrastructure heritage, the development of automated control and maintenance plans is one of the issues on which the engineering and research community focuses its resources and efforts. In this study, an approach is proposed to automate the process of classifying defects in tunnels using deep learning techniques to protect and maintain the concrete tunnel lining. The acquisition of images from non-destructive monitoring techniques, such as Ground Penetrating Radar, within a supervised learning process allows the creation of an effective tool for the automatic detection of severe defects such as cracks, anomalies, and voids. The obtained results provided for a high degree of accuracy in identifying the tunnels' structural condition. The use of the developed strategy, based on machine learning and non-invasive inspection techniques, is cost-effective for infrastructure managers. Such a procedure reduces both the number of invasive interventions on the tunnel lining and the time and cost associated with employing specialized technicians.
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Keywords: cultural heritage, planning, sustainable development, technologies, data integration

1. Introduction and related works

The Italian context is of significant importance due to the presence of artistic and cultural sites, most of which have been declared World Heritage by UNESCO. Bridges, tunnels, and viaducts stand out among these heritage works as examples of remarkable engineering techniques.
The two largest mountain chains in Italy, the Alps and the Apennines, have always been natural obstacles to mobility, leading man to carved tunnels into the rock. For this reason, over time, many tunnels have been built to overcome these natural barriers to facilitate the exchange of people and goods.
Between 1964 and 1984, the most important Italian tunnels were built: Mont Blanc Tunnel (1965), Fresjus Tunnel (1980), Gran San Bernardo Tunnel (1964) and Gran Sasso Tunnel (1984).
Those listed are only the most famous and outstanding examples of civil engineering.
However, until the 1980s, infrastructures were characterized by a significant plano-altimetric flexibility that minimized the use of tunnels. The road layout evolved over time, becoming more dominatedby straight and curves with large radiuses, as well as an increase in the number of tunnels. These last,

conforming to current guidelines and being object of an increasing attention, represent an effective solution to reduce impact on the natural landscape.
In the Civil Engineering field, development, and research of possible indicators of structural state alteration have been increasingly interesting. These indicators aim at providing an "early warning" in case of upcoming danger.
Today, the Italian engineering heritage is formed by an increasing number of buildings which may be subject to collapses and failures. These events are caused by non-linear phenomena and disproportionate behavior. For this reason, the adoption of investigation technologies based on non-destructive techniques (NDT) and artificial intelligence (AI) is pivotal.
The possibility to use these techniques for risk predictive models, structural stability assessment, and optimization purposes for design is very interesting...
In particular, image diagnosis is the most widely used methodology for structural condition analysis.
The proposed work is focused on tunnels; however, this concept can be reasonably applied to other civil structures such as bridges.
The issue of tunnel safety became very important especially after the catastrophic events of Mont Blanc and Tauern. For this reason, several European countries have adopted specific safety protocols following *Directive 2004/54/EC "Minimum safety requirements for tunnels in the Trans-European Road Network"*.
The structural conditions are mainly influenced by deterioration and presence of voids that can worsen the structural conditions [1]. Other factors affecting the structural state are freeze-thaw cycles in the case of not water-proofed tunnels [2] [3], the presence of construction defects, and damages due to seismic actions [4].
Investigations and inspections are traditionally carried out by periodic and visual observations through non-destructive and non-invasive techniques. However, these methodologies are affected by several critical issues such as the cost of operator training, the strong subjectivity of the data interpretations, and the time required to perform them.
In this paper, a strategy based on a multilevel convolutional neural network for damage detection and classification is presented.
The aim is to detect and classify potential damage in structures through the synergy of artificial intelligence algorithm and structural health monitoring (SHM) techniques [6].
This would allow the creation of a rapid and robust tool that can provide a during maintenance phase by setting up structural conditionmapping.

2. AI and Convolutional neural network

The motivation for the great interest in artificial intelligence techniques, especially in the field of Civil Engineering, lies in the amazing key concept of such methodology: the ability to automate the problems resolutions and the activities typically carried out by the human mind.
The strengths of these techniques are the computation speed and, first of all, the ability to automatic manage a large number of data.
Within the artificial intelligence field, this research is based on deep learning (DL) techniques that can solve different problems starting from experimental data [7] by means of the artificial neural networks.
However, the process of extracting the needed information to perform a correct image classification is not immediate.
The result of a correct classification is based on the training process, where the images provided as input are associated with the associatedclassification. The network is then tested on a set of images to assess its accuracy and robustness.
Among the several neural networks, a Convolutional Neural Network was chosen. It is based on the convolution mathematical operation where a series of layers are intended to receive, resize, and extract significant features from images by translating the analyzed images into categories [8].
A training process based on a large amount of images, such as the present case, would haveimplied excessive computational time. For this reason. the technique of "transfer learning" was applied. It uses pre-trained neural networks determining a fast network configuration and a promising accuracy even with less training data. These networks are pre-trained on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) classification and location dataset, based on 100000 training image, 50000 validation images and 100000 test images [9,10].

