

Conclusions Advancements in Deep learning made the Deep Neural Networks (DNN) to industry-ready. Nevertheless, respectively. Overall, the performance of OOD detection is better with Deep Ensembles than with Flipout or Dropout.

Lessons learned The following are the lessons learned during the duration of the thesis

Training and evaluation of 3D DNNs are time-consuming and resource-intensive. Even a single forward pass on the test LiDAR datasets have huge memory requirements even for preprocessing or computing metrics.

With this level of requirements, finding a proper prior for Flipout layers is hard. In turn, this makes the tuning of the F. Picking the suitable candidates for the OOD benchmark requires in depth analysis of datasets like structural similarities. Because the DNN is not perfect, few points in the training dataset are classified as OOD points. These points have a low

Future work The following are the ways this study can be further extended.

Since this study is performed on the point-based model, this can be extended to a projection based model like RangeNet. From the survey, we observe that the current 3D model's performance is not like its counterparts in 2D semantic segmentation. The OOD datasets proposed in this dataset are static datatype which has a higher point density. It would be interesting. We observed another potential candidate for the OOD dataset, and it is the Toronto3D dataset. The Toronto3D dataset. The adverse weather conditions to the training dataset can be applied as [?] proposed LiDAR fog injection module, and This study can be extended to apply non post-hoc methods such as Mahalanobis distance-based OOD [?] or MetaSeg [?]