Improving Urban Point Cloud Classification Using Dynamic Local Context-Based Point Confidence

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Abstract

Urban mapping for planning and monitoring requires high-resolution spatial data, especially in areas with high landcover diversity. Airborne LiDAR Scanning (ALS) provides accurate 3D point cloud data, but its classification remains challenging due to computational complexity, irregular point distribution, noise, mislabeling and outliers in the dataset. These challenges are amplified in dense urban environments with mixed vegetation and infrastructure. Existing local context-based classification methods consider all points equally, overlooking the impact of their spatial position of the point in the dataset. To address this, we propose a dynamic local context-based point confidence-based optimization that improves classification accuracy by leveraging the spatial context of each point. This approach selects points based on confidence levels derived from position indices in training data and predicted by binary classifiers in test data to enhance robustness of classifier. We evaluated the proposed approach using boosting-based machine learning classifiers on two datasets: Thiruvananthapuram Aerial LiDAR Dataset (TALD) from India and the ISPRS 3D semantic labeling dataset from Vaihingen, Germany. The results showed 90.3% accuracy on TALD and 90.0% on Vaihingen, achieving a 2–4% improvement over conventional local context-based classification.

1. Introduction

Technology like ALS (Airborne LiDAR Scanning) play a crucial role in capturing high-resolution three-dimensional data over large areas (Cai et al., 2022). Point clouds obtained from ALS are accurately mapped to provide detailed insights for further utilization in various applications (Shariatpour et al., 2024). The rapid progression in 3D point cloud data acquisition technologies has resulted in a notable surge in data accessibility. In this context, point cloud classification has emerged as a pivotal research area, involving the categorization of individual points within a dataset into different classes based on attributes such as geometric features, intensity values, and contextual information. The utilization of classified point clouds has become the norm and is essential across diverse fields like 3D urban mapping, road infrastructure management, power line identification, and vegetation cover analysis (Xu and Stilla, 2021). In all these applications, the effective interpretation of 3D point cloud data depends upon accuracy in assigning semantic labels to individual points.

Classifying 3D point clouds obtained from airborne LiDAR data poses significant challenges, mainly because of their complex characteristics, unstructured nature, computational complexity involved to handle the extensive volume of data, and their irregular distribution in the scene (Poux et al., 2020). One of the key factors that significantly influences the accuracy of classification is the availability and quality of the training dataset used for supervised learning algorithms (Ramezan et al., 2021). A meticulously curated and diverse training dataset aids the algorithm in generalizing the classification model for more precise outcomes.

There has been significant progress in the classification of 3D point clouds through the application of supervised learning techniques. This progress includes advancements in both point-based and segment-based approaches (Vinodkumar et al., 2023). In point-based methods, individual points within the cloud are classified based on their attributes and relationships with neighboring points. In contrast, segment-based approaches involve dividing the point cloud into distinct segments or clusters, with each segment being classified according to its overall characteristics and spatial context. The point-based methods are particularly effective in areas where point cloud density is variable and topological irregularities are present, as it enables precise classification of individual points based on their characteristics.

The most widely used techniques for point-based classification involve classifying extracted point-based features using machine learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), AdaBoost, and XGBoost (Ismail and Abdulazeez, 2024). For instance, Huang et al. introduced a method focused on optimizing feature extraction for point clouds by extracting multi-scale feature representations within a robust subspace (Huang et al., 2023). Similarly, Li et al. (2020) introduced the Multi-Scale Neighborhood Feature Extraction and Aggregation Model (MNFEAM), which enhances feature extraction by considering the multi-scale neighborhood characteristics of points within the cloud (Li et al., 2020). Additionally, some scholars have explored applying 2D-3D transformations to establish mapping relationships between image and point cloud coordinates, to facilitate efficient feature extraction by leveraging information from both domains (Pham et al., 2020). These advancements in point cloud feature extraction methodologies play a crucial role in enhancing point-based classification techniques (Zhao et al., 2023, Dey et al., 2023).

Advancements in deep learning have greatly improved 3D point cloud analysis by integrating local context for accuracy. PointNet (Qi et al., 2017a) pioneered direct point cloud processing, while PointNet++ introduced hierarchical feature learning(Qi et al., 2017b). DGCNN enhanced local relationships with dynamic graphs, and RandLA-Net optimized large-scale processing (Hu et al., 2020,

