Automated assessment of AAR damage in concrete in progress

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Abstract

Over the last decades, different techniques with the aim of assessing the actual damage of aging concrete infrastructure have been proposed around the world. A method that has increasingly been used in North America is the Damage Rating Index (DRI). This microscopic and semi-quantitative petrographic tool was developed to provide a reliable characterization of both nature and degree of damage in concrete distressed by alkali-aggregate reaction (AAR) and combined mechanisms. However, carrying out the DRI is time-consuming, its results may vary somewhat among petrographers and only a few professionals worldwide are properly trained to perform it. This study proposed the use of machine learning (ML) techniques to automate the DRI test protocol, in particular the detection of cracks of various types as normally performed by the human professional during test protocol. This was done by training a so-called Convolutional Neural Network so it can predict results (machine assessment) that are close to the expected ones (human assessment). This automation of the DRI test protocol, by means of ML techniques, is a revolutionary step towards more ubiquitous use of the DRI in civil engineering, since it speeds up the process, avoids variability among petrographers and enables non/less experienced professionals to take advantage of this powerful microscopic tool. Further development is still required and currently is being conducted so that the automated DRI may become a reliable approach for the concrete community in the foreseeable future, after validations.

Keywords: *automated condition assessment; crack detection; damage rating index, machine learning*

1. INTRODUCTION

Civil infrastructure is an important part of social development, connecting nation's business, communities and people. It directly influences the economy and life quality across generations. Usually, civil infrastructure is designed with a service life of about 50-75 years, depending on the code used and structure type (i.e. dams, bridges, tunnels, stadiums, etc.). It is widely known that several critical structures built from 1960s to 1980s in Canada and worldwide are now reaching the end of their service lives. Thus, it is necessary to take certain actions so that these structures keep their performance without presenting risks to users over their last years of service or even to increase their remaining service life. Furthermore, many of these structures already display clear signs of distress due to severe damage mechanisms, which may reduce the structure's performance to unacceptable thresholds (Figure 1.1).

In this context, alkali-aggregate reaction (AAR) is one of the most important Internal Swelling Reaction (ISR) mechanisms affecting the overall performance of concrete infrastructure worldwide [1]. AAR is often divided in two types:

- Alkali-silica reaction (ASR): chemical reaction between the alkali ions present in the concrete pore solution (Na^+, K^+ and OH^-) and some unstable siliceous mineral phases from the aggregates. It is by far the most common reaction mechanism found in concrete around the world [1,2]; and
- Alkali-carbonate reaction (ACR): chemical reaction in the presence of carbonate rocks (i.e. limestone and/or dolomite aggregates). Currently, there is no consensus in the technical community on the real mechanisms causing ACR-induced expansion and damage. Yet the dedolomitization of dolomite seems to be one of the potential causes [2,3].

a) b)

Figure 1.1: Bibb Graves Bridge. a) north face. b) cracking on of archway supporting 5th span. Wetumpka, Alabama. Adapted from [7].

The concrete industry currently relies on standardized techniques and methods to perform infrastructure assessment, diagnose the possible causes of existing damage and the damage extension (i.e. diagnosis), evaluate the potential of further distress over time (i.e. prognosis), structural implications and, selection of rehabilitation strategies. Currently, assessment is largely based on tools that evaluates mechanical properties, physical integrity and durability of deteriorated structural materials and components [4-6]. Making a correlation between the damage cause(s), current and future mechanical properties and durability losses is a critical step in the structure management [2,4-6].

To assess the current condition and predict the potential for further distress of AAR-affected concrete, engineers and researchers have been trying to develop new visual, non-destructive, mechanical and microscopic protocols. A special attention has been given to the Damage Rating Index (DRI), a semi-quantitative microscopic procedure, as well as to some quantitative image analysis techniques through the use of fluorescent epoxy dyes [6]. Although the DRI is an accurate method with consistent results, it is quite time consuming and requires suitable judgement on the part of the petrographer analyzing the sample. The results are directly linked to the experience of the petrographer performing the test which them unscalable and also somewhat variable since each petrographer may find a different result. On the other hand, in recent years a number of *Machine Learning* (ML) techniques have had dramatic success classifying objects in photos and videos. This raises the hope to use these to detect and forecast damage in concrete. However, very few data are available in the literature on the use of ML systems for diagnosing concrete affected by AAR.

