Comparitive Analysis of OOD Detection Methods

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Inspired by [6], we aim to perform a comparative analysis of out-of-distribution (OOD) detection methods and frameworks on a newly released ImageNet based dataset [3] that has been created to aid research in OOD detection. This dataset is the first of its kind, and we aim to provide a comprehensive study of some of the current state of the art OOD detection methods on this novel dataset. Furthering the work done by [6], our goal also includes understanding the relationship between dataset statistics and the performance of these methods, and gain insights about the scenarios in which these OOD detection methods will perform consistently.
Some of the approaches that we are considering to include -

1. The baseline MSP by Hendrycks et. al. ([2])
2. ODIN by Liang et. al. ([4])
3. Pairwise OOD Detection by Tajwar et. al. ([6])
4. Mahalabobis Distance by Ren at. al. ([5])
5. Abstaining Classsifier by Thulasidasan et. al. ([7])
6. TailGAN by Dionelis et. al. ([1])

References

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