Abstract

Deep neural networks are commonly used in various applications, but they are still vulnerable to out-of-distribution (OOD) samples, which are drawn from a different distribution than the one used during training. One approach to address this issue is using techniques to detect OOD samples. There are several benchmarks for assessing OOD approaches, but most of them rely on far-OOD samples from very diverse distributions, which makes it challenging to capture the complexities of real-world scenarios. Our work introduces a comprehensive benchmark for OOD detection based on ImageNet and Places365, where individual classes are assigned as in-distribution or OOD based on their semantic similarity with the training set. The experimental results show that the effectiveness of OOD detection techniques varies depending on the chosen benchmark and that confidence-based methods might perform better than classifier-based methods on near-OOD samples.