Uncertainty Aware Proposal Segmentation for Unknown Object Detection Supplementary Material

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1. Additional Details of Sec. 4.3

We select 4000 training and 550 testing images from ADE20K Scene Parsing dataset from the following indoor scene types: 'bathroom', 'bedroom', 'kitchen', 'living room', 'office', 'dining room', 'hotel room', 'dorm room', 'home office', 'waiting room'.

The proposal segmentation model is trained with these known classes: wall, floor, ceiling, bed, window, cabinet, door, table, plant, curtain, chair, painting, sofa, shelf, mirror, carpet, bathtub, cushion, sink, fridge, toilet. And *lamp* is the novel class we left out to detect during testing.

2. Additional Experiment

2.1. Mask-RCNN false positives

We take the proposals and their feature maps from Mask-RCNN trained on Cityscapes and pass them into our proposal classification model. The model miss-classifies the same objects, but correctly estimates the high uncertainty of the predictions. Figure 2 shows two examples from Road Anomaly dataset where animals are confidently predicted as 'person' by Mask-RCNN. There are 13 wrong detections and 12 of them have uncertainty above 0.5.

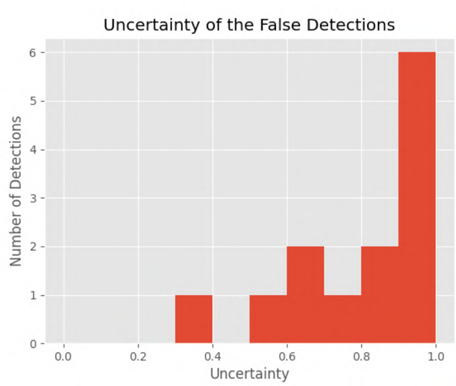

Figure 1. Proposal Uncertainties Histogram for false detections.

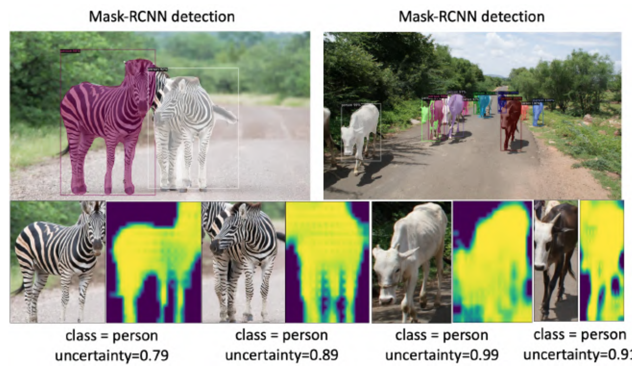

Figure 2. Compare Mask-RCNN predictions with our model. Mask-RCNN detects the OOD animals as 'person' with high score (over 95%). While our model also classifies these animals into 'person' but with high uncertainty.

3. Additional Results

We showed additional results of proposal segmentation (Fig. 3), whole image segmentation (Fig. 4, 5). The whole gaussian blob toy example is visualized at Fig 6. More proposal segmentation results on indoor scenes are visualized at Fig 8, 9.

4. Model Architecture

Here we draw the figures of the architecture of the proposed proposal segmentation (Fig. 10) and proposal classification (Fig. 11) model. Details of RBF network is shown in Fig. 12.