Widyaningrum et al., 2021). PointCNN's X-Conv and KPConv's kernel convolutions refined local feature learning (Li et al., 2018, Thomas et al., 2019). PointASNL further improved feature extraction with attention mechanisms (Yan et al., 2020). However, despite the potential of these technologies, the complexity of deep learning models, particularly their reliance on large, labeled datasets of high quality, has been a recurring issue in literature.
In complex urban landscapes with multilayered dense vegetation closely situated buildings, classifying point clouds becomes significantly challenging. The high land cover diversity, combined with irregularly shaped houses and varying levels of vegetation intermingled with structures, leads to points which are mislabeled or equally close to points of more than one class. This creates ambiguity for local context-based classification. This complexity increases the likelihood of errors in training the classification model, thereby limiting the accuracy and precision of the resulting test data. Furthermore, aside from human labeling errors, noise from outliers and clutter objects (such as flower pots on roof boundaries) can compromise the accuracy of the training dataset, leading to inconsistencies in the generated model. These limits the classification accuracy, particularly in areas of high land cover diversity index with dense settlements, complex urban structures, and multi-level vegetation.
Past studies on local context-based point cloud classification have considered all points uniformly while training machine learning models, neglecting the impact of point positions within point clouds on model development, especially in regions of high landcover complexity. This oversight hampers the efficiency of classification algorithms, as certain points may contribute to be obscure in training the model while others hold more significant spatial relevance. The dynamic occlusion or devaluation of perplexing points can aid in mitigating these challenges.
Thus, to bridge this research gap, this study introduces dynamic local context-based point confidence for point cloud classification. For each point in the dataset a point position-based confidence is associated that considers the spatial arrangement of points within its local context. In the training dataset the point confidence is derived by utilizing the class distribution within the local context of each point. In the test dataset, point confidence is predicted using the point's feature set and binary classifier models, developed from the training dataset. This enables the prioritization of points or the dynamic occlusion of points that could hinder robust model development for accurate classification. In this work, logistic regression, XGBoost, random forest and gradient boosting were evaluated as binary classifiers to predict the point confidence. To validate the effectiveness of incorporating dynamic local-context-based point confidence, its performance was evaluated using boosting based classifiers - XGBoost, random forest, and LGBM were experimented on two regionally distinct datasets: Thiruvananthapuram Aerial LiDAR Dataset TALD (Vijaywargiya and Ramiya, 2025) and ISPRS 3D Semantic Labeling Vaihingen dataset (Niemeyer et al., 2014).
The research aims to address the following questions:

1. How does local-context-based point confidence impact the efficiency of point cloud classification?
2. Can dynamically occluding points based on spatially derived point confidence enhance model robustness in point cloud classification?
3. What is the statistical significance of model performance across different classes in two distinct regional datasets, and how does it reflect the practicality and effectiveness of the proposed method?

2. Methodology

The proposed methodology involves three key steps: preliminary feature extraction, point confidence estimation, and training and evaluation of machine learning models. Figure 1 summarizes the methodological workflow and algorithm of this study.

2.1 Preliminary feature extraction

The methodology entails extracting local context features for each point by considering its nearest neighbors. The geometric features are extracted from nearest neighbors, and density features are extracted from spherical neighborhoods (Thomas et al., 2018, Atik et al., 2021). The individual point features like Height (H), color (RGB) or intensity information (I), Return number (RN) and number of returns (NR) are directly available for each point. The neighborhood-based geometric features are calculated mathematically as shown in table 1.

Feature	Formula
Normal along X (N_x)	$N_x = \dfrac{v_x}{\sqrt{v_x^2 + v_y^2 + v_z^2}}$
Normal along Y (N_y)	$N_y = \dfrac{v_y}{\sqrt{v_x^2 + v_y^2 + v_z^2}}$
Normal along Z (N_z)	$N_z = \dfrac{v_z}{\sqrt{v_x^2 + v_y^2 + v_z^2}}$
Curvature (C)	$C = \dfrac{\lambda_1 + \lambda_2}{2}$
Linearity (L)	$L = \dfrac{\lambda_{\max} - \lambda_{\min}}{\lambda_{\max}}$
Planarity (P)	$P = \dfrac{\lambda_{mid} - \lambda_{\min}}{\lambda_{\max}}$
Scattering (S)	$S = \dfrac{\lambda_{\min}}{\lambda_{\max}}$
Verticality (V)	$V = \arccos(N_z)$

Table 1. Mathematical formula of geometric features

Here, λ_1, λ_2 and λ_3 are the eigenvalues of the covariance matrix and eigenvectors (v_1, v_2 and v_3) corresponding to the least eigen value. The feature vector, denoted as F, is represented mathematically as: F = [H, RGB or I, RN, NR, N_x, N_y, N_z,C, L, P, S, V, Radial Density]. Each feature contributes to enhancing the overall analysis and interpretation of 3D spatial data.
The neighborhood size plays a crucial role in both feature extraction and point confidence estimation. It determines how much local context is considered around each point and is heuristically selected based on point density and distance between adjacent classes. In the high point density datasets, larger neighbourhood size should be considered. Small neighborhoods capture fine-scale geometric structures and sharp boundaries but can be sensitive to noise and irregular sampling, whereas larger neighborhoods provide more stable statistics but can cause blurring at the class transitions in high heterogeneous regions. In this study, considering medium point density in both the datasets, a neighbourhood size of eight points is selected and considering distance between classes, radial neighbourhood of 2 meter is considered.

