Materials Research Proceedings 42 (2024) 18-21 https://doi.org/10.21741/9781644903193-5

Digital optics and machine learning algorithms for aircraft maintenance

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Keywords: Image Processing, Aircraft Maintenance, Deep Learning, Convolutional Neural Networks, Computer Vision

Abstract. The objective of this study is to present a novel approach for airplane inspection to identify damages on the fuselage. Machine learning algorithms in the aeronautic industry can be used as an instrument for automating the process of inspection and detection, decreasing human error, and increasing productivity and security for operators. An overview of the problems, methods, and recent developments in the field of deep learning algorithms used for general damage detection on aircraft components is provided in this extended abstract. Data were collected using a high-quality acquisition system and the dataset was populated by collecting defect images from 2 typologies of aircraft: a commercial partial full-scale airplane fuselage section in primer paint and a general aviation fuselage white painted, both situated in the laboratory of heavy structures of University of Naples Federico II. The Convolutional Neural Networks (CNNs) and machine learning models were trained on large datasets of annotated images, enabling them to learn complex features associated with different types of damage. Data augmentation techniques are adopted to add diversity to the training data. Transfer learning techniques, which leverage pre-trained models on large-scale image datasets, have also proved to be effective in achieving accurate and robust detection results.

State of the art

As of 2018, the inspection of aircraft is primarily done manually with 80% of the inspection being carried out visually**.** In the case of aircraft structures, initially**,** Structural Significant Items (SSI) are identified, whose failure can compromise the structural integrity of the aircraft. Then, categories are assigned based on the type of item identified, which can include fatigue damage, environmental deterioration, and accidental damage. Consequently, the most effective inspection method is chosen, which can be [1, 2, 3]:

- *General visual inspection*: visual examination of the item for damage. This inspection is normally performed at an arm's length and under normal lighting conditions. Sometimes a mirror may be used to ensure visual access to all areas to be inspected.
- *Detailed inspection*: intensive visual examination of the item for damage. An additional light source with appropriate intensity is used. Mirrors and magnifying lenses may be used to make the refurbishment operations more visible.
- *Special Detailed Inspection*: Specific and in-depth examination of the item for damage. Specialized inspection techniques and Non-Destructive Testing (NDT) equipment are extensively used.

Since the early 90's, the field of artificial intelligence has experienced a dramatic reinvigoration. Research and development in this field have been exponentially growing, particularly in the field of deep learning, a broad family of machine learning algorithms within the field of AI. One of the reasons why deep learning has become increasingly popular is that it eliminates hand-picked features, a time-consuming process in classical machine learning. Among the many deep learning architectures, the convolutional neural network [4] is one of the most popular architectures for image classification. To our knowledge, the very first deep CNN application for visual inspection was performed by Zhang et al. [5] for road crack detection on concrete structures by using 6 layers of ConvNet. Since then, similar works using CNN for crack detection have been performed in civil infrastructure such as buildings, pavement, and concrete surfaces [6]. In the Aerospace field, many applications of deep learning are in developing flight mechanical, flight tests, health monitoring of aeronautical structures, and aircraft maintenance [7].

Methodology

The main objective of this topic is to study and identify new methodologies for aircraft maintenance. To do this, many approaches are investigated:

- *Image processing and segmentation*
- *Convolutional neural networks*
- *Computer vision algorithms*

Starting from image processing, it can be possible to investigate some general parameters of digital cameras. The first trade-off phase for the selection of the acquisition system is to set up the digital optics system to be used in the industrial application. In particular, many different systems were compared (in terms of resolution, weight, and size of images) to collect damage examples on a full-scale aircraft section. These images were taken by drones or blimps, which allow for reaching remote areas on the aircraft that are not easily accessible by operators. Convolutional neural networks aim to split images into databases for the training, validation, and test phases. This architecture forms the basis of computer vision algorithms: regions of interest are traced in the images of the database, then the training phase is conducted, and finally, the validation phase is carried out, where the detected types of defects are identified and classified. Computer vision algorithms gave output segmentation in images with the identification and classification of the damages. In the first work, the procedure was to apply the transfer learning technique [8] to a convolutional neural network to identify and classify three types of defects:

– *Missing rivet*
– *Corroded rivet*

Transfer learning is a technique in deep learning where a pre-trained model, which has already been learned from a large dataset, is used as a starting point for a new task or a different dataset. Starting from the tracing of regions of interest in the images of a database (constructed with images taken on the fuselage of a civil transport aircraft placed in the laboratory of the heavy structure of the University of Naples Federico II). The next training phase occurs by optimizing two functions: the *accuracy function* and the *loss function*. In particular, the objective is to minimize the loss function to improve the network's performance. Fig. 1 to Fig. 4 represents the results obtained during the testing phase of the CNN. The label “rivetto macchiato” translates to corroded rivet, and the label “rivetto mancante” translates to missing rivet.

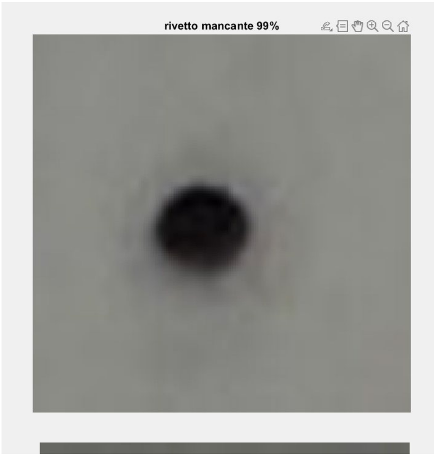

Fig. 1 - Test 1 for CNN

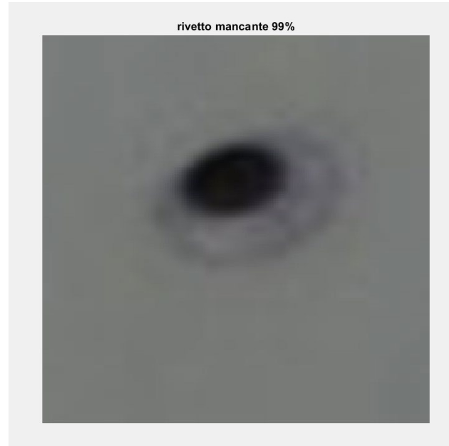

Fig. 2 - Test 2 for CNN

Fig. 3 - Test 3 for CNN

Fig. 4 - Test 4 for CNN

Conclusions

Starting from a trade-off phase for the choice of the acquisition system, an image database was built and used to train a CNN capable of classifying defects on rivets. The trained convolutional neural network shows high accuracy in classifying rivets; in particular, there is a maximum accuracy of 99% for missing rivet class and a maximum accuracy of 87% for corroded rivets class.

Future works

The results obtained from training the CNN previously described have been useful for transitioning to a different approach in image processing: defects were no longer merely classified, but they were also spatially localized during post-process. In future work, an optimization process will be carried out on the network, which will be able to identify and classify a greater number of defects with higher accuracy. Computer vision algorithms aim to replicate human vision capabilities by analyzing and extracting meaningful information from visual inputs. This approach offers operators the possibility to perform near real-time maintenance under conditions of increased safety, both during scheduled maintenance and pre-flight checks.

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