References

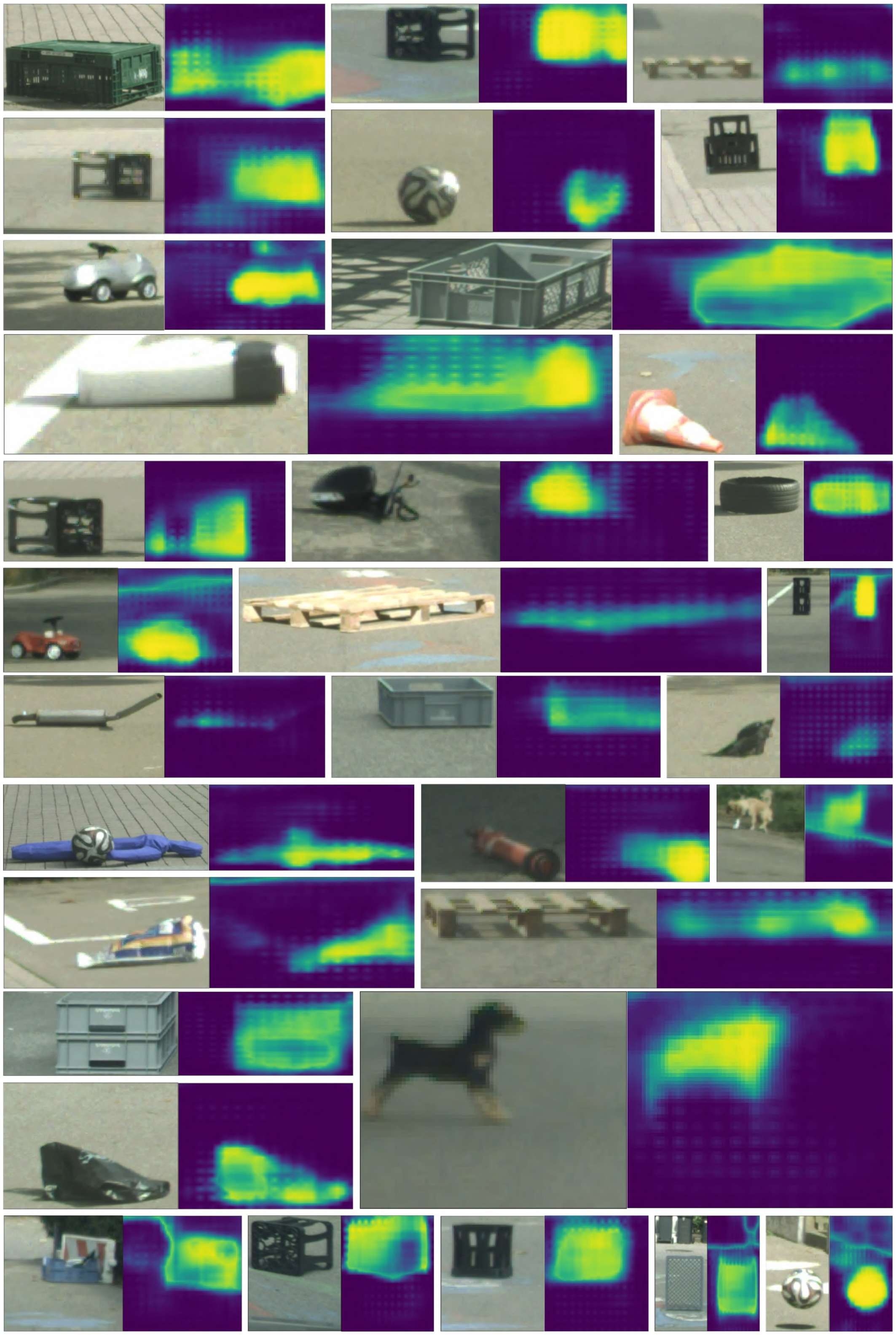

Figure 3. OOD proposal segmentation on Lost&Found dataset. We showed the input proposal and uncertainty estimation results.

