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Investigating the performance of novel class discovery (NCD) approach for semantic segmentation on realworld SLAM LiDAR point cloud data

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Abstract

The development of SLAM LiDAR enables efficient 3D point cloud acquisition, but the complex characteristics of the data pose challenges for semantic segmentation, especially when using a closed-set learning approach. One open-set learning approach that can be used for semantic segmentation is novel class discovery (NCD). Several studies have used this approach for semantic segmentation on three-dimensional data, but not many studies have segmented with this approach on SLAM LiDAR data. Therefore, this study evaluates the application of Novel Class Discovery on SLAM LiDAR data to identify known classes and form novel clusters in real-world SLAM LiDAR data. This process begins with preparing the acquired SLAM LiDAR dataset, followed by adjusting the dataset format, feature extraction, implementing the NCD framework, and ends with an analysis of the model's performance in 3D semantic segmentation on SLAM LiDAR data. The results of this study indicate that the model can recognize ground, vegetation, and buildings with high quantitative performance. NCD also successfully separates unknown points and groups them into several novel classes, but the cluster distribution is not yet stable, and most clusters still contain fragments of the base class. This condition indicates that the success of NCD is greatly influenced by the quality of the base class, confidence threshold, embedding, and characteristics of SLAM LiDAR data such as point density variations, noise, and object heterogeneity. The results show the potential of NCD for real-world point cloud segmentation, but its application requires further development to improve the stability and reliability of segmentation.

Keywords: SLAM LiDAR, novel class discovery, semantic segmentation, point cloud

1. Introduction

The evolution of light detection and ranging (LiDAR) technology has significantly impacted the mapping field, particularly in supporting three-dimensional data acquisition with increasingly high levels of detail. This technology enables the collection of spatial data in the form of point clouds, capable of representing objects and environmental conditions in detail. Compared with several conventional survey methods, data acquired using LiDAR generally has a high level of precision, good point density, and spatial resolution, allowing for a more detailed depiction of surface variations (Dhruwa & Garg, 2023). In addition to the quality of the data produced, the acquisition process using LiDAR is also relatively fast, thus increasing efficiency in mapping activities and the creation of three-dimensional models (Warchoł dkk., 2023).

Along with these developments, an acquisition approach based on Simultaneous Localization and Mapping (SLAM) has emerged, further expanding the use of LiDAR technology. This approach allows the system to perform mapping and position estimation simultaneously during the recording process, allowing the environment around the sensor to be reconstructed directly without relying entirely on a global positioning system. This capability is achieved through the integration of several sensor components, such as LiDAR, cameras, and Inertial measurement units (IMU), which work simultaneously to estimate the device's position and orientation during the acquisition process (Cao dkk., 2023). This multi-sensor integration makes SLAM LiDAR more flexible for use in environments with limited GNSS signals and in areas requiring high acquisition mobility (Abdelaziz & El-Rabbany, 2022).

In the early stages of its development, SLAM LiDAR technology was primarily utilized for indoor mapping, particularly in three-dimensional building modeling due to its ability to perform acquisitions without relying entirely on GNSS. However, in recent years, its use has begun to expand to outdoor environments to support various needs, such as urban mapping, infrastructure, environmental monitoring, and the development of three-dimensional city models for 3D city modelling. The use of SLAM LiDAR in outdoor environments offers high

acquisition efficiency and operational flexibility, but at the same time also produces more complex data characteristics due to variations in point density, changes in lighting conditions, object movement in the field, and the accumulation of position estimation errors during the recording process (Hu dkk., 2025). The complexity of these data characteristics then becomes a challenge in the advanced analysis process, including the process of semantic segmentation and automatic object identification.

Accordance with the evolution of LiDAR technology in data acquisition, point cloud processing has also experienced significant progress, particularly in the field of three-dimensional semantic segmentation. Semantic segmentation aims to assign labels or semantic information to each point in a point cloud based on the object category it represents, such as land, buildings, vegetation, or other objects (He dkk., 2023). Semantic segmentation of point clouds can be performed manually or automatically. Manual segmentation generally requires a lot of time, expertise, and is relatively expensive, especially when applied to point cloud data with a large number of points and a wide coverage area (Krisanski dkk., 2021). Therefore, various automated approaches have been developed to accelerate the process of object identification in three-dimensional data. However, automatic segmentation still faces several challenges, particularly because the quality of the results is strongly influenced by the characteristics of the input data, the quality of the annotation, and the model's ability to distinguish patterns between objects (McVicker dkk., 2024).

The above conditions can cause geometric characteristics between different objects can be similar, so that the automatic semantic segmentation process is not always able to produce consistent object classification. In addition, most commonly used semantic segmentation approaches still operate in a closed-set learning scheme, which the model can only recognize object classes that have been previously defined and labelled (He dkk., 2023). As a result, when there is a new object or an object variation that is not covered in the training data, the model tends to classify it into one of the known classes, even though the object actually has different characteristics.

The closed-set learning approach remains a widely used paradigm in developing semantic segmentation methods on point cloud data. Problems arise when the model is applied to data containing objects or object variations outside the training classes. Under these conditions, the model tends to force new objects into one of the known classes, even with a high level of prediction confidence. This phenomenon is known as overconfident misclassification and is one of the main limitations of the closed-set learning approach (Hu dkk., 2025). This limitation becomes even more significant in SLAM LiDAR data acquired from outdoor environments. This characteristic causes the class distribution in the point cloud to be more heterogeneous than in the benchmark dataset (McVicker dkk., 2024).

To solve these limitations, the novel class discovery (NCD) approach has been developed as an alternative for learning new class representations and classifying. NCD approach aims to expand the model's capabilities to not only recognize known classes but also discover new patterns or object groups not yet present in the training data (Roy dkk., 2022). The NCD approach utilizes a combination of information from labelled and unlabelled data to expand the model's ability to recognize known classes while simultaneously discovering new class structures. With these characteristics, the NCD approach has the potential to be applied to semantic point cloud segmentation, particularly in real-world SLAM LiDAR data, which has more complex object variations, data quality, and spatial uncertainty than more controlled benchmark datasets.

Several recent studies have begun to explore the application of novel class discovery (NCD) to point cloud data. (Riz dkk., 2023). For example, the novel point segmentation (NOPS) method was proposed, which utilized online clustering and uncertainty estimation to generate pseudo-labels, enabling the model to automatically identify new classes. Further development was also carried out by (J. Du dkk., 2025), who demonstrated that the NCD approach is capable of recognizing new classes in three-dimensional point cloud data using several benchmark datasets, such as S3DIS, Toronto-3D, Semantic STF, and Semantic POSS. The results of this study demonstrated improved performance compared to the NOPS method in the process of discovering new classes in point cloud data. However, most NCD research on point clouds is still conducted on benchmark datasets that are relatively controlled, both in terms of data structure, annotation quality, and class distribution. Evaluation on real-world SLAM LiDAR data, especially in outdoor environments, is still relatively limited. However, point clouds generated from SLAM LiDAR acquisitions have more complex characteristics, such as variations in point density, noise, position uncertainty, differences in recording angles, and high object heterogeneity. These conditions can affect the model's ability to form stable base class representations and consistently distinguish new classes (Petras

dkk., 2023). Therefore, this study focuses on evaluating the limitations of the NCD approach on SLAM LiDAR point cloud data in outdoor environments.

Based on this background, the main contributions of this research include the following:

1. Evaluating the performance of novel class discovery (NCD)-based semantic segmentation on outdoor SLAM LiDAR data.
2. Analysing the relationship between the quality of base class representation and the formation of novel classes in three-dimensional semantic segmentation.
3. Identifying factors that cause failure of the novel class discovery process on real-world SLAM LiDAR data.
4. Analysing the influence of intensity and geometry features on the model's ability to distinguish object classes in three-dimensional point cloud data.

Based on these contributions, this research is expected to provide a more comprehensive understanding of the performance, including the reliabilities and limitations, of the NCD approach for semantic segmentation of real-world SLAM LiDAR data.

