AUTOMATED CONCRETE CRACK DETECTION

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ABSTRACT

Structural Health Monitoring (SHM) have become paramount to prevent systems from severe damage, especially if they are subject to continuous operation in harsh conditions. Nowadays, because visual inspection strongly depends on manual activities, the inspection process tends to be costly, time-consuming, labor-intensive, hazardous, and biased. In this context, advances in Computer Vision (CV) provide the means to the development of automated, accurate, non-contact and non-destructive inspection methods. Therefore, this paper proposes and compares two different approaches to detect cracks in images automatically, one based on texture analysis and machine learning methods (TA+ML-based), and the second based on deep learning (DL-based). We analyze the performance of both approaches with a real crack database considering six distinct dataset sizes. The results showed that for small dataset sizes, the DL-based approach achieved a balanced accuracy (BA) of ~74%, while the TA+ML-based approach obtained a BA >95%. For greater dataset sizes, the performances for both approaches present comparable results.

1. INTRODUCTION

Structural Health Monitoring (SHM) have become paramount to prevent system, environment, and users from exposure to severe damage, and it is of particular interest for aging structures. The earliest stage of degradation is expressed in the form of surface cracks, and then its continuous exposure may lead to severe damages and even the collapse of the structure [1]. For instance, in 2019, a building in Fortaleza (Ceará, Brazil) collapsed, causing at least three deaths and seven people injured [2]. In 2021, a significant fracture was found in a bridge linking Arkansas and Tennessee (US), causing traffic shut down and millions of dollars in loss for the trucking industry because it could affect the bridge's integrity [3]. Authorities blame an inspector for missing early crack detection.

Nevertheless, emerging technologies bring opportunities to support decision-makers on structure inspection since the automation of the process is expected to improve efficiency, reduce cost, and lead to more frequent inspection cycles [4]. Specifically, machine learning (ML) and deep learning (DL) techniques may be used to solve such problems that were impossible (or impractical) to be represented by explicit algorithms, relying on the available data to learn specific patterns [5]. Therefore, this paper aims at comparing different approaches for crack detection from images, based on ML and on DL, across different datasets sizes to provide insights regarding the proper usage of each approach.

2. DESCRIPTION

The proposed methodology for the TA+ML-based approach, based on classical Computer Vision (CV) techniques related to Texture Analysis (TA), is summarized in Fig. 1 where several features are extracted from the input images and fed to five well-known classes of ML models: Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), AdaBoost (AB), and K-Nearest Neighbors (KNN).

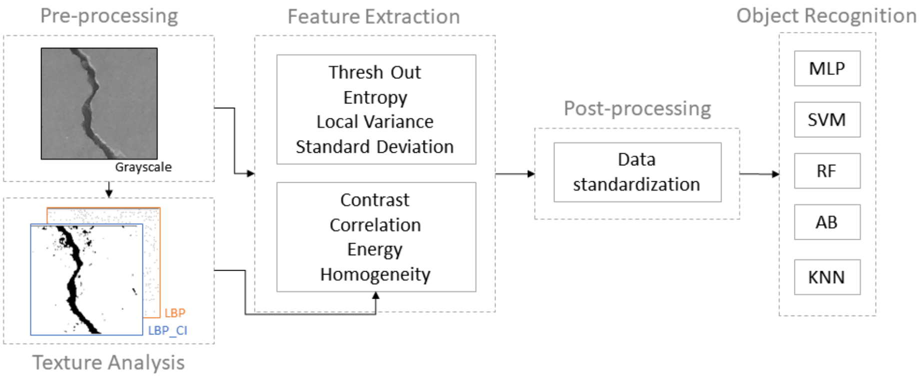

Fig.1 – ML-based approach methodology.

For the DL-based approach we considered four Convolutional Neural Networks (CNN) architectures based on basic structures represented as a sequence of Convolutional – Pooling – Fully Connected Layers, as depicted in Fig. 2.

