

A Quantitative Comparison of Epistemic Uncertainty Maps Applied to Carotid Artery Segmentation

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Introduction

1. Uncertainty assessment is of great value in clinical practice as it gives insight on how trust-worthy is the prediction of a model.
2. Bayesian Deep Learning proposes a mathematically grounded framework to assess epistemic uncertainties. The most popular technique in Medical imaging is the Monte-Carlo dropout[1].
3. Application to carotid artery segmentation on a multi-sequence, multi-center dataset of MR images (PARISK [3])

Aim

1. Compare epistemic uncertainty maps in two scenario: combined uncertainty maps (One uncertainty measure per voxel), class-specific uncertainty maps (One uncertainty measure per voxel per class)
2. Compare two metrics, in a class-specific scenario: class-specific AUC-PR and class-specific BRATS-UNC [2]

Conclusion

1. Combined strategy: Multi-class aggregation method performs the best
2. AUC-PR: Good performance for both Multi-class and One-vs-all aggregation methods
3. Class-specific strategy: Different results between the class-specific AUC-PR and the class-specific BRATS-UNC
4. Consistent results across centers

Studied uncertainty maps

uncertainty map \rightarrow aggregation method + uncertainty measure

6 Combined uncertainty maps:

- Averaged variance, Averaged entropy
- Similarity Kullback-Leibler divergence, Similarity Bhattacharya
- Multi-class entropy, Multi-class mutual information

4 Class-specific uncertainty maps:

- Class-wise entropy, Class-wise variance
- One-vs-all entropy, One-vs-all mutual information

Experiments

144 set of hyper-parameters under study:

- Dropout rate (0.1, 0.2, ..., 0.9)
- Dropout type (Gaussian or Bernoulli)
- Training set size (3, 5, 9, 15, 25, 30, 40 and 69 patients)

Evaluation:

- **Segmentation** : Dice
- **Combined uncertainty maps** : Combined AUC-PR
- **Class-specific uncertainty maps** : Class-specific AUC-PR, Class-specific BRATS-UNC [2]