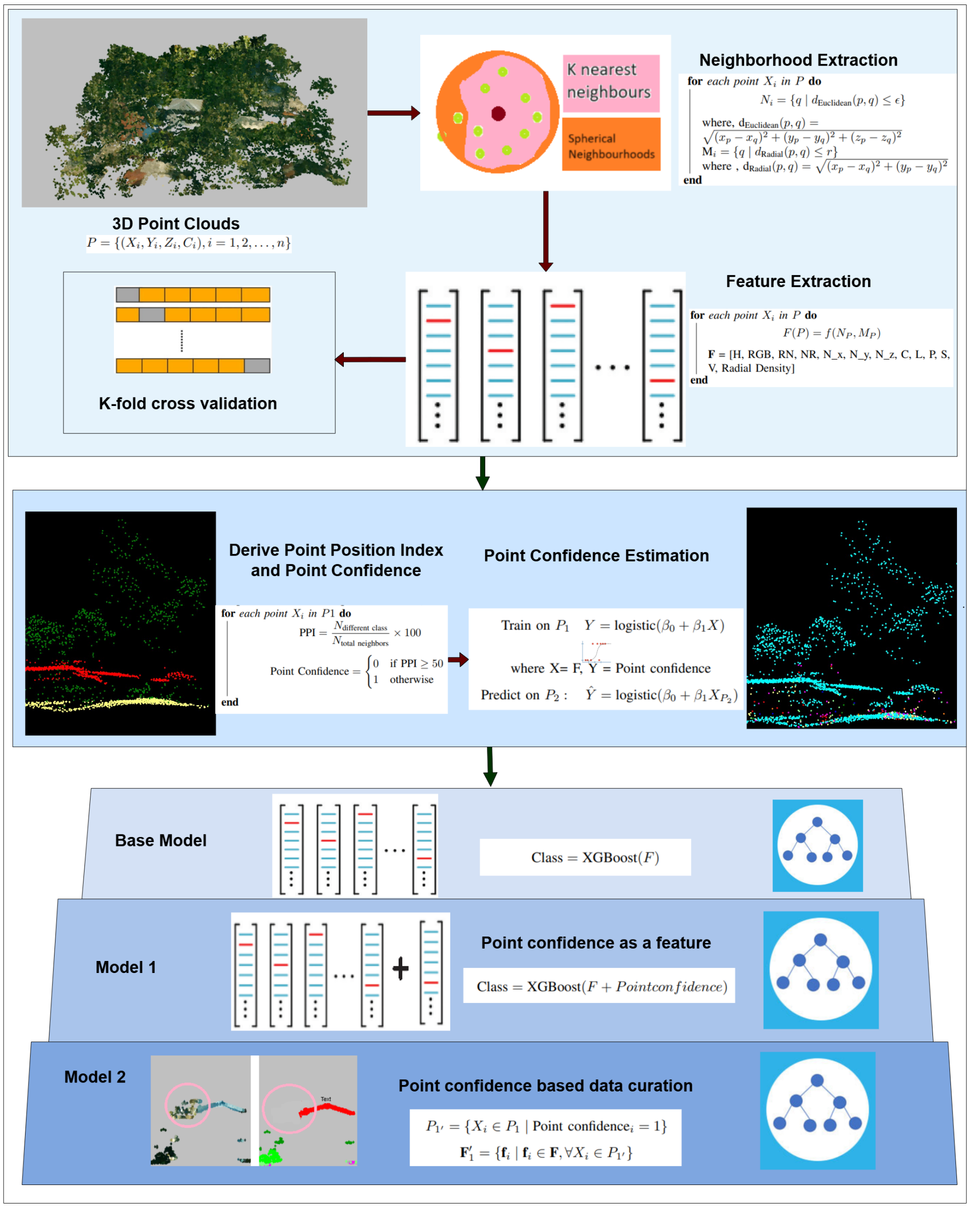

Figure 1. Methodology and algorithm for evaluating dynamic local-context based point confidence for point cloud

