Uncertainty Quantification by Conformal Prediction for Agricultural Computer Vision

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Abstract

As machine learning approaches become the *de facto* modeling and prediction methods in a large spectrum of agricultural technologies from decision support systems to autonomous robots, it becomes increasingly important to provide quality guarantees on the predictions they make. Indeed, most of these methods, including the now commonly used neural networks, do not provide any trustworthy measures of the uncertainty in their predictions nor formal guarantees on their reliability. The current work constitutes a first introduction to uncertainty quantification in machine learning oriented towards the agricultural technology research community, taking the problem of precision weeding by deep learning computer vision methods as an illustrative use case. In particular, the presentation offers a didactic exposition of the *conformal prediction* framework that transforms any black box predictor into a *set predictor* with formal guarantees on the coverage of the true value at a chosen level of confidence, thus allowing for the quantification and control of the model's uncertainty. The usage of the framework is illustrated via four different experiments, highlighting particular aspects of its utility: for calibrating neural networks to achieve coverage, for benchmarking multiple trained neural networks, for adapting a neural network to distribution shifts without re-training, and finally to achieve coverage on each and every class in the dataset.