The aim of this work is to use ML techniques to assess damage in concrete in an automated fashion. First, a set of data of AAR-affected concrete will be selected and used for training through a Convolutional Neural Network (CNN)-based ML algorithm. Then, this algorithm will be used to assess AAR damage from untrained data. The final goal of the project is to fully automate the DRI test protocol to assess AAR-affected concrete and predict not just crack types and amounts but rather the actual DRI number. It is worth noting that the methodology presented in this project is focused specifically on concrete distress caused by AAR, however, the approach used could also very likely be applied to evaluate other deterioration mechanisms (e.g. freeze-thaw damage, delayed ettringite formation, etc.). Therefore, this work provides a preliminary basis for identifying and isolating the effects of several mechanisms that may be present simultaneously in a single sample, a task that is currently very difficult to evaluate through manual methods.

Since the eventual utilization of the above tools will largely depend on their reliability, an essential component of this project will be the validation of the planned automated tools through the assessment of real structures that are exposed to different macro-climates.

2. METHODOLOGY

2.1 Techniques for Assessing Damage in Concrete

Aiming to improve the assessment of concrete structures, Bérubé et al. [8] developed a management protocol of aging infrastructure based on several chemical, physical, and mechanical laboratory test procedures. Building on these, improved guidelines have been introduced [7]. Several researchers [2,4-6] proposed optimized testing protocols and models to diagnose and better understand numerous distress processes in concrete, such as AAR, delayed ettringite formation (DEF), and freezing and thawing cycles (FT). The established approach is a multi-level analysis, which makes use of advanced microscopic examination and mechanical testing techniques. Amongst the most promising proposed techniques are microscopic methods such as the Damage Rating Index (DRI) and quantitative image analysis (IA) techniques [1,6] (Figure 2.1).

The DRI procedure is performed using a stereomicroscope (15x-16x magnification) to identify features usually associated with AAR. These features are analyzed in squares drawn on affected samples with a grid of 1cm^2 (i.e. 10 x 10 mm units). Concrete samples under analysis are cut in half, and their surfaces are polished prior to the grid's drawing [10,12,13]. The number of counts corresponding to each type of petrographic feature are then multiplied by weighting factors, whose purpose is to balance their relative importance towards the mechanism of distress, in this case AAR. The factors used in the method were selected on a logical basis, but relatively arbitrarily [2,11]; they were recently modified in order to reduce the variability between the petrographers performing the test [11]. For comparative purposes, the final DRI value is normalized to a 100 cm² area. It has been shown that DRI values are clearly associated with induced expansion and damage caused by AAR, DEF, and FT [2,9-11].