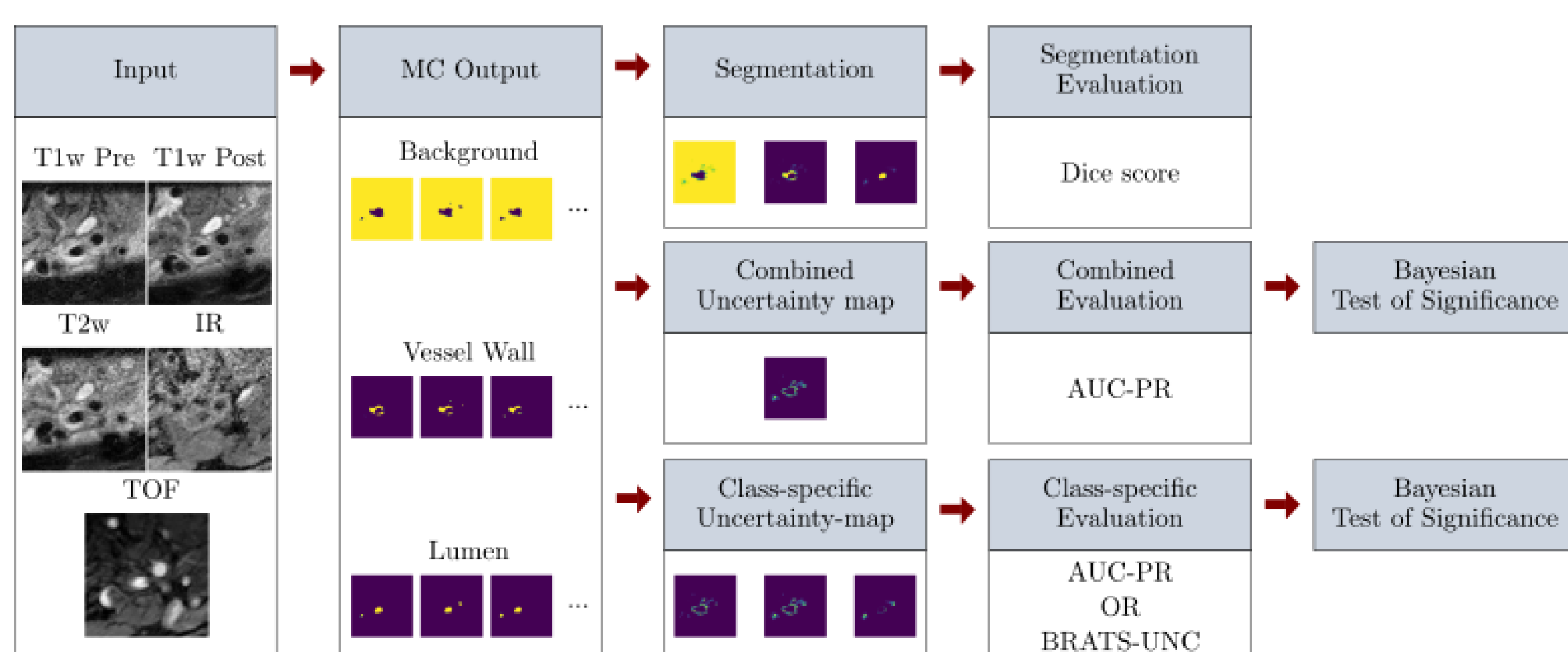


Figure 1: Description of the method

Results

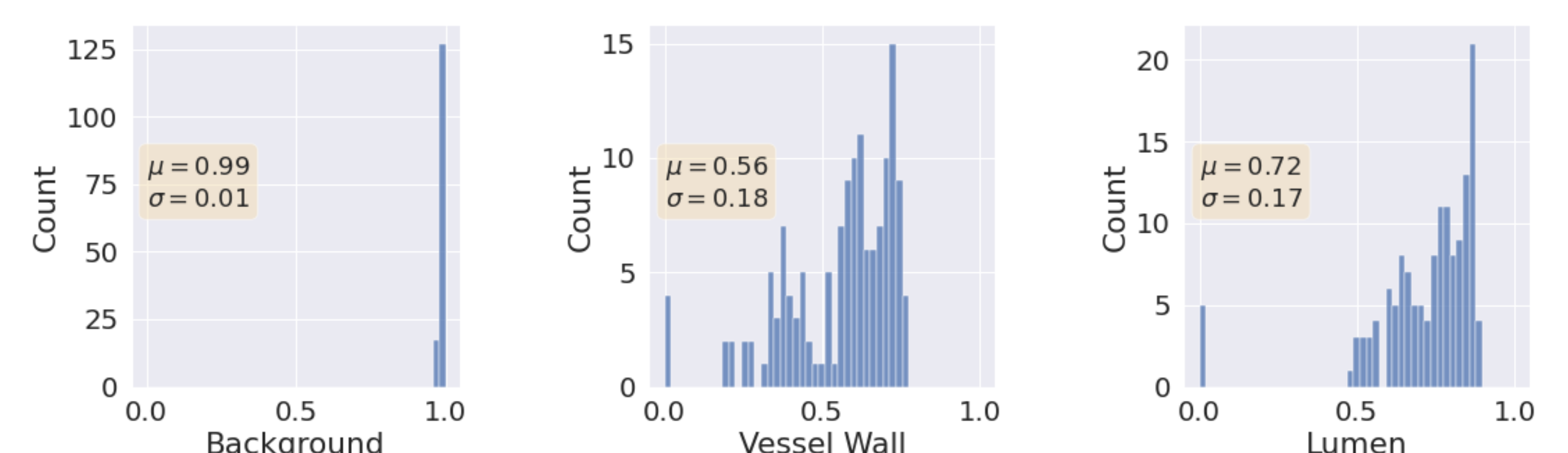


Figure 2: Distribution over the 144 models of the Dice coefficient averaged over the test set, for each of the three classes.