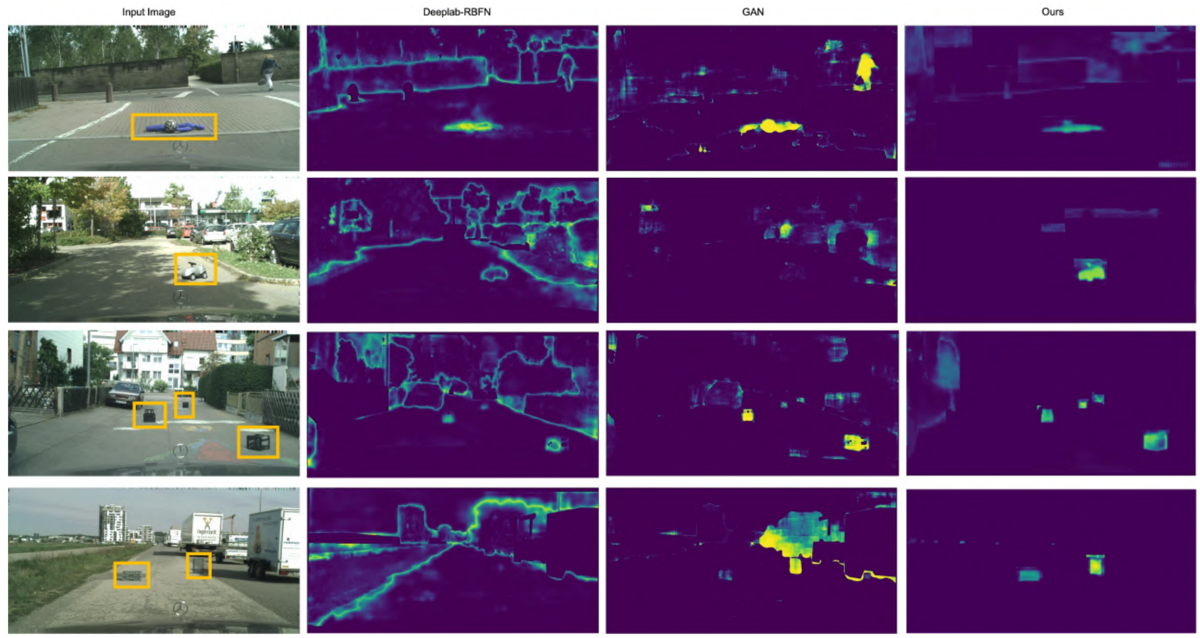

Figure 4. Whole image OOD object segmentation results on Lost&Found dataset. From left to right are the input image, Deeplab-RBFN method result, GAN method result and our method result.

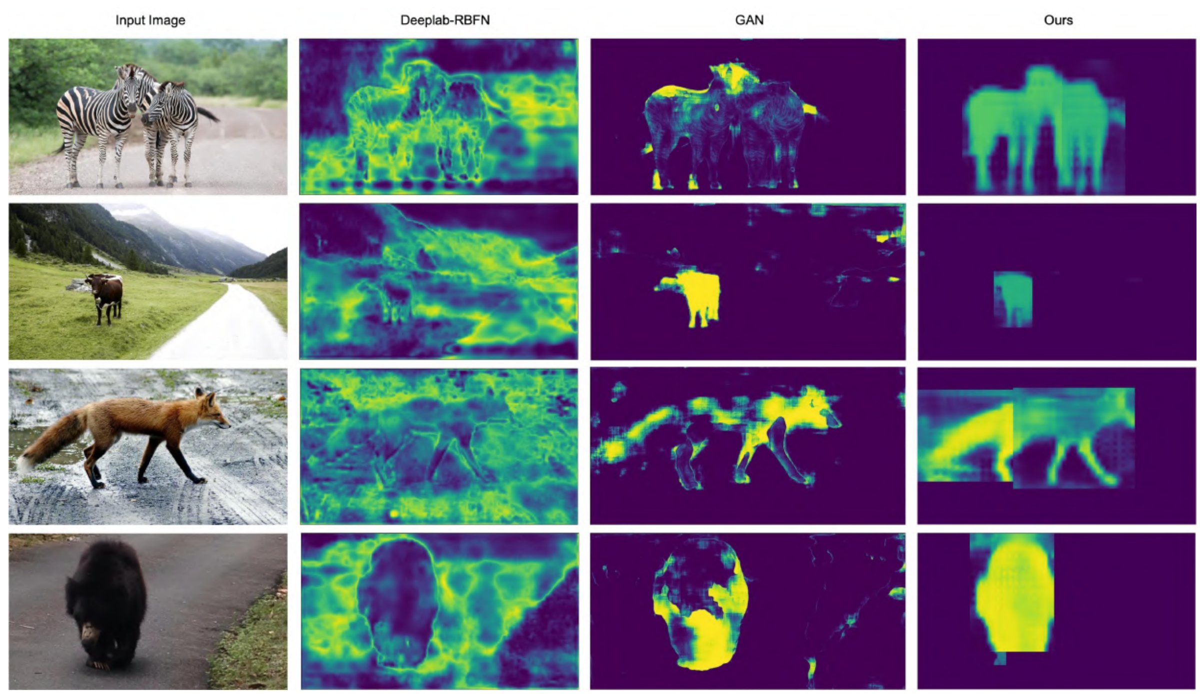

Figure 5. Whole image OOD object segmentation results on RoadAnomaly dataset. From left to right are the input image, Deeplab-RBFN method result, GAN method result and our method result.