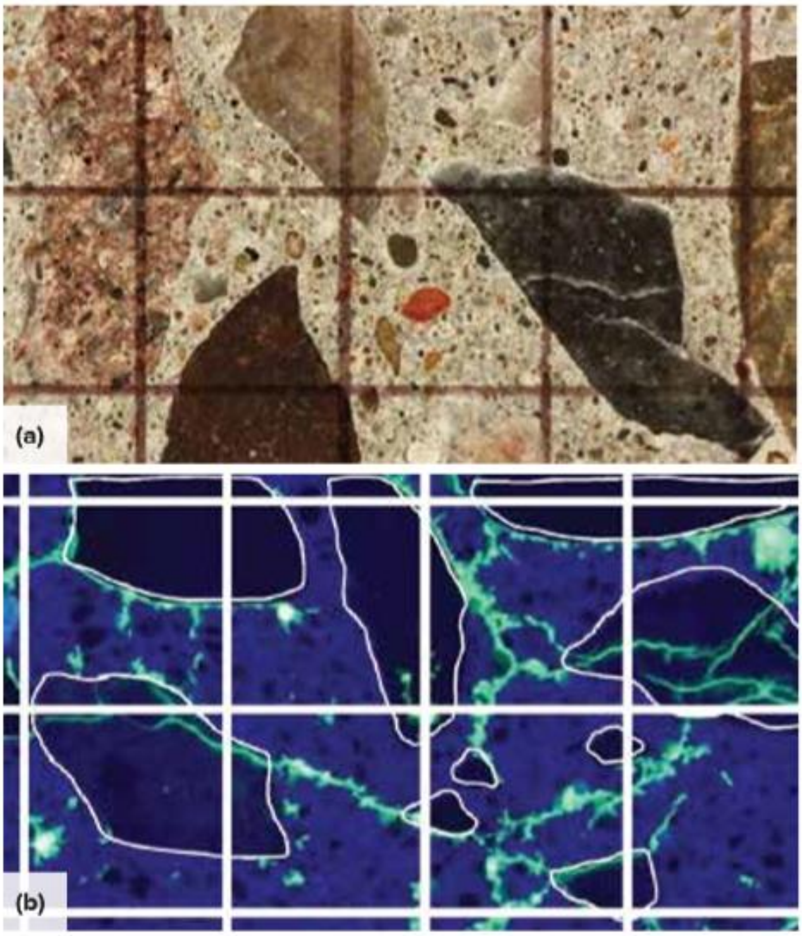


Figure 2.1: Polished concrete samples: (a) sample prepared for damage rating index (DRI) analysis by drawing 10 mm (0.4 in.) square grids on the surface; and (b) sample prepared for quantitative image analysis (IA) by impregnating with an epoxy dye that fluoresces under UV illumination [9].

The DRI has shown great correlation between expansion measurements and damage caused by AAR to concrete presenting different compressive strengths and incorporating a wide spectrum of reactive aggregates [6]. However, the DRI is also time-consuming, which could be at least partially improved using automated techniques such as machine learning (ML) processes [13,14]. Moreover, DRI values depend largely on the skill and experience of the researcher/petrographer involved in the analysis and it can be somewhat subjective. By training computers to perform automated analysis, more consistent and objective results can be expected.

Recently, Rivard et al. [6] proposed a quantitative IA technique (refer to Fig. 2(b)). Crack density and total length have been correlated with induced expansion; yet a proper crack quantification was found to crucially dependent on successful sample preparation (polishing and impregnation with epoxy). Both DRI and quantitative IA require experts to perform time-consuming procedures on affected samples. Thus, the methods are not scalable, and they are not widely accessible [1-11]. This means that for the foreseeable future, many structures may remain with neither proper inspection nor adequate protection against potential loss of serviceability and performance. However, machine learning (ML) techniques may provide potential solutions, enabling to lessen the subjectivity of the testy, yet increasing its speed, reproducibility, and accessibility.

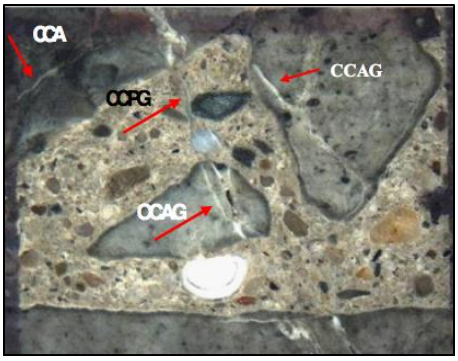
2.2 Automating Microscopic Procedures through Machine Learning

Machine Learning (ML), is the technical area of artificial intelligence that develops algorithms to allow systems to make predictions or take actions based on data/experience, instead of following explicitly pre-programmed commands [14,15].

In this project, a first phase was conducted where a proof-of-concept assessment used deep learning, i.e. an ML architecture comprising many layers of artificial neurons, to recognize the seven distinct types of damage features in the DRI method (Figure 2.2(a)). More precisely, a so-called Convolutional Neural Network was trained on just over 200 square grid digital images on 24 concrete samples affected by AAR.

Petrographic Characteristics	Abbreviation	Weighting Faction
Closed cracks in coarse aggregate	CCA	0.25
Opened cracks in coarse aggregate	OCA	2
Crack with reaction product in coarse aggregate	OCAG	2
Coarse aggregate debonded	CAD	3
Disaggregate/corroded aggregate particle	DAP	2
Crack in cement paste	CCP	3
Crack with reaction product in cement paste	CCPG	3

a)



b)

Figure 2.2: Using the damage rating index (DRI) method, weighting factors are applied to damage features identified in a petrographic examination: (a) weighting factors are assigned to each feature to reflect its relative importance toward deterioration; and (b) an exemplar micrograph of a 10 mm (0.4 in.) square grid section on a specimen, with labels added to indicate damage features [9].