3. Techniques: Ground Penetrating Radar, Algorithm, and Image pre-processing

3.1 Ground Penetrating Radar

Ground Penetrating Radar (GPR) [11] was chosen from among the various non-destructive investigation methodologies (NDTs) [12] for detection of defects in tunnel lining. Due to its ease of use and transport [13] and its penetration capacity, this instrument has proved to be a valuable tool for damage detection, location, and classification.
It is based on the transmission of pulses of electromagnetic waves of frequency in the studied material using an antenna with a frequency between 10 and 2600 MHz. The dielectric characteristics of the material significantly affect the propagation of that pulse.
The study was based on a GPR campaign focused on Italian tunnels, most dated from 1960 to 1980. Two types of GPR were used in that campaign. The first utilizes a dual-frequency antenna, the second a high-frequency antenna. Tables 1 and 2 summarize the technical characteristics.
The outputs of this techniqueare profiles with a vertical axis indicating the depth of the examined thickness and a horizontal axis representing the structural progressive distance. The described profiles were interpreted by specialized technicians during the campaign. An example of a GPR profile with relative interpretations is shown in Figure 1.

Table 1. Technical characteristics of GPR with dual frequency antenna.

GPR with dual frequency antenna features	value
Min. number of channels	4
Pulse repetition frequency (kHz)	400
Range (nsec)	0-9999
Min.number of scans/second	400
Power (Volt)	12
Primary dual-frequency antenna (MHz)	400-900
Secondary dual-frequency antenna (MHz)	200-600

Table 2. Technical characteristics of GPR with high-frequency antenna.

GPR high frequency antenna features	value
Min. number of channels	4
Pulse repetition frequency (kHz)	400
Range (nsec)	0-9999
Min.number of scans/second	400
Power (Volt)	12
High-frequency antenna (GHz)	≥2

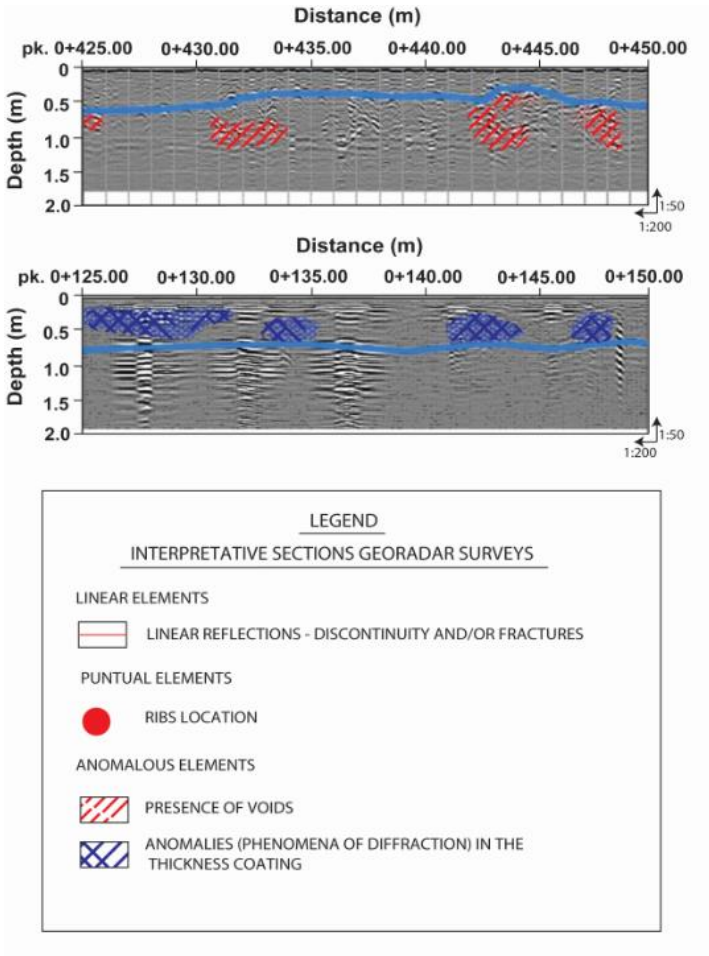

Figure 1. An example of a GPR profile with defect patterns interpretation [14]

3.2 Algorithm and Image pre-processing

Among the several pre-trained networks, Resnet-50 was chosen and was applied within the programming environment MATLAB 2020b.
The network, designed in 2015 by Kaiming He et al [15], is composed by 177 layers, of which 1 is fully connected, while 49 are convolutional. The strength of this network is the presence of "residual/skip connections" that base their operation on the presence of activating functions such as the Softmax layer and the Linear Unit Rectified (Relu).
The presence of skip connection reduces the problems related to the excessive depth of the network allowing to learn the differences between input and output layer. The choice fell on this network for its high depth and very low computational level for the resolution of classification problems. Input data of the algorithm are the GPR profiles described above. However, before using GPR profiles as input data they have been subject to previous operations, such as removing axes, applying filters to reduce the effect of noise, noise tails, and interference, by the Data Provider. Then, each profile was divided into elements of variable size through the free online module PineTools. A data augmentation technique was used to increase the data by rotating the images with respect to the vertical axis, as several literature studies suggest [15–17].