2. Related Works

Three-dimensional semantic segmentation is a crucial step in point cloud processing, assigning semantic labels to each point based on the object category represented, such as land surface, building, vegetation, or other objects (He dkk., 2023). Through this process, a collection of points that initially represented only geometric information can be transformed into more meaningful spatial information and used for various further analyses. In general, deep learning-based semantic segmentation approaches for point cloud data can be grouped into three main categories: projection-based, voxel-based, and point-based (Atik & Duran, 2022; Gezawa dkk., 2022; Lowphansirikul dkk., 2019). Projection-based approaches project three-dimensional data into a two-dimensional representation to simplify learning and adapt to network architectures originally developed for imagery. One implementation is demonstrated by Atik & Duran, (2022) through the SegUNet3D architecture, which combines the characteristics of U-Net and SegNet to improve segmentation quality on complex point cloud data. On the other hand, the point-based approach is one of most widely used methods because it works directly on point cloud data without prior representation transformation. Various architectures such as PointNet, PointNet++, PointCNN, DGCNN, and SPGraph have been developed to capture spatial relationships between points more effectively. Research by Lowphansirikul dkk., (2019) showed that PointNet and SPGraph-based approaches achieve high segmentation performance in urban environments, while Ning dkk. (2021) found that DGCNN outperforms PointNet and PointNet++ in direct point cloud segmentation.

Various deep learning-based semantic segmentation approaches developed for point cloud data have generally been applied to data acquired through Airborne Laser Scanning (ALS) and Terrestrial Laser Scanning (TLS). However, the application of similar approaches to data acquired via Simultaneous Localization and Mapping (SLAM) LiDAR remains relatively limited. This distinction is important because the characteristics of SLAM LiDAR data differ fundamentally from conventional LiDAR data. Point clouds generated by the SLAM LiDAR process are generally affected by sensor movement dynamics during acquisition, resulting in a non-uniform point distribution, higher noise levels, and more complex spatial and temporal variations (Liu, 2022; Trybała dkk., 2023). In this context, several studies have begun to integrate deep learning-based semantic segmentation into SLAM LiDAR system. Yang dkk. (2023), for example, combined the LEGO-LOAM and RangeNet++ algorithms to improve ground-point extraction and achieve higher segmentation quality. Another study by Li dkk (2021) using semantic-aided LOAM (SA-LOAM) and by Yang dkk (2023) using Se-LOAM showed that semantic information can also be used to improve loop closure accuracy and separate static and dynamic objects during the mapping process.

Most deep learning-based semantic segmentation approaches currently used on point cloud data still adopt the closed-set learning paradigm. While this approach has demonstrated strong performance across various benchmark datasets, its generalization capability is limited when the model encounters objects or patterns that fall outside the training distribution. This limitation leads the model to consistently predict one of the recognized classes, even though the observed objects have different characteristics. This phenomenon is known as overconfident misclassification, in which the model produces high-confidence predictions for classes that are actually inappropriate (Hu dkk., 2025).

In response to the limitations of the closed-set learning approach, various learning methods for handling classes that are missing during training have emerged. One approach that has gained popularity in recent years is open-set learning. Open-set learning has been applied in various fields, including remote sensing and geospatial analysis. For instance, Oliveira *et al.* (2023) implemented this approach on remote sensing imagery using a fully convolutional architecture with the OpenFCN and OpenPCS methods. The results of this study indicate that the open-set approach can improve the model's ability to recognize pixels from classes not used during training without reducing classification performance on known classes.

One further development of this concept is Novel class discovery (NCD), an approach designed to automatically discover and form new class groups from unlabeled data (Colin *et al.*, 2024). Unlike open-set approaches, which generally focus only on detecting the presence of objects outside known classes, NCD aims to build representations that enable new objects to be grouped into more structured semantic classes. Building on this, various strategies have been developed, including clustering-based approaches, contrastive learning, and the formation of prototypical representations (Kim *et al.*, 2024).

In three-dimensional point cloud data, NCD applications have shown promising results. Riz *et al.* (2023) proposed novel point segmentation (NOPS), which uses online clustering and uncertainty estimation to automatically generate pseudo-labels. Subsequent work by Du *et al.* (2025) integrated cluster-based sampling and proximity hashing to improve the ability to discover new classes in three-dimensional point cloud segmentation. In addition, a similar approach was used in research of Y. Li *et al.* (2025), which employed a causal representation and causal reasoning based approach to improve the model's ability to distinguish between base class and novel class. Despite demonstrating improved performance on several benchmark datasets, most of these studies still use relatively controlled data and have not evaluated NCD's performance on SLAM LiDAR data, which is more dynamic and complex.

Based on various studies, deep learning-based three-dimensional semantic segmentation has advanced significantly and demonstrated strong performance across diverse types of point cloud data. However, most research on semantic segmentation and NCD for point cloud data is still in development and is evaluated using relatively controlled benchmark datasets. Notably, point cloud data from SLAM LiDAR acquisition has different characteristics from the commonly used benchmark datasets. As a result, there is still limited research specifically evaluating how SLAM LiDAR data, particularly in understanding the relationship between the quality of base class segmentation and the model's ability to generate novel classes.

3. Methodology

3.1. Study Area and SLAM LiDAR dataset

The research located in area of Faculty of Engineering at Gadjah Mada University, covering approximately 18 hectares. This area contains various objects with quite diverse characteristics, such as buildings, vegetation, supporting facilities, and other objects scattered throughout the campus. The research location is shown in Figure 1. Faculty of engineering area was selected for its environmental heterogeneity, making it suitable for testing and evaluation 3D semantic segmentation, particularly using the Novel Class Discovery (NCD) approach. The presence of buildings of varying shapes, roads, sidewalks, green open areas, and small objects provides a representative environment for assessing the model's ability to distinguish various objects categories in point cloud data.