The samples contained a wide range of reactive aggregate sizes and mineral types; exhibited distinct mechanical properties (i.e. compressive strength of 25, 35 and 45 MPa); and expansion levels (i.e. 0.05, 0.12, 0.20 and 0.30%). All specimens were prepared by cutting and polishing, and the DRI was conventionally conducted on each of them. The images were then labeled to identify the damage characteristics in each one, and these labeled images were used as training data for the ML algorithm.

CNN algorithms comprise of a class of artificial neural networks that have been applied very successfully to classify objects in photos and videos [16,17]. Depending on the depth of the network and the number of pixels in the incoming images, CNN's algorithms may include thousands (in some cases millions) of parameters (commonly called weights). These weights are successively adjusted during training of a CNN model, in which the algorithm's feature predictions are compared with actual data (labeled images). Errors between predictions and ground truth data are successively reduced by adjusting the weights in repeated passes through the training data.

A CNN model can predict the labels very accurately on new images, provided it is trained with sufficient examples. For the experience of this project, the training examples were images with 10 x 10mm grids drawn on polished concrete samples, labeled with 0 or 1 (yes or no) for each of the seven DRI damage characteristics. Several CNN architectures were tested, and the one that produced the best performance was selected for the continuation of the project.

3. RESULTS AND ONGOING DEVELOPMENTS

Once trained, the ML system adopted in the first phase could predict the seven different petrographic characteristics (or concepts) with an average accuracy of 64%. Given the small amount of training data (only 200 images), this is a reasonably high accuracy, as CNN models of this size are often trained with thousands of images. However, the DRI value was not computed for any of the images because the crack detectors developed in this first approach were still considered to be too inaccurate.

At the moment, a second phase of the project is being conducted, using additional training data to enhance the accuracy of predictions and thus enabling DRI numbers calculations. The goal is to completely automate the DRI test protocol to evaluate AAR-affected concrete, predicting not only types, amounts and features of cracks, but also the overall DRI evaluation. Finally, an additional step in the current and second phase of the project will take place, which is intended to use the refined ML system to evaluate other damage mechanisms such as external and internal sulfate attack, FT damage, and steel corrosion, so that the proposed approach can become a comprehensive protocol for evaluating critical aging infrastructure (Figure 3.1).