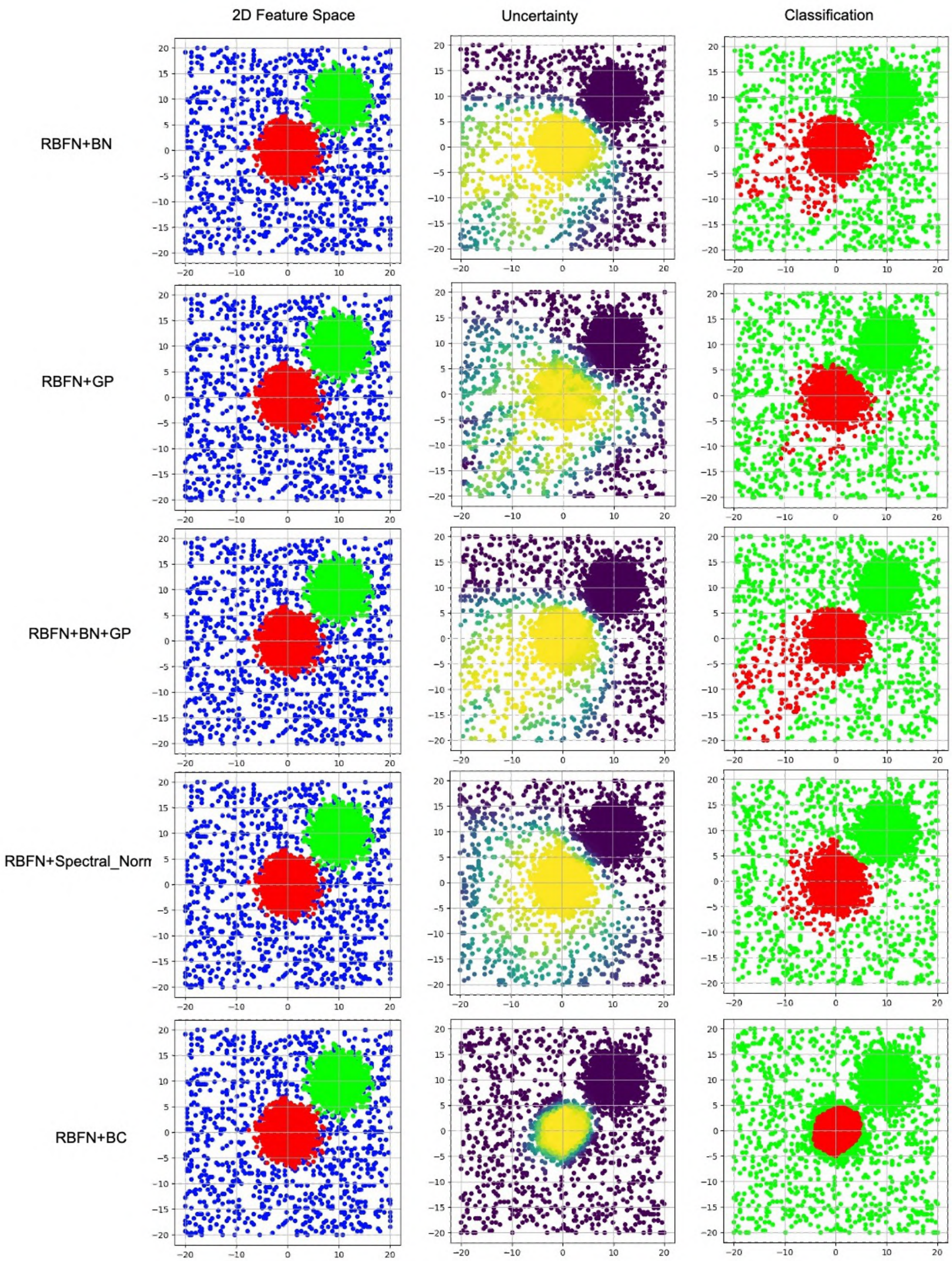

Figure 6. Visualization of the toy example with gaussian blobs on 2d space. Columns from left to right are the test data, uncertainty estimation results (brighter color means lower uncertainty) and classification into the center blob based on uncertainty. For each row from top to bottom, are RBFN+BatchNorm(BN), RBFN+GradientPenalty(GP), RBFN+BatchNorm+GradientPenalty, RBFN+SpectralNorm and RBFN+BoudnaryConstraint.