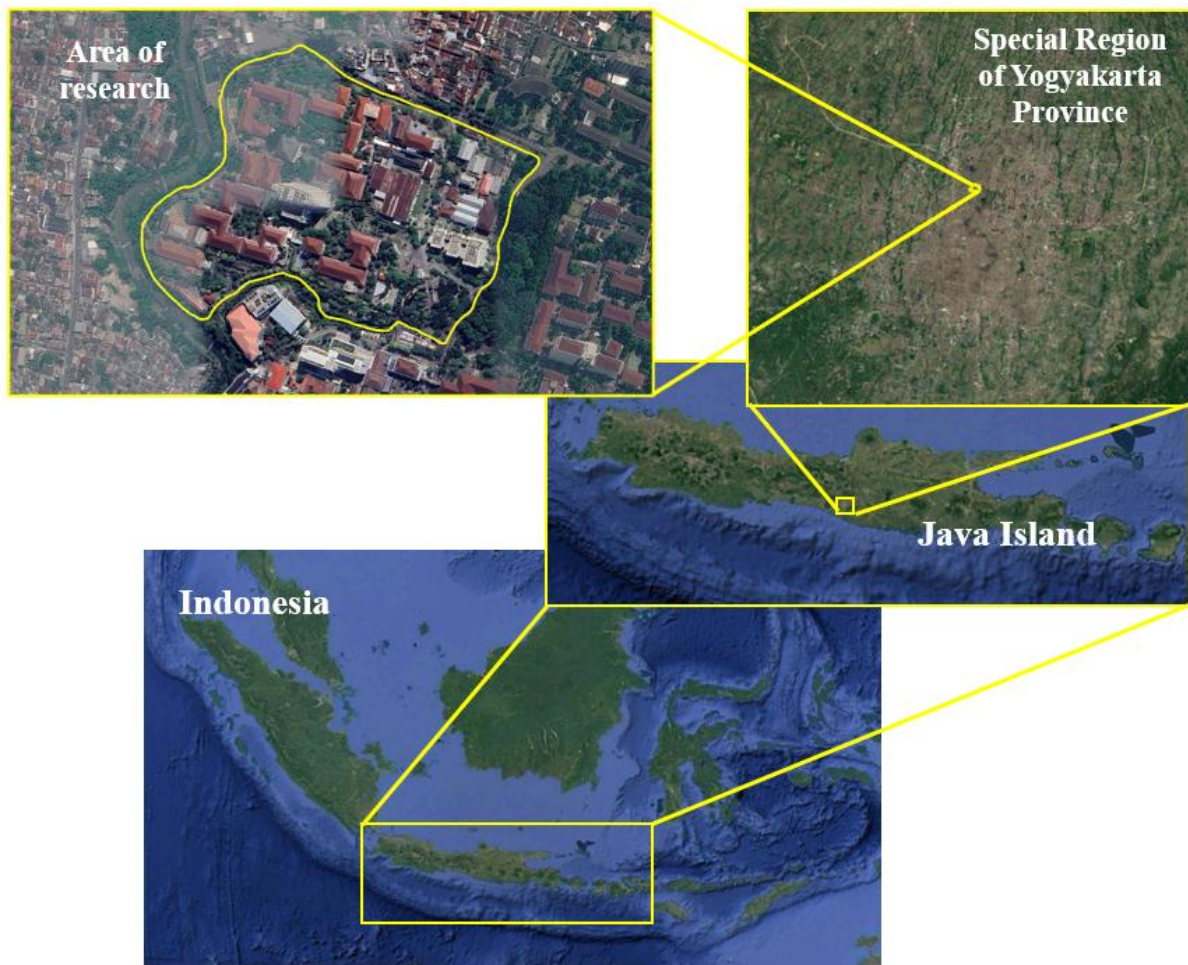


Figure 1 Study research location (source: Google Earth Pro)

The point cloud data was acquired using a handheld SLAM LiDAR device. The acquisition process was carried out by operator, who carried the device directly to record objects within the research area, ensuring loop closure conditions were met during recording. Therefore, the acquisition path was designed as shown in Figure 2. The figure displays line features representing 15 trajectories used during the LiDAR SLAM data acquisition process. The dataset generated by acquisition process serves as the basis for evaluation the limitations of applying the NCD approach to the semantic segmentation of SLAM LiDAR data.

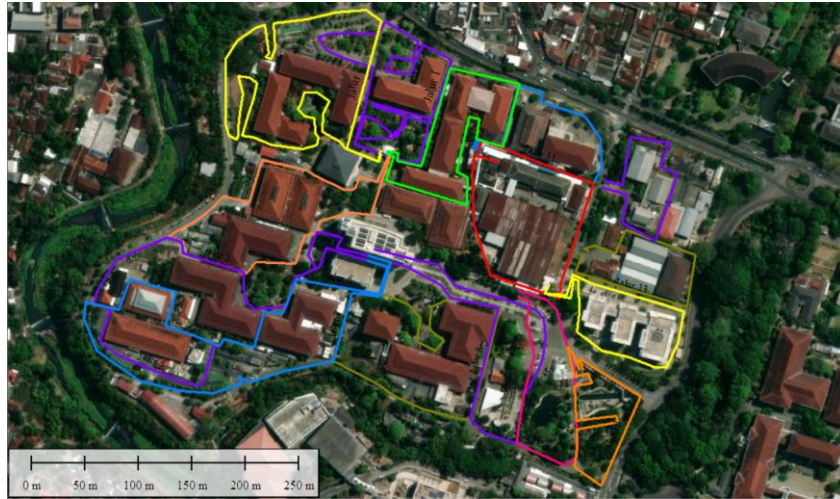


Figure 2 the 15 SLAM LiDAR paths (basemap source: World Imagery)

3.2. Dataset preparation and feature extraction

During dataset preparation, raw point cloud data is initially filtered to remove noise and outlier using statistical outlier removal (SOR) method. The implementation of SOR uses two parameters in sequence: the number of points for mean distance estimation, which determines the neighborhood considered in the average distance calculation, and the standard deviation, which sets the threshold for classifying outlier. In this research, the number of parameter for mean distance estimation is 6, while the standard deviation parameter is set at 1. The results of this filtering process can be seen in Figure 3.

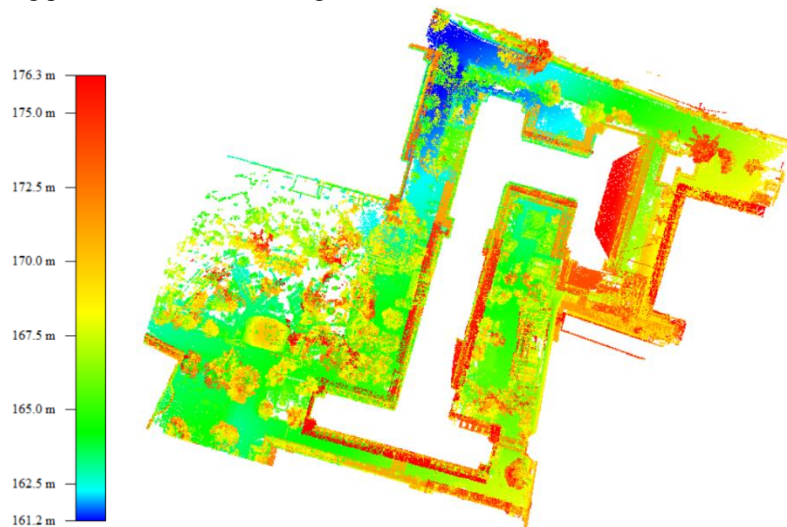


Figure 3 Filtering stage

Once filtering is complete, the workflow integrates all SLAM LiDAR datasets along each loop-closure path via inter-path registration. This registration is performed using a cloud-to-cloud method assisted by the Iterative Closest Point (ICP) algorithm. Achieving high-quality registration is essential to prevent analysis of the NCD approach's limitations from being affected by positional discrepancies between paths. Therefore, dataset quality checks follow registration to ensure the completeness, thickness, and density of the resulting point cloud data.

The next step is manual labelling or annotation of the point cloud data used as reference data in the model training process. In this study, annotations were performed for three main classes: ground, vegetation, and building. To evaluate the NCD approach's ability to recognize new classes, the annotation process was performed only on approximately 30% of the total point cloud data, as shown in Figure 4. With this scheme, approximately 70% of the remaining points were unlabelled (unknown), consisting of points from the base class that had not been previously identified.