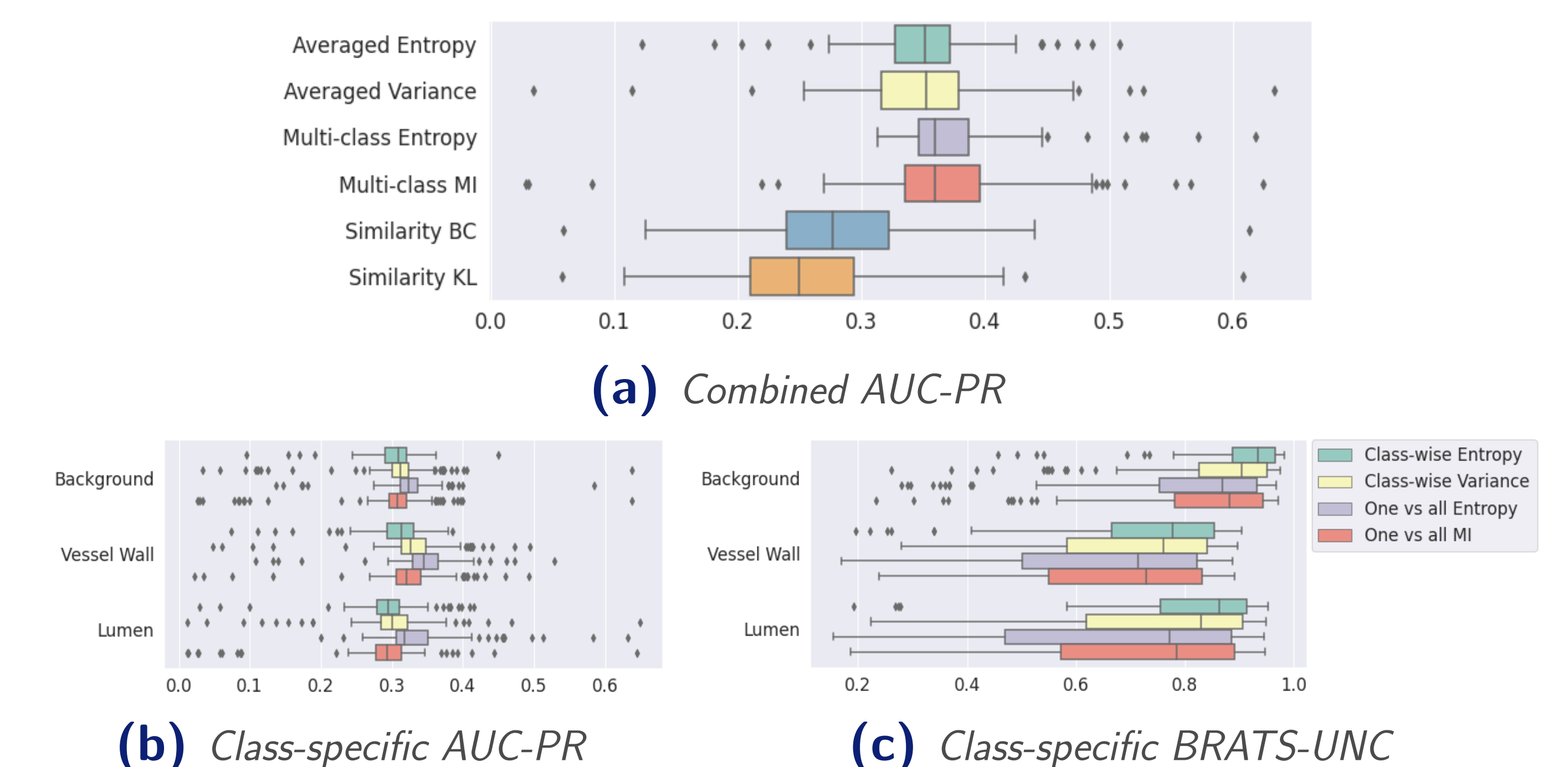


Figure 3: Distribution over the 144 models of a performance measure over the test set. The whiskers represent the 5% to 95% interval.

References

- [1] Gal et al. Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning. In *Proceedings of The 33rd International Conference on Machine Learning*, 2016.
- [2] Mehta et al. Uncertainty Evaluation Metrics for Brain Tumour Segmentation. In *Medical Imaging with Deep Learning*, 2020.
- [3] Truijman et al. Plaque At RISK (PARISK): prospective multicenter study to improve diagnosis of high-risk carotid plaques. *International Journal of Stroke*, 9(6):747–754, 2014.

Bayesian test of significance

- Estimation of $p_{A>B}$ the proportion of experiment where an uncertainty map A out-performed an uncertainty map B.
- Updated with Bayes rule
- $p_{A>B} \sim \text{Beta}(1 + k_{A>B}, N - 1 - k_{A>B})$

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