4. The multi-level damage classification

The adopted network allowed the implementation of a multi-level hierarchical procedure. Seven models were created, each performing a binary classification. The minimum number of samples in each class was used to balance the classes in each level to avoid imbalance issues between them. By moving from the lowest to the highest levels, more detailed knowledge can be gained about the presence and type of structural damage. This approach aims to associate a degree of attention to the critical issues that deserve a thorough examination of the ongoing structural decay. When a new GPR profile is analyzed, it can be associated with one of the 14 classes, as described in Table 3.

Table 3. The 14 Classes of the multi-level classification

	Class names	**Descriptions**
LEVEL 1	C1: Healthy and reinforcing	images associated with healthy structural conditions and with the possible presence of reinforcement
	C2: Damaged	images with at least one or more types of damage.
LEVEL 2a	C3: Healthy	images associated with healthy structural conditions
	C4: Reinforcement	images with reinforcement,
LEVEL 2b	C5: Warning mix	Images combinated with of two or more types of damage.
	C6: Warning all	images corresponding to the presence of a single type of damage.
LEVEL 3	C7: Crack	Images in this class are characterized by the presence of cracks
	C8	Images in this class may present anomalies, simply voids, detachment, or excavation.
LEVEL 4	C9: Anomaly	Images in this class show abnormalities, i.e., inhomogeneities within the cover casting.
	C10: Mixed voids	Images in this class show the presence of voids of several
LEVEL 5	C11: Simply empty	Images in this class are associated with the presence of medium-sized and deep voids.
	C12	The images in this class are related to detachment and excavation phenomena
LEVEL 6	C13: Detachment	This phenomenon produces external voids, also presenting some cracks.
	C14: Excavation	This phenomenon brings internal voids with large dimensions

5. Results

The propsed work has shown very promising results, such as a maximum value of accuracy for level 5 equal to 98.3% and for the other levels, however, greater than 90.4%. These accuracy values are derived from the confusion matrices of each level, as shown in the table 4. Such matrices represent one of several useful methods for defining the classification algorithm performance. Their rows showing the real classes and their columns representing the predicted labels. The accuracy value is determined by the ratio of the matrix trace to the total sum of its terms. Each level of the proposed classification shows the accuracy value and the confusion matrix related to an arithmetic average of the results obtained from the application of K-fold cross validation. For each classification, the elements were randomly divided into k groups (with k equal to 10) of which (k-2) were used for network training, one for validation, and one for testing. The term k was assumed equal to 10 because, according to several empirical studies, this value produced estimates of the test error rate that were not affected by either excessive bias or high variance [18,19,20].

Table 4. Confusion matrices for the 6 levels

	Confusion Matrices			Performance Metric
	Real Class	C1: Predicted	C2: Predicted	
Level 1	C1	93.3%	6.7%	Accuracy: 92.6%
	C2	8.1%	91.9%	
	Real Class	C3: Predicted	C4: predicted	
Level 2a	C3	98.4%	1.6%	Accuracy: 97.3%
	C4	3.9%	96.1%	
	Real Class	C5: Predicted	C6: Predicted	
Level 2b	C5	90.9%	9.1%	Accuracy: 90.4%
	C6	10.1%	89.9%	
Level 3	Real Class	C7: Predicted	C8: Predicted	
	C7	92.7%	7.3%	Accuracy: 95.9%
	C8	0.9%	99.1%	
	Real Class	C9: Predicted	C10: Predicted	
Level 4	C9	94.9%	5.1%	Accuracy: 91.8%
	C10	11.3%	88.7%	
	Real Class	C11: Predicted	C12: Predicted	
Level 5	C11	98.8%	1.2%	Accuracy: 98.3%
	C12	2.2%	97.8%	
Level 6	Real Class	C13: Predicted	C14: Predicted	Accuracy: 95.3%

	C13	96.6%	3.4%
	C14	5.9%	94.1%

6. Conclusion

In this paper, a hierarchical approach of a multilevel classification related to GPR profiles of highway tunnel linings is reported. Its goal is to create an automated defect classification system. The multilevel classification concerns 7 different CNN models trained through the transfer learning technique, starting from the pre-trained Resnet-50 network. The present work describes the use of artificial intelligence algorithm, as a structural health monitoring (SHM) technique, highlighting the its potentialities and reliability for the automatic classification of tunnel defects. This could be crucial. in a perspective of potential safeguard and maintenance of the Italian infrastructural heritage.

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