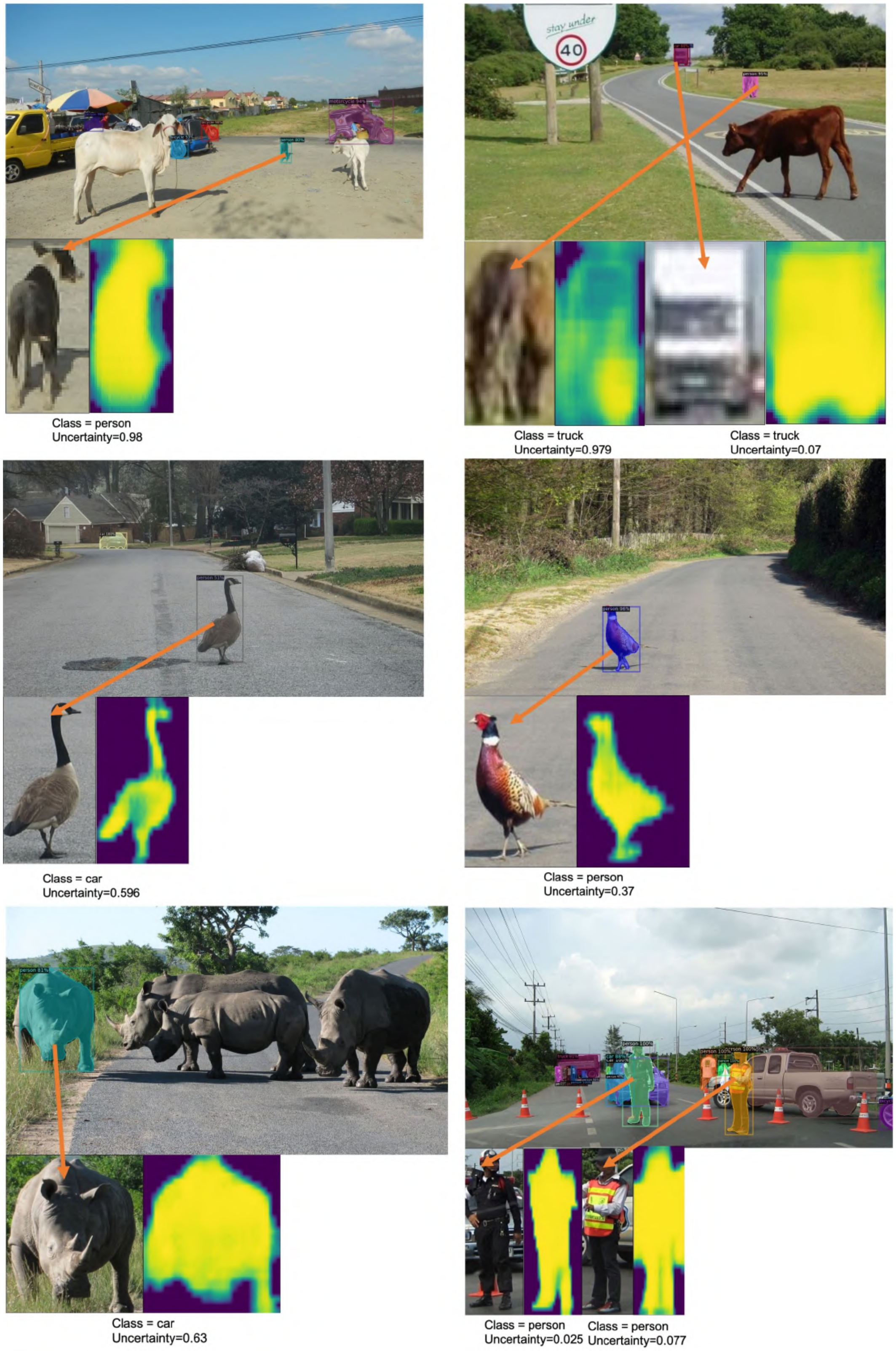

Figure 7. Compare Mask-RCNN predictions with our model.