2.2 Point confidence estimation

The proposed methodology introduces the notion of point confidence, which quantifies the contribution of point in model development. For instance, in the complex region, the trees and buildings are densely located and are in close proximity to each other. A few points which are in close proximity to trees as well as building create confusion in development of discriminative plane while training classification model using supervised machine learning algorithms. The point confidence is calculated based on Point Position Index (PPI) of the point in the training dataset. The Point Position Index (PPI) assess the variability of class distribution in the vicinity of the point in the point cloud dataset. By calculating the percentage of neighboring points that belong to different classes relative to the total number of neighbors, PPI offers valuable insights into the spatial configuration and class distribution within the local context. Elevated PPI values indicate diverse neighborhoods containing points from various classes, suggest low confidence in extracted features of the point for training, whereas lower values indicate uniformity within the neighborhood and confidence in the accurate representation of its features. Figure 2 shows the class and PPI values from TALD dataset. Consequently, the determination of point confidence is contingent upon the computed PPI value: if the PPI is equal to or greater than 50 percent, the point confidence is assigned a value of 0; otherwise, it is assigned a value of 1. In cases where PPI suggests uncertainty or complexity around a point, its confidence is marked as 0, indicating reduced certainty in classification. Conversely, if the PPI indicates a relatively clear local context, the point’s confidence is labeled as 1, signaling higher confidence in its classification. Further in the test dataset, a binary classifier model is trained from training points to predict point confidence for points in test dataset. The input features for this intermediate model, encompass various attributes extracted from the point cloud data. Through the binary classification model, the relationship between the input features X and the corresponding point confidence values Y is established. Incorporating point confidence into classification algorithms enriches their adaptability to the local context, consequently elevating accuracy and reliability of point cloud classification. For a comprehensive evaluation, additional classifiers like logistic regression, XGBoost, random forest, and gradient boosting were explored to enhance analysis (Lai et al., 2021).

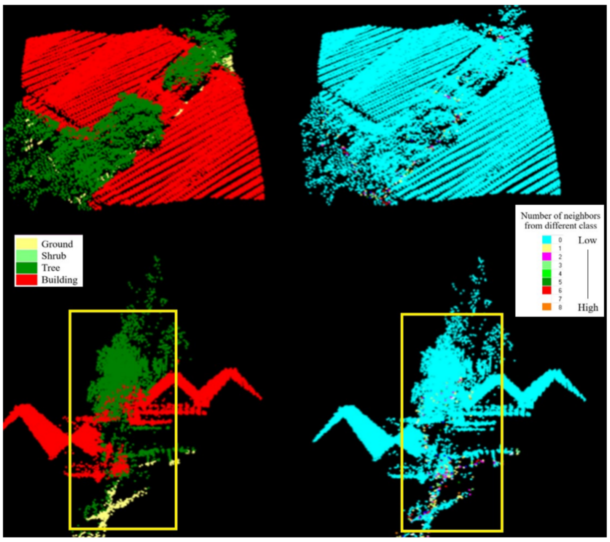

Figure 2. Spatial distribution of land cover classes and corresponding Point Position Index (PPI) values in the TALD dataset.

2.3 Classification model and performance evaluation

In this study, three distinct models were developed to explore the effectiveness of incorporating point confidence into the classification process:
1. Base Model: The base model employed the classification algorithm to predict the class labels based solely on a feature set, denoted as F. This model served as the foundational benchmark, providing a comparison point for subsequent models that introduced point confidence.
2. Model 1: This model incorporated point confidence as an additional feature alongside the preliminary feature set F.
3. Model 2: This introduces a data curation based on point confidence. In this model, only the data points with high confidence were considered for training and predicting using the classification model. This selective approach aimed to improve the model’s accuracy by focusing on the most reliable data.

Each model was subsequently evaluated to assess the impact of incorporating point confidence on the overall performance of the machine learning algorithms. This was done by introducing point confidence in two ways: either as an additional feature in the dataset or through data curation processes aimed at refining the input data. The classifiers used for this evaluation included boosting-based algorithms such as XGBoost, Random Forest (RF), and LightGBM. By examining these models, the study aimed to determine whether point confidence could enhance prediction accuracy, model stability, and generalization capabilities. The comparative analysis provided insights into how these models responded to the presence of point confidence, particularly in terms of improved overall classifier performance in diverse data scenarios.

The evaluation of performance involved utilization of various metrics to ensure a comprehensive assessment. These metrics encompassed Average Accuracy (AA), Overall Accuracy (OA), Kappa coefficient (κ), and Adjusted Rand Index (ARI). The OA metric quantifies the proportion of correctly classified points in relation to the entire dataset, while the Kappa coefficient measures the level of agreement between observed and expected classifications. ARI, on the other hand, assesses similarity between predicted and observed class labels across all pairs of points and their groupings. To conduct a detailed analysis of class-specific performance, the F-score for each class was also computed. Furthermore, the determination of statistical significance involved the calculation of the t-statistic and pvalue. This allowed for the identification of statistically significant differences in the observed results. If the computed p-value was found to be below a predetermined significance level of 0.05, it indicates that the observed improvement in the model’s performance is statistically significant.

