CS230

Corrosion Induced Cracking Indication in Reinforced Concrete (Computer Vision)

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1 Problem Description

We propose an application of deep learning to corrosion induced cracking, which can then be used in digital twinning [1]. The resulting model will take in corrosion patterns and concrete material properties and output whether there is a crack on the concrete's surface. There is a need for deep learning here because although existing modelling techniques are accurate, they are too computationally expensive, taking 12hrs to run on a 5cm diameter sample. Concrete is usually repaired when cracking (usually driven by corrosion) reaches the surface; by being able to predict this quickly at a large scale, the need for tedious visual inspection of large bridges/buildings is negated.

2 Related Work

To our knowledge, there has been no prior work using corrosion patterns as inputs for any task, as well as no prior work predicting surface cracking from any inputs [1]. The closest similar work was done by Boukhatem et al., which uses only 90 experimental data points to predict time-to-cracking based on concrete material properties [2]. Several other projects use concrete material properties to predict other outputs, including compressive strength [3], carbonation depth [4], and rebar corrosion level [5].

3 Challenges

Datasets of corrosion patterns and the resulting cracks are difficult to gather. Most data that exists are generated in labs, which are not representative of real world corrosion and still these datasets are very small. We propose training on data gathered from a finite element model which has been validated using experimental results.

4 Dataset

First, COMSOL, a modeling tool typically used in digital twinning, is used to generate a dataset of corrosion patterns (2D floating-point matrices representing the corrosion depth on a cylindrical rebar surface). Approximately 9,450 of these corrosion patterns along with concrete material properties will be put into a lattice finite element method (FEM) to produce crack patterns (3D boolean matrices representing the crack points in a 3-dimensional concrete block). From a crack pattern, we will extract the target label- whether there is a crack on the surface of the concrete.

[1]A digital twin is a virtual model of a real-world physical object

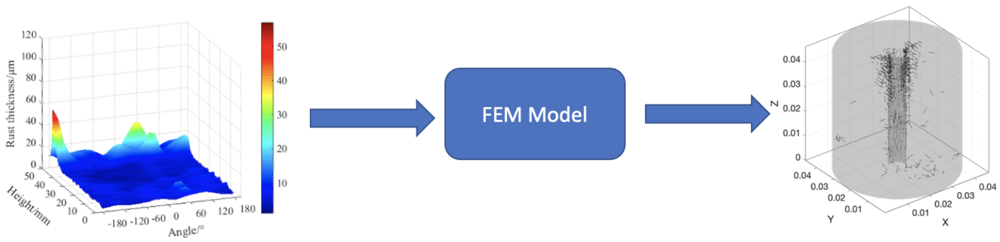

Figure 1: Input (corrosion pattern) and Output (crack pattern) of FEM

5 Learning Method

The model input is a corrosion pattern along with features of the concrete material. Predicting COMSOL is outside the scope of this project. The model output is whether there is a surface crack.

Since the primary input is a matrix representing a 2-dimensional surface, we expect convolutional neural networks to perform the best. We will also try other methods, including feedforward neural networks, decision trees, or combinations of the above.

We will explore data augmentation to increase our training dataset size without running FEM on new corrosion patterns. For example, rotating a corrosion pattern should not affect whether there will be a surface crack.

Since COMSOL is computationally cheaper than FEM, we can collect a larger dataset of unlabeled corrosion patterns, on the order of 100,000 samples. We will explore unsupervised learning approaches, such as PCA, which may be able to utilize unlabeled data to improve the performance of our supervised learning models.

6 Evaluation

We will evaluate our models on two test sets,

- A held-out 20% subset of the FEM data.
- A small (around 10 samples) set of experimental results. The experimental results accelerate the electro-chemical reaction of corrosion by soaking the concrete sample in a chloride bath and running an electric current through the rebar. Once the experiment is completed the corrosion depth on the reinforcement is measured. For our labels, we will manually inspect the concrete for surface cracks.

We will implement our own baseline using logistic regression. We'll measure standard classification metrics (precision, recall, F1 score), with a preference for high recall, since false negatives (failing to identify a crack) pose a greater risk than false positives (requiring visual inspection).

References

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