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

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 lo

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 RangeNe
From the survey, we observe that the current 3D model's performance is not like its counterparts in 2D semantic segme
The OOD datasets proposed in this dataset are static datatype which has a higher point density. It would be interestin
We observed another potential candidate for the OOD dataset, and it is the Toronto3D dataset. The Toronto3D datase
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 [