2.4 Dataset description and experiment

This study utilizes two diverse datasets, TALD (Thiruvananthapuram Aerial LiDAR Dataset) and ISPRS Semantic 3D Benchmark dataset from Vaihingen. The TALD Dataset, acquired over Thiruvananthapuram, India, features an average point density of $9 - 10$ points per square meter, portraying diverse building structures and land cover patterns. Each TALD data point (P_{TALD}) includes spatial coordinates (X, Y, Z), color (R, G, B), and class label (C) from classes namely ground, shrub, tree and building. The dataset has high complexity due presence of classes like building, trees and shrub in very close proximity. The benchmark Vaihingen 3D dataset from Germany, has a point density of 8 points per square meter and encompasses nine distinct categories. Vaihingen data points ($P_{Vaihingen}$) include spatial coordinates (X, Y, Z), intensity value (I), and a class label (C) with classes namely powerlines, low vegetation, impervious surface, car, fence, roof, facade, shrub, and tree. The TALD dataset comprises 902,226 points, while the Vaihingen dataset contains 753,876 points. Figure 3 and 4 shows the TALD dataset and Vaihingen dataset respectively. The experiment involved evaluating classification models on two datasets with 20% test data and 80% train data, with k-fold cross validation, through several key steps. Initially, the feature matrix for each dataset was extracted to capture the relevant features for classification. Point confidence, which serves as a crucial factor, was then calculated for each data point. This point confidence was predicted using four different approaches. Following this, three classification models XGBoost, Random Forest (RF), and LightGBM were employed to assess performance of the three mentioned models, base model, model 1 and model 2. These models were applied to both datasets, and metrics such as accuracy, precision, recall, and F1-score were analyzed to measure the classification effectiveness. Overall, the experiment provided a detailed evaluation of how point confidence influenced predictive accuracy with the comparative performance of the classification models across two varying datasets of comparable size.

3. Results

3.1 Point confidence estimation

In predicting the point confidence the logistic regression achieved an accuracy of 94.65 % on the TALD dataset with 4 classes and 95.57 % accuracy on the Vaihingen dataset with 9

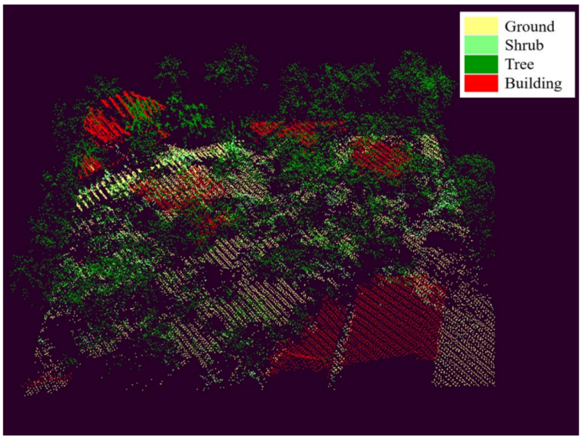

Figure 3. TALD airborne LiDAR point cloud showing land cover classes and urban structural complexity.

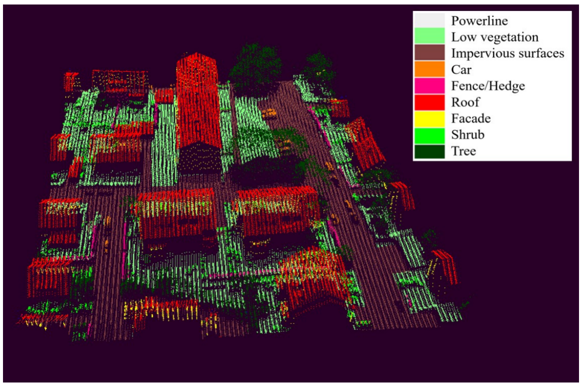

Figure 4. ISPRS Vaihingen 3D point cloud illustrating diverse urban objects and land cover categories.

classes. This performance is comparable to accuracy from other binary classifiers used. The binary classifiers experimented for estimating the point confidence, and their performance, are shown in Table 2. Logistic regression was considered for further steps, due to its less computational complexity.

3.2 Classifier performance

The overall accuracy of the three models: base model, model 1 using point confidence as a feature, and model 2 with point confidence based on data curation on TALD and Vaihingen datasets using boosting based classifiers random forest, lightGBM and XGBoost as a classifier is presented in Table 3.