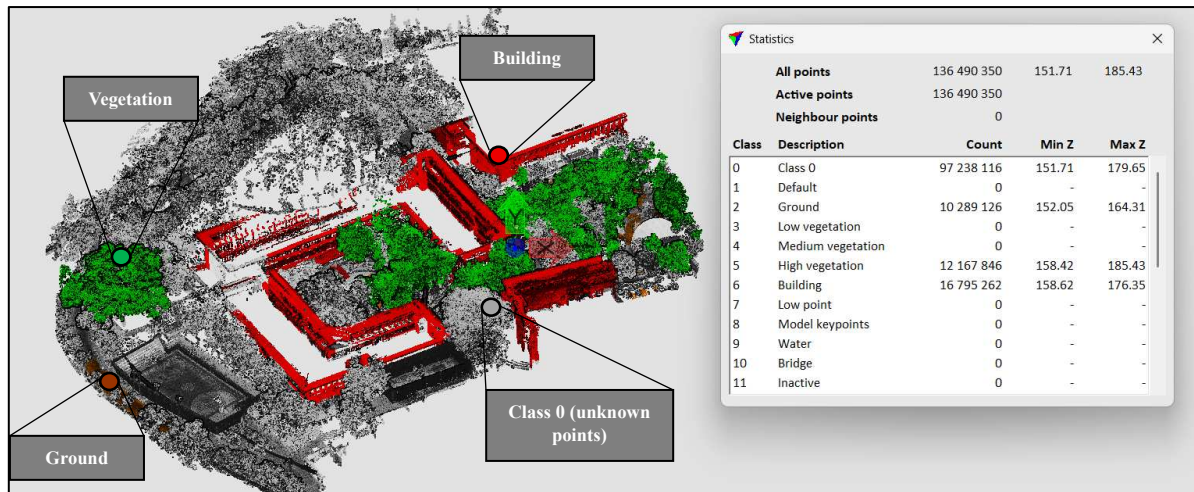


Figure 4 Manual anoting stage

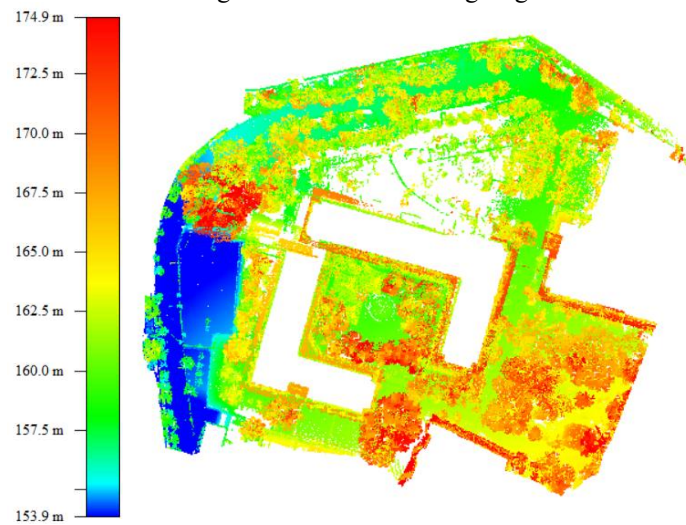


Figure 5 Subsampling stage

Subsampling process was performed to reduce the number of point clouds processed without losing important information that characterized the object's shape and distribution. In this process, subsampling is performed using a minimum space between points parameter of 0,5. Based on this, each point retained has a minimum distance of 0,5 meters from other points. Points within range of less than 0,5 meters are reduced, resulting in lower data density and a more efficient dataset size. The results of this process can be seen in Figure 5. Following this process, 11 features were extracted from each point cloud, including roughness, change normal rate, omnivariance, planarity, linearity, surface variance, sphericity, verticality, local height, global height, and intensity. All these features were then used as input to the semantic segmentation model during training.

3.3. NCD-based semantic segmentation framework

In applying the novel class discovery approach framework to point cloud data, the process is divided into several main stages: adjusting the point cloud data format to a bin/feature/label format, dataset division, training the base class model, and implementing the NCD framework. The first stage involves adapting the SLAM LiDAR data format to a commonly used benchmark dataset, in this case, the SemanticKITTI dataset. This format stores point coordinates, additional features, and class labels for each point in the point cloud. Furthermore, voxel downsampling is performed, a necessary step because MinkowskiEngine-based models operate using sparse tensor represented in voxels.

The next step, after completing the format adjustment and voxel downsampling stages for each dataset, is to divide the datasets. This dataset division ensures that the model not only learns patterns from the training dataset but also evaluates its ability to recognize patterns in data not used during training. In this study, the datasets were divided into three categories: training, validation, and test. In this study, the dataset split ratio was 60% for the training set, 20% for the validation set, and 20% for the test set.

The next step was to train the model using the previously restructured dataset. The model used was MultiHeadMinkUnet, whose architecture is shown in Figure 6. This model is a sparse convolution-based deep learning architecture designed to process three-dimensional data as sparse tensors in MinkowskiEngine. The model received input in the form of 11 pre-prepared feature dimensions. These features consisted of eight initially extracted features, one built-in point cloud feature (intensity), and two additional locally calculated features: local height and global height.

The MultiHeadMinkUnet architecture used in this study, as shown in Figure 6, generally consists of an encoder, a bottleneck, a decoder, and a classification head. The model input is a sparse tensor processed through a sparse convolution operation. The encoder section is responsible for gradually extracting features, with each encoder block downsampling the spatial resolution while increasing the number of feature channels, from 32 to 256 at the bottleneck. The bottleneck retains the highest level of abstraction of feature representations even though spatial information has been compressed. To improve the training of a deeper network, each encoder block is equipped with a residual block, which allows information from the input to be passed directly to the subsequent block, thereby enhancing learning. Mathematically, the residual block mechanism can be expressed as shown in equation 1:

$$y = F(x, \{W_i\}) + x \quad (1)$$

with the following feature transformation as shown in equation 2.

$$F(x) = W_2 \cdot \text{ReLU}(W_1 \cdot x + b_1) + b_2 \quad (2)$$

indicates that the input is processed through a convolution layer and an activation function before being summed back to the initial input.

Features that have passed the bottleneck are then processed in the decoder to restore the spatial representation at a higher resolution. The decoder utilizes skip connections from the encoder to preserve detailed spatial information, allowing abstract features from the bottleneck to be combined with the same level of spatial detail from the encoder layer. The classification head at the end of the architecture converts the feature representation into logits for three main classes: ground, vegetation, and building. The logit values are then converted to predicted probabilities using the softmax function, as shown in equation 3.

$$\hat{y}_{i,c} = \frac{\exp(z_{i,c})}{\sum_{K=1}^C \exp(z_{i,c})} \quad (3)$$

where $\hat{y}_{i,c}$ is the predicted probability of point i in class c , $z_{i,c}$ is the logit value, and C is the number of classes. The class with the highest probability is then selected as the final prediction result for each point in the point cloud.

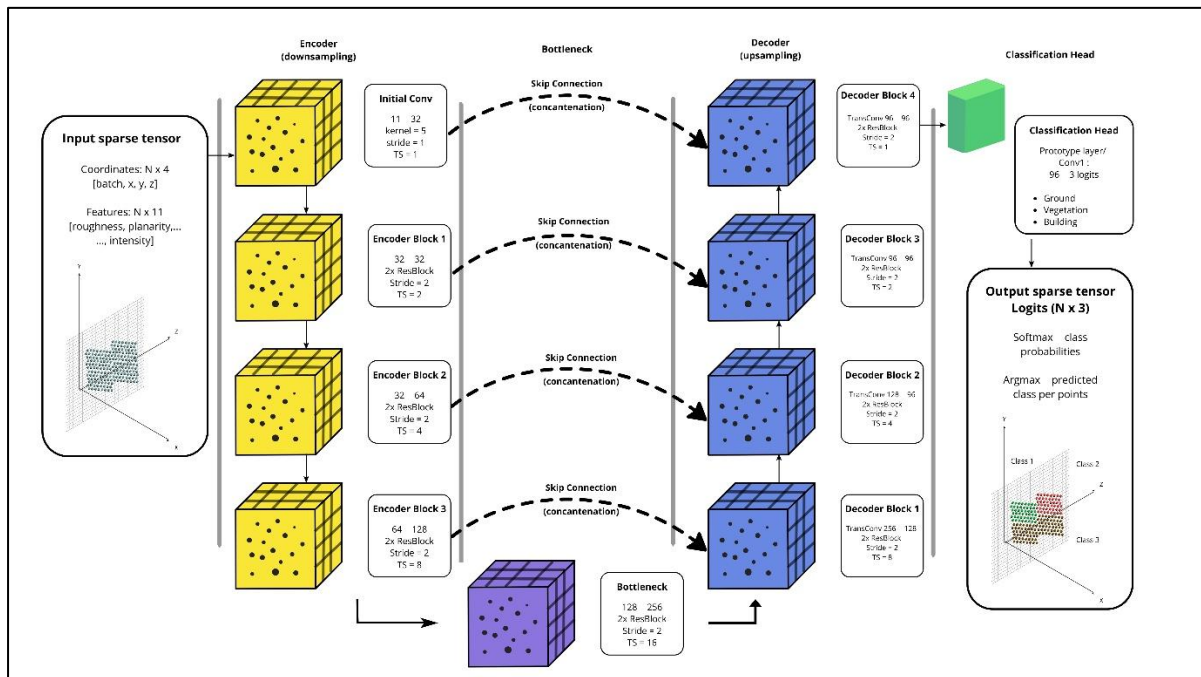


Figure 6 MultiHeadMinkUnet Architecture (source: adaptation of the concept in the MinkowskiEngine library)

This architecture is then used within the NCD framework for semantic segmentation. The process begins with base-class inference using the MultiHeadMinkUNet model to generate class predictions, confidence values, probability vectors, and ground-truth labels. Next, unknown points are identified based on confidence values with a certain threshold, as shown in equation 4:

$$\begin{aligned} x \in \text{Known}, & \text{ jika } \text{confidence}(x) \geq \tau \\ x \in \text{Unknown}, & \text{ jika } \text{confidence}(x) < \tau \end{aligned} \quad (4)$$

The identification results form a binary mask that separates known and unknown points. The core stage of NCD is performed by clustering unknown points, where feature embeddings are extracted from the intermediate layer or the logit model and then normalized via L2 normalization to ensure consistent feature scales. The final stage involves merging the base-class and novel-class predictions, which are then exported back to the LAS format. The final LAS file contains all attributes, including intensity and classification class, for each processed path.