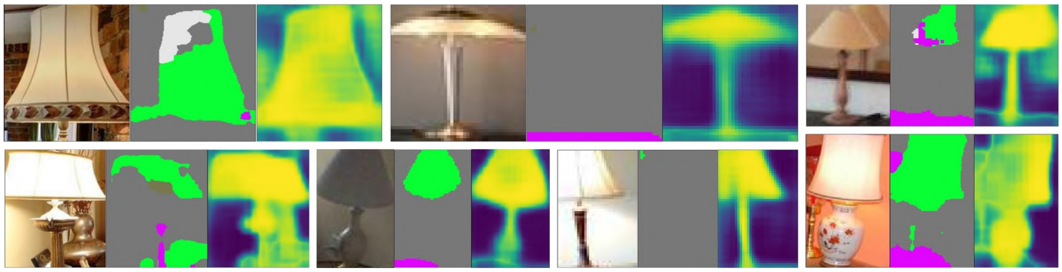

Figure 8. Proposal segmentation on lamps (unknown object) from ADE20K Dataset. For each tuple, we have the input proposal, semantic segmentation results and the uncertainty estimation.

Figure 9. Proposal segmentation on novel instances from AVD Dataset.

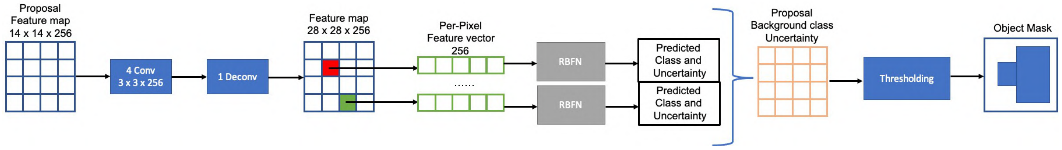

Figure 10. Proposal Segmentation Model

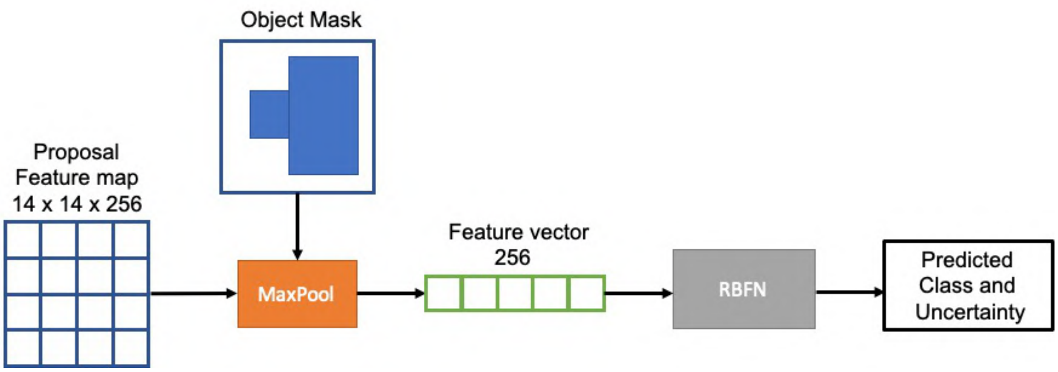

Figure 11. Proposal Classification Model

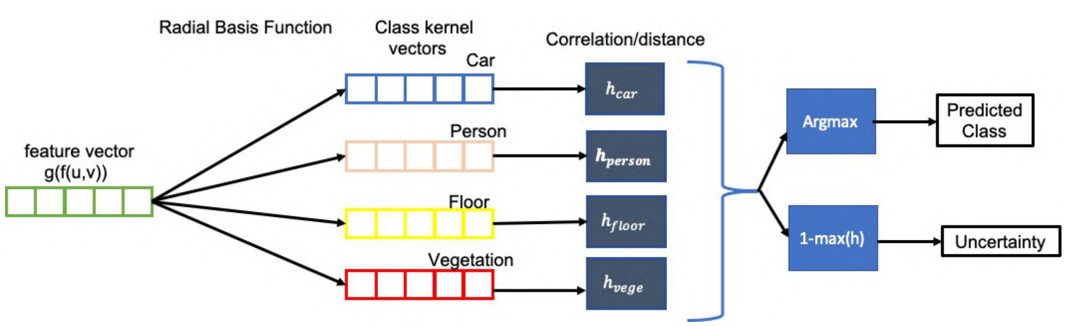

Figure 12. Radial Basis Function Network