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Uncertainty quantification for a sparse machine learning (ML) data set in non-destructive testing in civil engineering (NDT-CE)

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ML has been successfully applied to solve many NDT-CE tasks. This is usually demonstrated with performance metrics that evaluate the model as a whole based on a given set of data. However, since in most cases the creation of reference data is extremely expensive, the data used is generally much sparser than in other areas, such as e-commerce. As a result, performance indicators often do not reflect the practical applicability of the ML model. Estimates that quantify transferability from one case to another are necessary to meet this challenge and pave the way for real world applications.

In this contribution we invetigate the uncertainty of ML in new NDT-CE scenarios. For this purpose, we have extended an existing training data set for the classification of corrosion damage by a new case study. Our data set includes half-cell potential mapping and ground-penetrating radar measurements. The measurements were performed on large-area concrete samples with built-in chloride-induced corrosion of reinforcement. The experiment simulated the entire life cycle of chloride induced exposed concrete components in the laboratory. The unique ability to monitor deterioration and initiate targeted corrosion initiation allowed the data to be labelled - which is crucial to ML. To investigate transferability, we extend our data by including new design features of the test specimen and environmental conditions. This allows to express the change of these features in new scenarios as uncertainties using statistical methods. We compare different sampling and statistical distribution-based approaches and show how these methods can be used to close knowledge gaps of ML models in NDT.