3.4. Limitation investigation framework

The framework was created to evaluate the limitations of the Novel Class Discovery (NCD) approach by analyzing how well models perform on real-world SLAM LiDAR data. This framework looks at both base and novel classes. Its main goal is to identify factors that affect the reliability of semantic segmentation. It also helps explain how the quality of base-class representations relates to the model's ability to discover new classes. The evaluation has three main stages.

The first stage is Base-Class Evaluation, which assesses how well the model recognizes known classes using standard metrics such as Intersection over Union (IoU), precision, recall, F1-score, overall accuracy (oAcc), mean accuracy (mAcc), and Dice Similarity Coefficient (DSC). This stage is performed by measuring the model's accuracy as it represents base classes in complex point clouds and identifies errors, such as overconfident misclassification. Overall accuracy (oAcc) is calculated as shown in equation 5:

$$oAcc = \frac{\sum_{i=1}^C TP_i}{N} \quad (5)$$

where TP_i , is the number of true positives in class- i , C is the number of classes, and N is the total number of points (Wang dkk., 2026). Meanwhile, to see model performance more evenly across each class, we can use the mean accuracy with the equation, as shown in equation 6 :

$$mAcc = \frac{1}{C} \sum_{i=1}^C \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \quad (6)$$

where TP_i , TN_i , FP_i , and FN_i denote true positives, true negatives, false positives, and false negatives, respectively.

Another metric is the mean intersection over union (mIoU). This metric is widely used for evaluating semantic segmentation because it quantifies the degree of agreement between model predictions and ground-truth labels. The intersection over union (IoU) value for each class is calculated by comparing the intersection area between the prediction and ground truth to their combined area (R. Du dkk., 2023; Wang dkk., 2026). The IoU formula can be expressed as shown in Equation 7:

$$IoU = \frac{TP_i}{TP_i + FP_i + FN_i} \quad (7)$$

Next, the mIoU value is calculated from the average IoU across all classes using the equation 8 below:

$$mIoU = \frac{1}{C} \sum_{i=1}^C IoU_i \quad (8)$$

Based on this equation, a higher mIoU value indicates a better fit between the segmentation results and the reference labels. Therefore, this metric is used to assess segmentation quality more representatively, especially in data with an imbalanced class distribution.

In addition, the Dice Similarity Coefficient (DSC) is used as an additional metric to assess segmentation quality. DSC is similar to IoU but offers a different perspective on the degree of agreement between predictions and the ground truth (Rich dkk., 2023). The formula and equation for DSC can be expressed as shown in equation 9:

$$DSC_i = \frac{2 \times TP_i}{2 \times TP_i + FP_i + FN_i} \quad (9)$$

The DSC value ranges from 0 to 1. The closer it is to 1, the better the agreement between the model's prediction results and the reference labels. In this study, DSC is used as a complementary metric to strengthen the interpretation of segmentation quality.

The second stage is novel-class evaluation. In this stage, the model's ability to recognize unknown points and cluster them into several novel classes is evaluated. Unknown points are determined based on the model's confidence value, using a specific threshold in this research. The percentage of unknown points and their distribution are analyzed to assess the model's ability to predict on previously unseen data. After that, the clustering process is applied to the unknown points, and they are clustered into several novel classes. Then, the quality of the clustered result is evaluated using compactness and separation. The analysis assesses the consistency and validity of each novel class predicted by the model.

The final stage is analysis, which integrates the results of the base-class and novel-class evaluations to provide a comprehensive understanding of NCD's approach limitations. This analysis aims to identify the relationship between the quality of predictions against the base class and the success of the discovery process for SLAM LiDAR point cloud data, and to assess the influence of the features used and the characteristics of SLAM LiDAR data, including point density, noise, and object heterogeneity. Based on these stages, the framework for investigating the limitations of the application of novel class discovery can be used to identify factors that cause failure or decreased performance of NCD, while also providing insights to improve training strategies and feature engineering, thereby making the model more effective at recognizing both base and novel classes in real-world SLAM LiDAR data.

4. Result and Discussion

4.1. Model training and convergence

The MultiHeadMinkUNet model was trained on a SLAM LiDAR point cloud dataset that had undergone preprocessing, including filtering, subsampling, and 11-dimensional feature extraction. The model received a sparse tensor input representing all geometric features and intensities of each point in the point cloud. It was then processed through an encoder-bottleneck-decoder architecture to construct a spatial representation and to perform base-class classification (ground, vegetation, building).

Table 1 Training loss and validation loss result

Epoch	Training loss	Validation loss	Reduction
0	0.5728	0.4397	-
1	0.3767	0.2874	34.62%
2	0.2760	0.2190	23.82%
3	0.2222	0.1847	15.66%
4	0.2030	0.1700	7.95%
5	0.1897	0.1793	-5.47%
6	0.1795	0.1474	17.81%
7	0.1788	0.1468	0.38%
8	0.1560	0.1423	3.08%
9	0.1580	0.1427	-0.27%
10	0.1480	0.1351	5.33%
11	0.1282	0.1268	6.16%
12	0.1108	0.1426	-12.45%
13	0.1178	0.1099	22.92%
14	0.1323	0.1363	-24.06%
15	0.1099	0.1187	12.92%
16	0.1071	0.1092	8.01%
17	0.1232	0.1036	5.16%
18	0.1027	0.0996	3.85%
19	0.0929	0.0945	5.06%
20	0.1012	0.0909	3.79%
21	0.0872	0.0847	6.84%
22	0.0862	0.1317	-55.49%
23	0.1000	0.0809	38.57%
24	0.0772	0.0923	-14.04%

The convergence curve showed a steady decrease in training and validation loss across epochs, with minimal differences between them. This indicates that the model did not exhibit significant overfitting and effectively learned patterns in the data. Early stopping evaluation was used to determine the optimal epoch, stopping training when the loss decrease was no longer significant on the validation data.

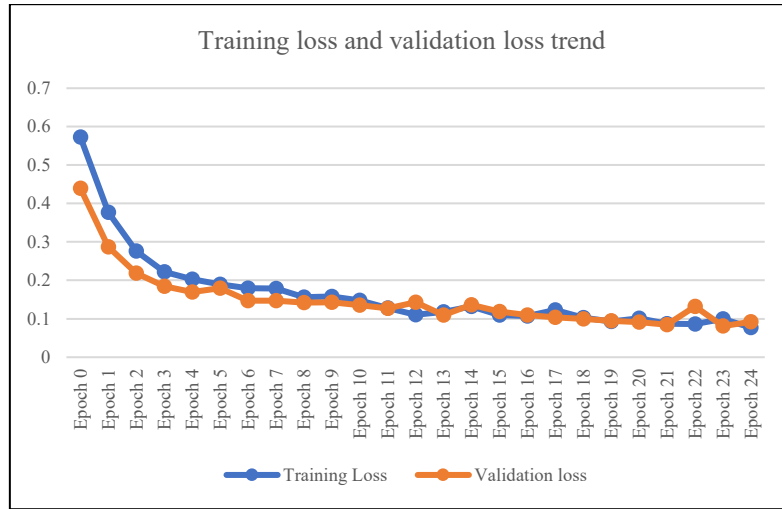


Figure 7 Training loss and validation loss trend

Based on the information presented Table 1, a summary of training metrics includes the number of epochs, learning rate, and final loss values on the training and validation data. In the table, the validation loss decreases from 0.4397 to 0.0809 at epoch 23. In addition, the decreasing trend in training results also appears quite stable as shown in Figure 7. The figure shows the loss curve across all epochs, illustrating the model's consistency in learning the base-class representation from SLAM LiDAR data. These results indicate that the model successfully learned the feature representation stably. This condition indicates that the model is ready to proceed to the next stage: base class inference and the Novel Class Discovery (NCD) process.

4.2. Base class performance results

After the model training process is complete, the next stage is base class inference on the entire SLAM LiDAR dataset. This process is carried out to evaluate the model's ability to recognize known classes: ground, vegetation, and buildings. The model generates a probability prediction for each point, which is then converted into a final label using the softmax function, categorizing each point in the point cloud into one of the base classes.