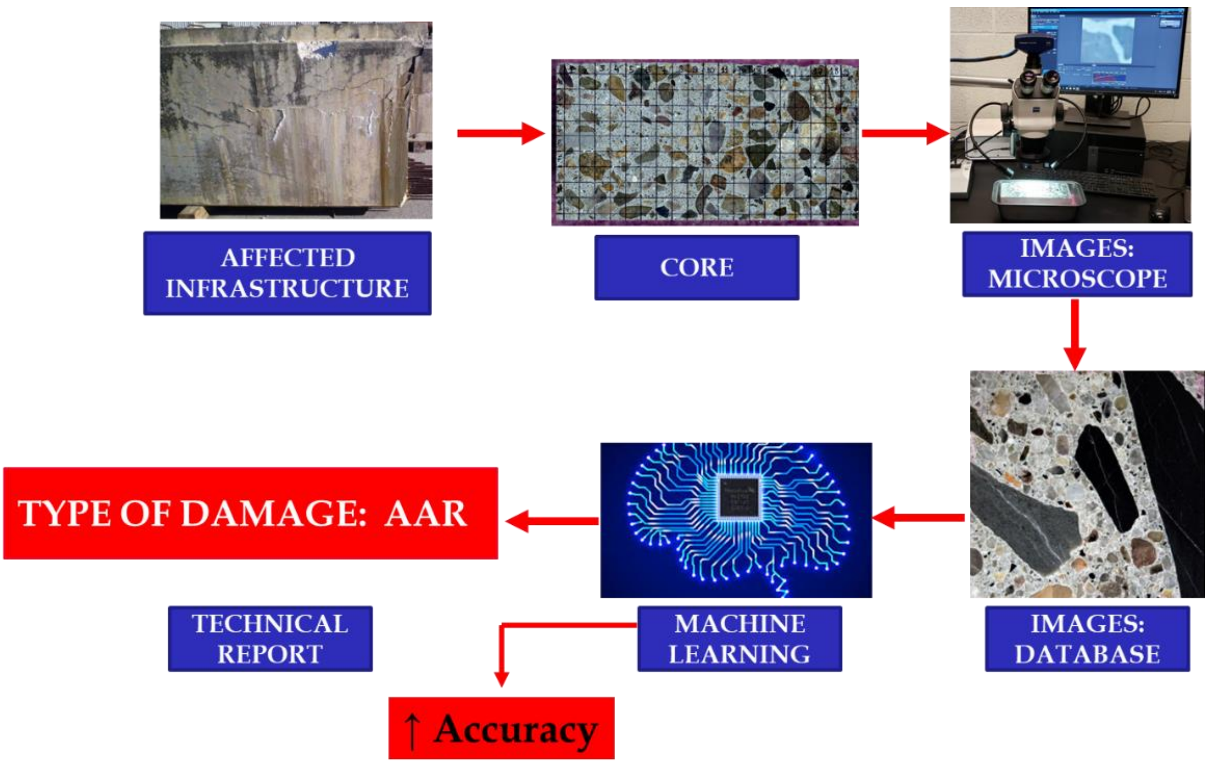


Figure 3.1: Comprehensive damage protocol for assessing damage in critical aging infrastructure [18].

Since the end of the first phase of the project, the crack detectors have already been significantly improved and may now recognize cracks through 1 mm^2 images with about 80% accuracy. Additional improvements are in progress to increase this furthermore. Moreover, 4000 new images are being incorporated in the research, from 36 new specimens (already DRI assessed) representing distinct mixtures and expansion levels. The latter might largely improve the results gathered so far.

4. FORTHCOMING PROJECTS

To use deep learning in any field, achieving high accuracy in principle requires training the model with large amounts of data. Fortunately, workarounds do exist. Transfer learning in particular allows experience in one leaning problem to help with another, and one instance of this in deep learning is the use of so-called pre-trained models. These are models which have been trained on similar data and the idea is that only a small percentage of the model weights must be retrained to identify unique features such as cracks in concrete.

Another workaround is the use of feature-extraction techniques. This project in particular will incorporate techniques that have been highly successful in texture analysis for biomedical images (for lesion detection),

With these innovations and approximately 10,000 new, high resolution images of DRI grid areas from AAR-affected concrete, it is expected to reach human accuracy levels of 90% or greater in the counting of cracks. To ensure interpretability, it is intended to apply the existing DRI method (combining crack counts for individual damage types), evaluated in conjunction with current CNN-based algorithm used. In this sense, the machine will replace only the petrographer’s ability to identify and count cracks associated with each damage feature.

Once the new automated DRI approach is successfully implemented for AAR cases, forthcoming steps will pursue its extension for a much wider variety of damage mechanisms, establishing a revolutionary comprehensive automated protocol for assessing damage in concrete. Finally, other innovative studies in this context are about to be started in parallel, including automation of the counting of entrained air voids in concrete, for example. Soon, it will be possible to develop applications (apps) that will automate visual inspection of critical concrete infrastructure by providing preliminary diagnoses of the causes and extents of damage using only images captured on smartphones.

5. FINAL REMARKS

All the above forthcoming steps have the purpose of raising the accuracy levels to numbers close to or above human accuracy levels of approximately 90%. This is crucial since in terms of crossover risks in infrastructure assessment, a misclassification from an outlier input could have potentially catastrophic consequences.

Since the eventual utilization of the above tools will largely depend on their reliability, an additional, important component of the research will require validation of the proposed automated tools through the assessment of real structures exposed to distinct micro/macro-climates. This new tool brings to light a novel, reliable and scalable tool to assess structures, facilitating proper inspection, and protecting against sudden and potential structural failures.

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