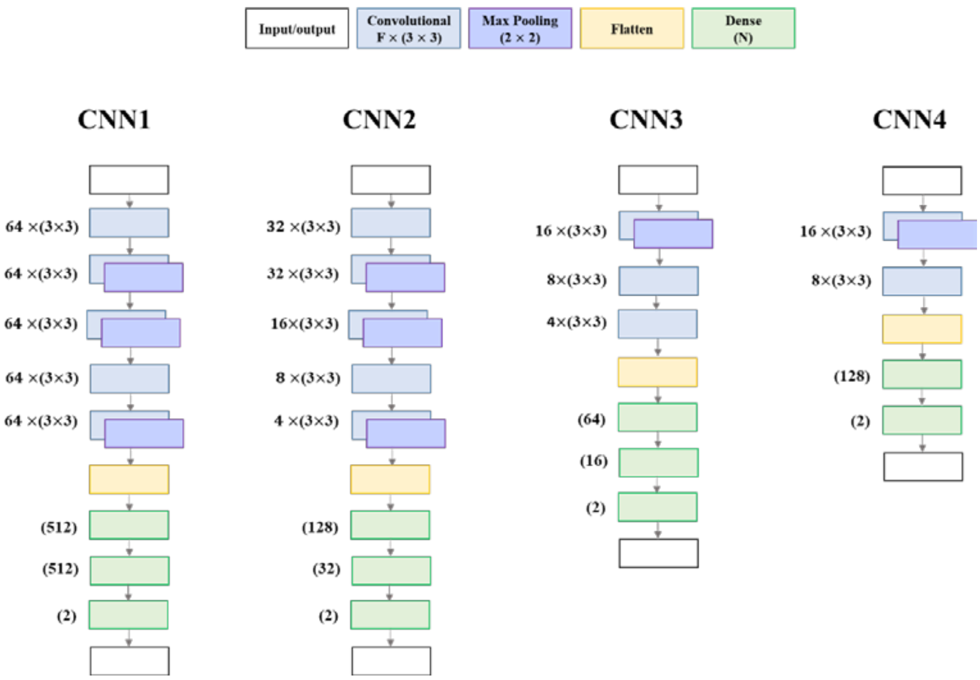

Fig.2 – DL-based approach methodology.

Both approaches were tested using the METU dataset [6], composed of images of different parts of concrete buildings that contain cracks or not. So, from this dataset, we selected 4000 images, maintaining a proportions of 60% for crack images and 40% for non-crack images. From this total, we also selected 5 different subsets, each with 1000, 200, 100, 50, and 25 images to evaluate the performance of the models. Each subset is contained in the previous and larger subset.

We randomly generated the training/testing split ten times for each image subset, always maintaining the proportion of 80-20% for training and testing, respectively. Thus, we ran each model 10 times for each image subset to investigate model variability due to the stochastic training/testing selection. The results are evaluated in terms of the mean Balanced Accuracy (BA) [7] across the different runs, as seen in Fig. 3.

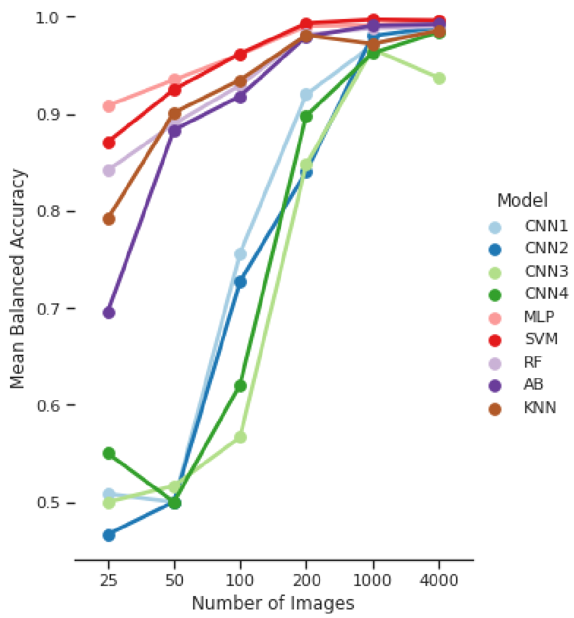

Fig.3 – Classification performance in terms of mean BA.

From Fig. 3 we can conclude that for the CNN models, few images represent no information whatsoever, but performance rapidly increases as the number of images grows. On the other hand, the ML models are generally able to learn some information with very few images, but it can be unstable in some cases. Also, for a large dataset (e.g., number of images >1000), the choice of the model becomes less significant as all of them achieve comparable performances in terms of mean BA.

3. DISCUSSION

When choosing between the approach for crack detection, if based on TA+ML or in DL, three aspects need to be considered: the labeled dataset size, the presence of expert insights about the problem (in order to verify the suitable features to describe the images), and the computational resources available. Table 1 summarizes the most expressive pros and cons of each methodology developed presented here.

Tab.1 – Pros and cons of each methodology

Methodology	**Pros**	**Cons**
TA+ML	Good performance, even for small datasets (100 images) Fast training time (seconds)	Expert insight (features selection and parametrization) Manual effort (feature engineering)
DL	Automatization of the feature extraction process (intrinsically in CNN models) Changes in the model are more simpler to be incorporated (easy layer addition on Tensorflow)	Large dataset size (at least 1000 images) Computation intensive (requires Tensorflow GPU and or training requires hours)

4. CONCLUSION

We analyzed two approaches to create an automatic crack detection methodology: the first one was based on TA+ML-based, while the second relies on CNN (DL-based). The idea was to evaluate and compare the performance of all the configurations of each approach, with six different dataset sizes (25, 50, 100, 200, 1000, and 4000 images) aiming to analyze the models' performances in small and bigger datasets. All the datasets had 60% of images with crack and 40% of images without crack. The results showed that the DL-based approach presented poor results for small datasets (e.g. 25 and 50 images). Even for 100 images, this approach reached only a BA of ~74% against a BA >95% obtained by the TA+ML-based approach using the SVM as the classification method. For bigger datasets (from 1000 images on), the results obtained by the two proposed approaches are comparable. Thus, in a real situation where only small datasets are available, the TA+ML-based approach is preferable, more specifically, SVM.

In future works, we expect to assess its performance with more challenging datasets that represents real situations better. Moreover, we expect that this methodology can be coupled in autonomous vehicles such as Unmanned Aerial Vehicles (UAVs), so that the health status of infrastructures could be systematically monitored and tracked, and, thus, effective inspection policies developed and implemented.

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