Table 2 Base class model performance

Class	Metric	Test (%)
Ground	<i>IoU</i>	96.85
	<i>DSC</i>	98.40
	<i>Accuracy</i>	97.35
Vegetation	<i>IoU</i>	94.92
	<i>DSC</i>	97.39
	<i>Accuracy</i>	98.99
Building	<i>IoU</i>	84.40
	<i>DSC</i>	91.54
	<i>Accuracy</i>	87.66

The base class inference results are quantitatively examined using some metrics, including IoU, precision, recall, F1-score, mean accuracy (mAcc), overall accuracy (oAcc), and Dice Similarity Coefficient (DSC). These results are presented in Table 2. Based on this information, a summary of the performance of each class across the entire dataset is provided, indicating which classes have more consistent segmentation and which still experience prediction errors.

The per-class analysis, as presented in Table 2, shows that the ground class performed the best, with the highest IoU, DSC, and accuracy values among three classes. Vegetation class also performed well, although there were still several misclassified points, particularly in areas close to other objects or at the boundaries between objects. The building class performed the lowest, with the most misclassifications occurring in the vegetation

class. This is accordance with the complex characteristics of building objects, including variations of roof, wall, and vertical element shapes, as well as the limitations of SLAM LiDAR data collection, which does not always capture the entire structure.

In addition to the numerical evaluation, segmentation results are also visualized for each SLAM path. Figure 8 shows the model's segmentation results for ground objects, while Figure 9 shows the model's segmentation results for buildings and vegetation objects. The results show that ground points are clearly segmented, while vegetation and buildings still show some discrepancies with the actual objects. Misclassified points tend to appear in areas with low point density, overlap between objects, or objects with similar geometric shapes. This can be seen in Figure 8. These results demonstrate that the model can segment the ground well, despite the varied terrain conditions. However, the model's ability to recognize buildings and vegetation objects remains poor, with frequent misclassifications. However, this error pattern is relatively consistent across datasets, including the new dataset, indicating that model imperfections are not due to specific path conditions alone but rather are a characteristic of the model when applied to real-world SLAM LiDAR data.



Figure 8 Ground segmentation result

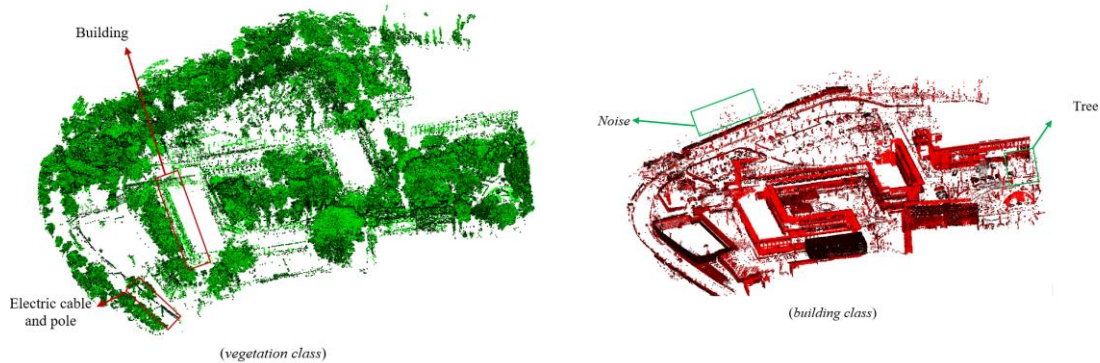
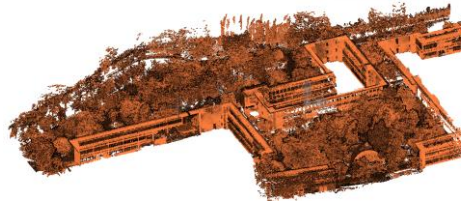


Figure 9 Vegetation and Building segmentation result

Based on this result, it can be concluded that base-class performance is an important factor influencing later stages, especially the detection of unknown points and the generation of novel classes. Base-class segmentation errors can cause points that should belong to known classes to be detected as unknown. This leads to suboptimal quality of novel clusters. Therefore, the stability of base-class segmentation remains an important focus when evaluating the limitations of the NCD approach on SLAM LiDAR data.

4.3. Unknown point detection and novel clustering performance

After base class inference, the next step is to identify unknown points and cluster them into several novel classes. In unknown point detection, these points are determined based on the predicted probability values from the model. If the probability for the base class is below a certain threshold, the point is categorized as unknown. The results of unknown point detection are shown in Figure 10.



a. Known points detected



b. Unknown points detected

Figure 10 Unknown (a) and known (b) detection result

After finding the unknown points, they are grouped into new classes based on a set number, using the NCD approach. Clustering uses feature embeddings from the model's intermediate layers. Before clustering, the features are normalized to keep their scales consistent. Table 3 displays the distribution of points per cluster on each SLAM LiDAR path. This table shows that the clustering process produced a relatively consistent pattern across all analyzed paths. Of all the novel classes, novel class 1 was the most dominant, followed by novel classes 2 and 3. However, the distribution of points across the clusters is uneven, representing the dominance of certain clusters and imbalance in cluster formation.

Table 3 Novel Class Clustering Results

Path datasets	Total points	Novel 1	Novel 2	Novel 3	Number of novel points	% novel
Path 1	11037614	574719 (5.2%)	171634 (1.6%)	44809 (0.4%)	791162	7.2%
Path 2	11671381	603798 (5.2%)	203546 (1.7%)	38104 (0.3%)	845448	7.2%
Path 3	6864102	473109 (6.9%)	120543 (1.8%)	23725 (0.3%)	617377	9.0%
Path 4	8697741	532667 (6.1%)	146720 (1.7%)	25870 (0.3%)	705257	8.1%
Path 7	9012171	487490 (5.4%)	151127 (1.7%)	31563 (0.4%)	670180	7.4%
Path 8	9297919	492987 (5.3%)	168239 (1.8%)	35744 (0.4%)	696970	7.5%
Path 9	5922769	289827 (4.9%)	119327 (2.0%)	27819 (0.5%)	436973	7.4%
Path 15	5822407	318154 (5.5%)	114175 (2.0%)	19032 (0.3%)	451361	7.8%

Visually, the clustering results are shown in Figure 11. The figure reveals that the novel class 1 can segment new classes, such as cables and electric pole. However, viewed as a whole, the set of points intended to represent the new objects still contains many points that are actually fragments of existing base classes. Some points that should belong to base classes have instead been assigned to the novel cluster, especially in the building and vegetation categories. This misclassification leads to pseudo-novel classes, in which points from a known class are misclassified as part of a novel class.

These results indicate that the formation of novel classes using the NCD approach on outdoor SLAM LiDAR data still faces several challenges. Most novel cluster merely represents fragments of existing base classes, while the number of truly distinct new objects is very limited. This misclassification leads to pseudo-novel classes. As a result, the accuracy of base-class representation plays a key role in clustering, since poor base-class segmentation can yield less meaningful novel clusters. Furthermore, outdoor SLAM LiDAR data is very mixed, with different point densities and noise. This makes it hard to clearly separate base classes from novel classes. As result, the model struggles to tell new objects apart from known ones. Although NCD can form clusters, cluster quality is still limited by the instability of the base class representation, varying point densities, and feature ambiguities in the embedding.