3.3 Optimum performance of XGBoost on Base model, Model 1 and Model 2

Using, K-fold cross validation, and XGBoost as classifier the evaluation on the TALD dataset, base model achieved an accuracy of 0.879 ± 0.001, while model 1 performed slightly better with an accuracy of 0.885 ± 0.000. Model 2 exhibited the highest accuracy of 0.903 ± 0.000. Statistical analysis revealed significant differences between the models, with p-values less than 0.001. Specifically, base model differed significantly from both Model 1 and Model 2 ($p < 0.001$), and Model 1 differed significantly from Model 2 ($p < 0.001$). Similarly, on the Vaihingen dataset, base model achieved an accuracy of 0.861 ± 0.001, while Model 1 yielded a slightly higher accuracy of 0.869 ± 0.001. Model 2 demonstrated the highest accuracy of 0.900 ± 0.001. Statistical analysis indicated significant differences between the models, with p-values less than 0.001. Specifically, base model differed significantly from both Model 1 and Model 2 ($p < 0.001$), and Model 1 differed significantly from Model 2 ($p < 0.001$).
The evaluation of the model's performance is presented both class-wise and overall. For the class-wise evaluation, metrics such as precision, recall, F1-Score, and accuracy were computed for each class individually. Figures 5 and 6 depict the class-wise F1-Score for the TALD and Vaihingen datasets. The overall performance, with metrics overall accuracy, average accuracy, kappa coefficient, and the Adjusted Rand Index (ARI) is shown in Table 4. The figure 7 and 8 showcases the confusion matrix for the best model on the two datasets.

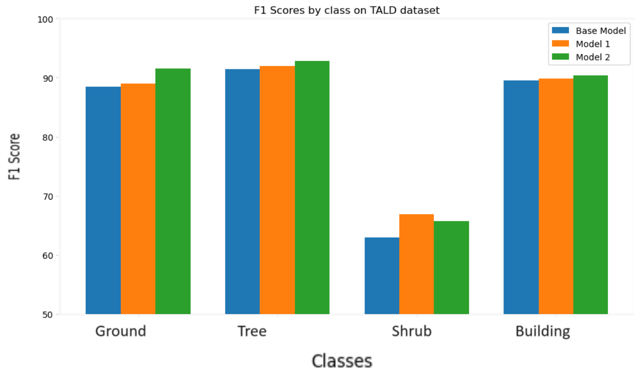

Figure 5. Class-wise performance evaluation of Base model, Model 1 and Model 2 on the TALD dataset.

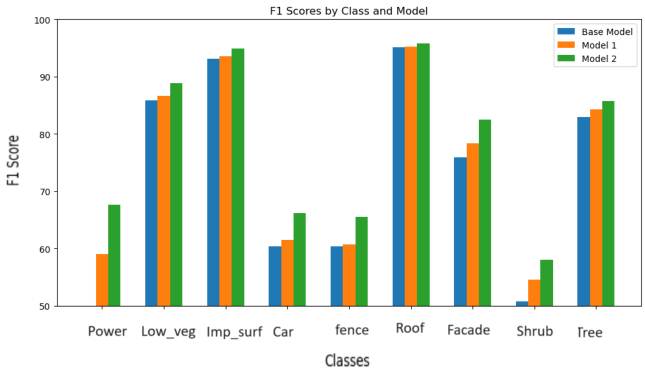

Figure 6. Class-wise performance evaluation of Base model, Model 1 and Model 2 on the Vaihingen dataset.

4. DISCUSSION

This study introduces a dynamic local context-based point confidence to enhance the classification of 3D point clouds obtained from Airborne LiDAR Scanning. The proposed approach leverages point position-based confidence and spatial context, resulting in notable improvements over existing local context based machine learning methodologies. This section covers the role of region complexity in classification, highlighting how varying levels of complexity influence the accuracy of the model. It also addresses the qualitative significance of point confidence, emphasizing its impact on enhancing classification reliability. Also, a quantitative assessment of the proposed approach is provided, demonstrating performance improvements through statistical

Binary classifier	Accuracy Score TALD dataset	Accuracy Score for Vaihingen 3D dataset
Logistic Regression	94.66	95.57
XGBoost	94.73	95.60
Random Forest	94.69	95.59
Gradient Boosting	94.69	95.58

Table 2. Performance of binary classifiers for point confidence estimation

Classifier Model	Overall accuracy over TALD			Overall accuracy over Vaihingen		
	Base model	Model 1	Model 2	Base model	Model 1	Model 2
Random forest	86.11	86.59	88.34	85.30	86.07	88.17
LightGBM	81.44	81.94	83.73	78.67	79.15	80.87
XGBoost	87.97	88.63	90.23	86.35	87.00	89.23

