Methodology and Experimental Setup This chapter will discuss the RandlLA-Net used for 3D semantic segmentatio
In random point sampling, We select K points uniformly from the original point cloud in random point sampling an
Figure **??** represents the local features aggregation module for the RandLA-Net. This module is applied parallelly o
Local Spatial Encoding The local spatial encoding (LocSE) module takes each point (p_i) in the point cloud (P) and

Finding nearest neighbours
Relative position encoding
Feature augmentation

In step 1, neighbour points for point (p_i) are collected using the Euclidean distance-based K-nearest neighbour (KN

where r_i^k is the relative position of point p_i with respect to p_i^k, here in p_i and p_i^k only the x,y and z positions are used.

Where g is the softmax function and W is the attention weights, $\hat{f_i^k}$ is the input feature vector to the attentive pooling
Dilated Residual Block Dilated Residual Block is a ResNet inspired module claimed by authors and represented as
To summarize, up to this point, we have studied the unique feature of RandLA-Net. That is how random point sam
RandLA-Net Architecture RandLA-Net is an encoder-decoder architecture with skip connections used in various seg
We chose RandLA-Net because of the following reasons:

Efficient extraction of complex structures progressively using Local Feature Aggregation (LFA) module.
Fewer parameters (1.24M) compared to other SOTA 3D semantic segmentation models, making training efficient, as 3D
Proven performance over various datasets such as Semantic3D and SemanticKITTI, along with ablation study of each s
No preprocessing such as range image representation as in [**?**] or farthest point sampling with a computational complexi
State of the art performance in point-based methods, consisting of Multi-Layer Perceptrons (MLP) and without expensi

3D Semantic Segmentation Evaluation Metrics To evaluate the performance of RandLA-Net over the training datas
Mean Intersection-over-Union (mIoU) Mean Intersection-over-Union is a widely used metric for performance evalua

Where N is the number of classes, p_k and g_k are predicted mask and ground truth mask of k^{th} class.
Accuracy Accuracy is another widely used metric, which can be quantified as a number of points in the point cloud

Where TP, TN, FP and FN are True Positives, True Negatives, False Positives and False Negatives, respectively, from t
Here, we conclude the study of RandLA-Net, the reason for its effective performance, argue the reasons to chose Ra
Despite their performance boosting ability, they are also used to estimate uncertainty as in [**?**]. [**?**] proposes that w
Flipout In this thesis, we also employed the Flipout version of the RandLA-Net model for uncertainty estimates, an

So the node output of the neural network is modified as

Here ϕ is the activation function, and x_n is the n^{th} input example in the mini batch. Also the vectors r_n and s_n are ind
At a glance, these random weight perturbations give us slightly different output estimates for every forward pass. I
[scale=0.5]images/flipout.jpg Illustration of test dataflow in Flipout. Here F_1 represents the Flipout trained model and
OOD Estimates In this section, we discuss the two methods used to generate the OOD score for classifying the OO
Maximum Softmax Probability First proposed in [**?**], Maximum Softmax Probability (MSP) uses the probability of

Entropy Entropy is defined by [**?**] as an "ill-defined notion of chaos or uncertainty". Entropy has its roots in therm

In theory, following this formula, if the point in the point cloud is from In-Distribution (ID), the softmax output is high
OOD Detection Evaluation Metrics This section will discuss the metrics used for evaluating OOD detection. Firstly
A ROC curve is generated, given a set of probabilities/scores and their true labels which are either positive or nega
Area Under an ROC curve Since the ROC curves are a two dimensional depictions and we need a single scalar valu
Experimental Setup In the previous sections, we discussed how RandLA-Net works and also the details of Deep En

Python - 3.6
Tensorflow - 1.15.0
Tensorflow probability - 0.7.0
Open3d-python - 0.3.0 (training), 0.13.0 (visualizations)

Deep Ensembles For Deep Ensembles, we trained 20 randomly initialized instances of RandLA-Net on the Semantic
every 5^{th} forward pass. [scale=0.42]images/fout$_{r}andlanet.pngFlipout - versionedRandLA - NetwherethelastthreeFC$