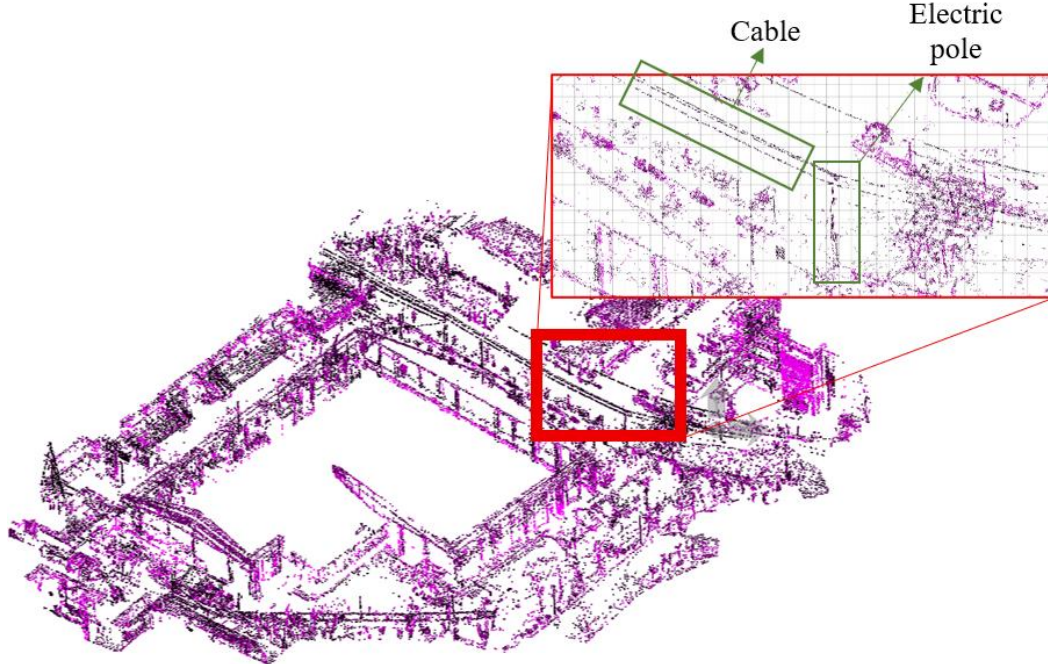


Figure 11 Visual of another class in novel class 1

Based on the result, it can be concluded that the success of novel class formation in NCD is inseparable from the stability of the base class segmentation. This condition is one of the main limitations when the NCD approach is applied to real-world SLAM LiDAR point cloud data, which has more complex characteristics than the benchmark dataset.

4.4. Base class segmentation performance on new dataset

To check how consistent the model is with new data, we used the same preprocessing steps as for the training set, including extracting 11 features, on a new dataset of seven SLAM LiDAR tracks (tracks 5, 6, 10, 11, 12, 13, and 14), which had 51,255,807 points. This way, the input data matched what the model was trained on before we started base-class segmentation.

When we ran the model on the new dataset, it labeled 46,716,196 points (about 91.14%) as known and 4,539,611 points (8.86%) as unknown, which could be new classes, as shown in Table 4. The percentage of unknown points was very similar across all tracks, with less than 0.1% difference between the highest and lowest. Figure 12 shows how unknown points are detected in the new dataset and highlights that the pattern remains uniform even as the number of points per track varies.

The base class performance evaluation results show that the MultiHeadMinkUNet model can recognize the ground, vegetation, and building classes with a relatively high level of confidence, both on the labeled dataset and on a new dataset that was not used in the model training process. The distribution of known points on each path demonstrates consistent model performance, with the percentage of points categorized as known points exceeding 91% in the new dataset, as shown in Table 4. Based on this, it can be concluded that the model can generalize to data different from the training data, despite varying path characteristics, object distribution, and point density.

A detailed analysis of the results shows that most unknown points come from the building class (49.56%) and the vegetation class (38.68%). The ground class has the fewest unknown points (11.76%), as shown in Table 5. This matches what we saw in the earlier labeled dataset. It suggests that the shape and complexity of objects from SLAM point cloud data affect the model's confidence in its base-class predictions.

Table 4 Known and unknown points distribution on new dataset

Path datasets	Total points	Known points (conf ≥ 0.7)	% known	Unknown points (conf < 0.7)	% Unknown
Path 5	16618882	15160394	91.13%	1458488	8.77%
Path 6	9961573	9075636	91.11%	885937	8.89%
Path 10	5087593	4642068	91.23%	445525	8.76%
Path 11	3764122	3429719	91.12%	334403	8.88%

Path datasets	Total points	Known points (conf ≥ 0.7)	% known	Unknown points (conf < 0.7)	% Unknown
Path 12	7405543	6746402	91.10%	659141	8.90%
Path 13	3665597	3337667	91.07%	327930	8.94%
Path 14	4752497	4324310	90.98%	428187	9.01%
Total	51255807	46716196	91.14%	4539611	8.86%

Table 5 Distribution of unknown points based on initial class predictions per path of new dataset

Path dataset	Number of unknown points	Unknown from ground	Unknown from vegetation	Unknown from building
Path 5	1386052	168671 (12.17%)	542458 (39.14%)	674923 (48.69%)
Path 6	901782	97928 (10.86%)	345651 (38.33%)	458203 (50.81%)
Path 10	423627	62156 (14.67%)	166118 (39.21%)	195353 (46.11%)
Path 11	362848	40864 (11.26%)	137036 (37.77%)	184948 (50.97%)
Path 12	637474	77363 (12.14%)	242967 (38.11%)	317144 (49.75%)
Path 13	387148	44753 (11.56%)	148146 (38.27%)	194249 (50.17%)
Path 14	440680	42310 (9.60%)	173562 (39.39%)	224808 (51.01%)
Total	4539611	534045 (11.76%)	1755938 (38.68%)	2249628 (49.56%)

Table 6 Distribution of known points per base class on the new dataset

Path datasets	Total points	Known point	%known	Ground	Vegetation	Building
Path 5	16618882	15160394	91.13%	2841188	8761915	5015779
Path 6	9961573	9075636	91.11%	1729948	4950189	3281436
Path 10	5087593	4642068	91.23%	548511	3916843	622239
Path 11	3764122	3429719	91.12%	670147	1428116	1665859
Path 12	7405543	6746402	91.10%	1424711	3294307	2686525
Path 13	3665597	3337667	91.07%	604930	1636688	1423979
Path 14	4752497	4324310	90.98%	841993	2137681	1772823
Total	51255807	46716196	91.14%	8661428	26125739	16468640