Table 3. Overall accuracy of different classifiers on TALD and Vaihingen dataset

Model (Dataset)	OA	AA	Kappa	ARI
Base model (TALD)	87.97	82.00	82.54	73.22
Model 1 (TALD)	88.63	83.63	83.54	74.49
Model 2 (TALD)	90.23	83.52	85.53	77.06
Base model (Vai)	86.14	68.54	82.56	74.76
Model 1 (Vai)	87.00	71.42	83.66	76.15
Model 2 (Vai)	89.23	74.07	86.35	79.79

Table 4. Performance Metrics on TALD and Vaihingen Dataset

comparisons with existing local context based machine learning methods.

4.1 Role of Terrain and Regional Complexity

In complex regions, beyond the challenges of point cloud classification, multiple regional factors also hinder accurate classification, as enumerated below:

1. Proximity of objects: In complex regions, for instance of Trivandrum vegetation and buildings often coexist closely, causing spatial overlap. ALS-derived 3D point clouds capture precise geometries, but mixed land cover with seamless transitions makes class differentiation challenging.

2. Undulating Terrain: Varying terrain and elevation add complexity, as slopes and uneven ground mix with buildings and vegetation, make accurate object classification challenging.

3. Dense Urban Development: In regions with a high density of objects within a small area, variable-sized houses and multilevel vegetation, distinguishing subtle variations becomes particularly challenging for traditional algorithms. This often results in increased classification errors, as algorithms struggle to accurately discriminate and identify distinct classes amidst the densely packed and vertically varied landscape.

4. Labeling Errors in Training Dataset: In complex regions, there is a greater scope for inaccuracies in labeling within the training dataset, whether due to manual errors or algorithmic limitations. Mislabeling or incomplete annotations introduce noise into the training process, causing the classifier to learn incorrect associations between features and classes. This can lead to poor generalization and increased errors, making it challenging to train robust models and ensure reliable classification outcomes.

The average Point Position Index (PPI) quantifies spatial complexity and object density in the dataset. A higher PPI indicates a densely packed environment, while a lower PPI reflects a sparser distribution. For the TALD dataset, the high average PPI of 0.77 indicated high complexity, while the Vaihingen dataset's moderate average PPI of 0.37 reflected less regional complexity.

The dynamic local context-based point confidence leverages the surrounding spatial context to better adapt to varying levels of complexity in the dataset. In complex regions, such as those found in the TALD dataset, classification becomes more challenging due to the intricate interplay between natural and man-made features. The dense proximity of vegetation and

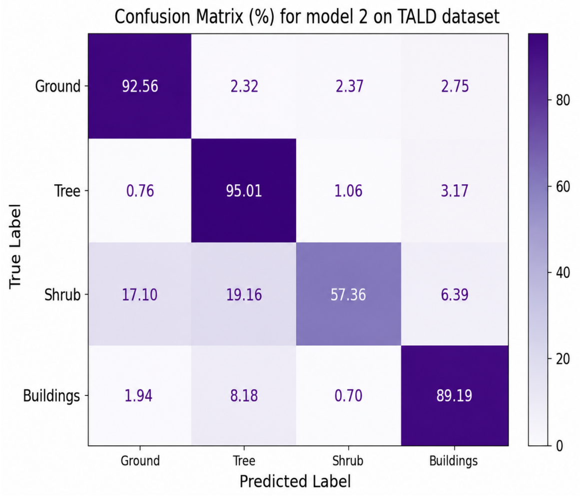

Figure 7. Confusion matrix of Model 2 for the TALD dataset, illustrating class-wise prediction accuracy and misclassification patterns.

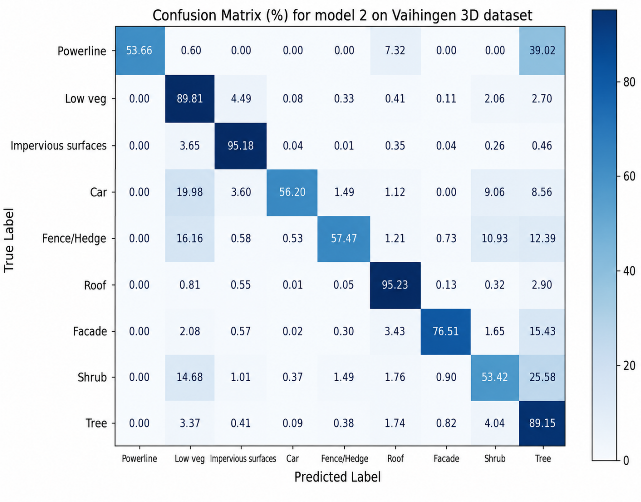

Figure 8. Confusion matrix of Model 2 for the Vaihingen dataset, illustrating class-wise prediction accuracy and misclassification patterns.

buildings, coupled with undulating terrain, creates overlapping data points that can easily lead to misclassification. Conversely, in less complex environments like the Vaihingen dataset, with clearer object boundaries and fewer mixed features, classification tasks are less prone to errors.