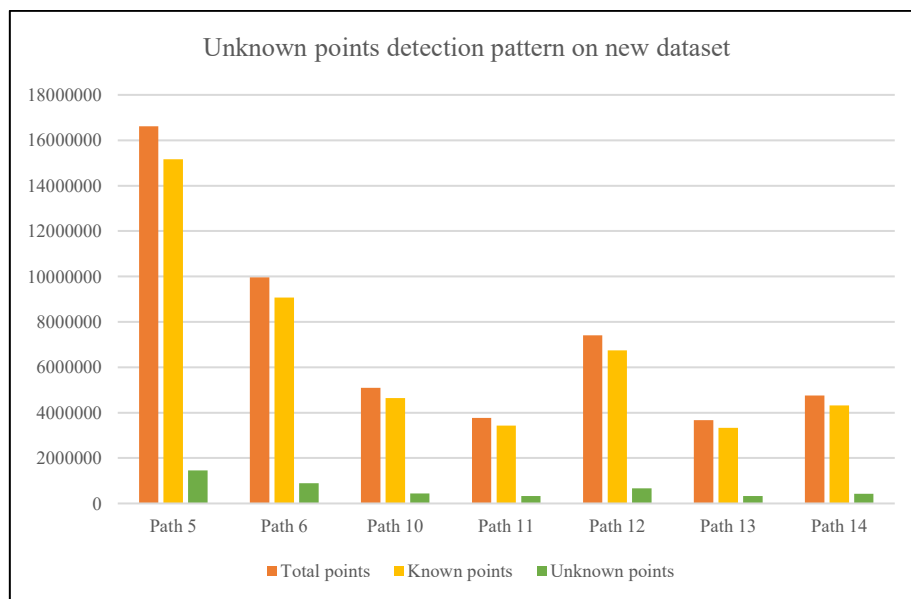


Figure 12 Unknown points detection pattern on new dataset

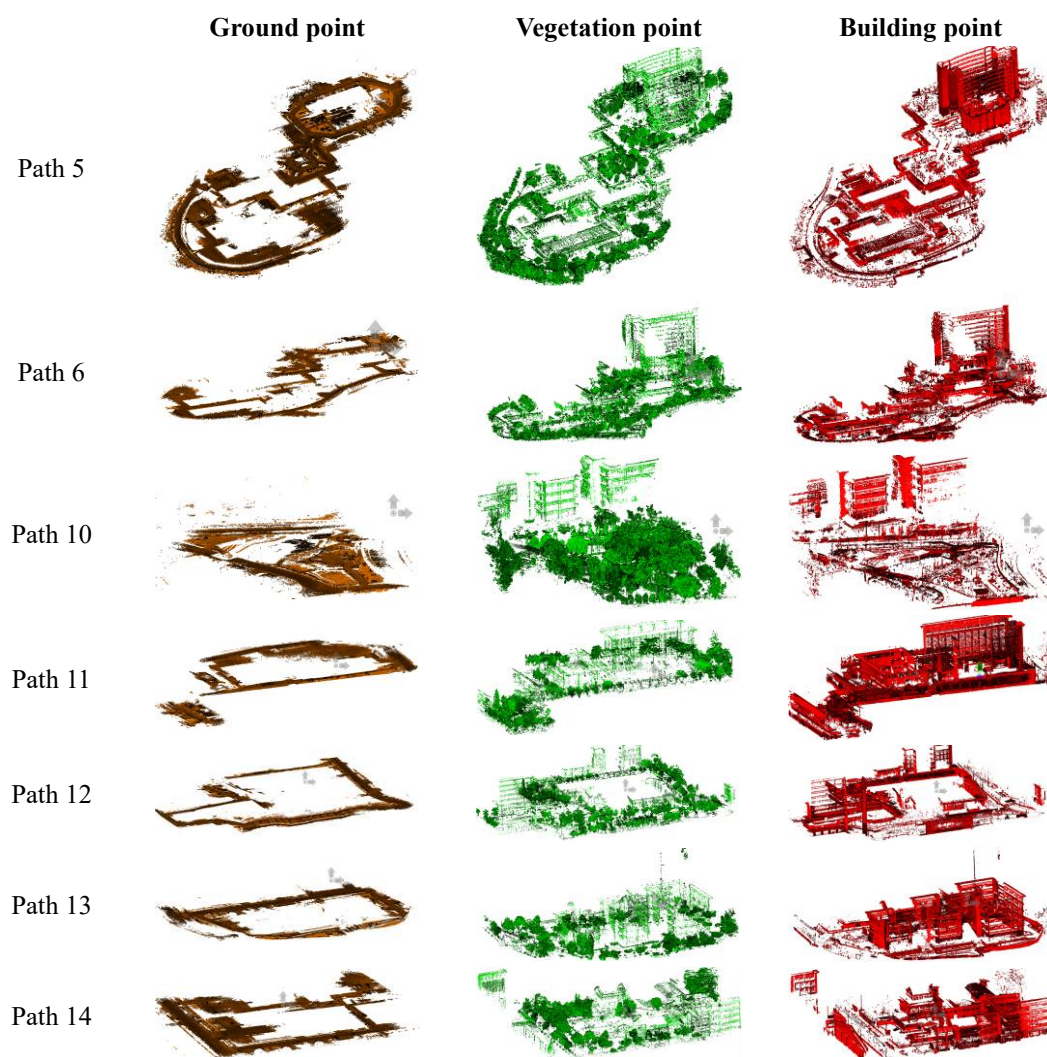


Figure 13 Visual display of segmentation results on base class on new dataset

After separating known and unknown points, the known points were then re-segmented into three base classes: ground, vegetation, and building. Table 6 shows the distribution of known points within each base class per path. Overall, vegetation remains the most dominant class with 26,125,739 points, followed by buildings with 16,468,640 points and ground with 8,661,428 points. The percentage variation between paths is relatively small ($<1\%$), indicating that the model's performance is stable when applied to the new dataset. A visualization of the base-class segmentation on the new dataset is shown in Figure 13, which confirms that the ground class has the clearest segmentation, while building and vegetation still show some misclassifications, especially in areas with complex objects or class overlap.

These base class errors have direct implications for the NCD stage. Points that should belong to the base class may be detected as unknown, while points from new objects or those with different characteristics may still be miscategorized. The segmentation results on the new dataset show that, although error patterns emerge, the model maintains consistent performance across different areas of the training data, forming the basis for the analysis of NCD limitations in the next stage.

4.5. Limitation of novel class discovery (NCD) approach

Based on the results of implementing the novel class discovery (NCD) approach on SLAM LiDAR data, several limitations affect the quality of the segmentation results and the discovery of novel classes. These limitations are not only related to the clustering process but also influenced by the quality of the base class model, the unknown point detection process, the characteristics of the SLAM LiDAR data, and the limitations in evaluating the resulting new classes. Therefore, an analysis of these limitations was conducted to understand why the novel classes generated do not fully produce the expected output.

First, the success of NCD is highly dependent on the performance of the base class. Inaccurate predictions of the base class can result in some points that actually belong to known classes being classified as unknown. This results in the formed novel clusters being less representative and containing many fragments of the base class (ground, vegetation, or buildings).

Second, using a confidence threshold to find unknown points brings its own challenges. Points with confidence below 0.7 are labeled as unknown. However, this method cannot always distinguish new objects from low-confidence predictions of the base class. These mistakes often happen in areas with objects close together, poor-quality data, or uneven vegetation and terrain. As a result, false unknowns can appear.

Third, the feature representation (embedding) used for clustering is still constructed from a model trained to distinguish only three base classes. This results in unknown points that should be semantically distinct being in adjacent embedding spaces. Meanwhile, points from the same object can split into different clusters if the feature representation is unstable.

Fourth, the fixed number of clusters ($k=3$) limits the adaptability of clustering to real-world conditions. If the number of new classes is smaller, some points will split into artificial clusters. Conversely, if the number of new classes is larger, several different objects may be grouped into the same cluster. This condition can lead to an uneven distribution of novel classes, with Novel Class 1 dominating the other clusters.

Fifth, the characteristics of outdoor SLAM LiDAR data, such as variations in point density, noise, occlusion, and potential distortions from sensor motion and loop closure, also affect NCD performance. Areas with low point density or incompletely captured object shapes tend to be difficult to recognize. This can certainly affect the confidence, embedding, and clustering results obtained.

The final limitation of the experimental results is the lack of ground truth for novel classes. Without reference labels for new classes, quantitative evaluations cannot be performed directly on novel classes. Therefore, assessing the success of NCD relies more on visual analysis and spatial interpretation. This limits the evaluation of novel classes, as it cannot be objectively determined whether the clusters formed truly represent new classes or are simply due to the model's uncertainty about the base class.

Based on an analysis of the identified limitations, the overall results of this study demonstrate that the NCD implementation approach can be applied to SLAM LiDAR data and can produce clusters of known and unknown points. However, the results do not fully demonstrate the stability of novel classes. The unbalanced distribution of novel classes, the dominance of novel class 1, and the emergence of novel points in areas still related to the base class indicate that NCD results are still heavily influenced by the quality of the initial segmentation, the choice of confidence threshold, the quality of the embedding, and the characteristics of the point cloud data. Therefore, the NCD approach to SLAM LiDAR data still requires further development, particularly by improving the performance of the base model, developing more adaptive unknown-detection methods, determining the number of clusters that is more appropriate for the data conditions, and conducting more systematic visual and spatial evaluation.

5. Conclusion

The results show that NCD approach can be applied to SLAM LiDAR data, detect unknown points, and form novel class clusters, but the resulting clusters are not fully semantically stable. Its performance is highly dependent on the quality of the base class, the confidence threshold, the embedding, and characteristics of SLAM LiDAR data such as variation in point density, noise, and object heterogeneity. The evaluation of the base class showed relatively consistent predictions, but vegetation and building classes still exhibit error in complex areas. The results of this research show that although NCD approach has potential for real-world point cloud segmentation, its application requires further development of the NCD approach, including enhancement to the base model, adaptive mechanisms for unknown detection, and systematic visual evaluation.

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7. Author Contribution

N.M.I. contributed to data acquisition, data preprocessing, model implementation, experimental analysis, visualization, and original manuscript writing. H. contributed to the conceptualization, methodological development and validation, validation the result, manuscript review, and finalization the manuscript. Both authors read and approve the final manuscript.

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9. Data availability

The data of this study are available upon reasonable request.

10. Declarations

Competing interests. The authors declare no competing interests.

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