4.2 Local context and point confidence

In environments with closely packed objects and indistinct boundaries, global techniques such as clustering may struggle to differentiate between overlapping objects of distinct class. Local context-based approaches address these challenges by focusing on the immediate surroundings of each point. Previous research on local context-based point cloud classification consider all points equally during model training, neglecting their individual spatial positions and their influence on model performance. This generic approach limits classification effectiveness, as some points might create confusion in the model while others are essential for accurate spatial representation.
To address this issue, this study introduces a dynamic method for local context-based point selection using point confidence. Integrating point confidence allows to prioritize the most relevant points and dynamically exclude those that might degrade the model's robustness. By integrating local context and point confidence, the classification process becomes more effective in handling the intricacies of complex datasets.
The point confidence is most effective in improving accuracy in the geometrically complex regions where multiple classes are in proximity and class boundaries are ambiguous. In this study, the points located near the interface of trees, shrubs, and buildings have mixed local neighborhoods that confuse conventional local context-based classifiers, leading to mislabeled training features and unstable decision boundaries. By occluding points with high Point Position Index (PPI) and low confidence, the model is trained primarily on spatially consistent neighborhoods, which reduces the influence of noisy feature vectors and yields more reliable discriminative classification. Also, for classification of the minor classes such as powerlines, shrubs, and facade in the Vaihingen dataset the proposed method produces notable gain in the accuracy over the base model.
The point confidence threshold of 0.5, is a trade-off between retaining training data and curating misleading points. At a low threshold (for example 0.3), only highly ambiguous points are excluded, leading to presence of noisy or mixed-context points. This weakens the discriminative power of the classifier. On increasing the threshold (for example 0.8), the training set becomes restricted to very homogeneous neighborhoods. This also reduces the representation of class boundary points, which limits the discriminative and generalization capability of the model.
In future work, the binary point selection using point confidence can be extended to a soft weighting scheme. For example, the points with high confidence could receive larger weights, while points in uncertain neighborhoods are less weighted but not completely removed.

4.3 Quantitative assessment of the proposed approach

The proposed approach in model 2 of dynamic selection of point's based on point confidence demonstrated statistically significant improvements in classification accuracy. For the TALD dataset, the method achieved an accuracy of $0.903 \pm 0.000\%$, while for the Vaihingen dataset, it reached $0.900 \pm 0.001\%$. These results represent a 2-4% increase in accuracy over traditional local context-based machine learning approaches. This improvement underscores the effectiveness of integrating point position-based optimization and spatial context into the classification process.
The proposed method (Model 2) also showed notable advancements in class-specific accuracy in comparison to the base model. For the TALD dataset, improvements were observed in several categories, including ground (3.02%), tree (1.31%), shrub (2.81%), and building (0.90%). In the Vaihingen dataset, significant gains were achieved across various categories: powerlines (23.48%), low vegetation (3.02%), impervious surface (1.77%), car (5.83%), fence hedge (5.12%), roof (0.70%), facade (6.55%), shrub (7.26%), and tree (2.83%). These enhancements reflect adaptability of proposed optimization in accurately classifying a wide range of object types within different datasets. The integration of spatial context-based point confidence effectively quantifies the importance of each point for training the classification model, thereby improving classification performance, particularly in complex urban landcover scenarios.

5. Conclusion

This paper presents dynamic local context-based point confidence estimation and point selection to enhance point cloud classification over high landcover diversity regions. Traditional methods often consider all points equally, overlooking their importance and impact on classification. The proposed local context-based optimization bridges this gap by incorporating point confidence, which evaluates the significance of each point based on its spatial relevance and contribution to model accuracy. The results demonstrate that the proposed method of point confidence-based point selection and data curation (Model 2), significantly enhances classification accuracy, particularly in complex urban environments. Its performance was validated using two regionally distinct datasets, Vaihingen 3D and TALD. The proposed method achieved statistically significant classification accuracy improvements, reaching 90.3% for TALD and 90.0% for Vaihingen, outperforming existing local context-based approaches by 2–4% and showing notable class-specific gains, including 3.02% for ground TALD and 23.48% for powerlines (Vaihingen). The proposed approach improves classification accuracy and reliability by handling diverse terrains and object densities, enhancing airborne LiDAR point cloud classification for urban mapping and monitoring.

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