Automatic DTM and Building Footprint Extraction from Imageries and Point Clouds in Indonesia's Land Registration Drone Survey: A Roadmap Towards Reconstruction of LOD1 3D building model

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Key words: Building footprint, ground extraction, Geo-Carta, LOD1 building model

SUMMARY

Accurate and automatic Digital Terrain Model (DTM) and building footprint extraction from drone survey has become essential and challenging work for cadastre verification, modernization and updating. In the context of multipurpose cadastre, the integration of land parcels with other spatial information such as building footprint, terrain elevation, and 3D model, allows for detailed representation of land information. This facilitates spatial analysis and adjacency information within the real-world objects above the ground. In this paper, we introduce an approach for automatic DTM and building footprint extraction by implementing deep-learning methods (i.e., YOLO v8 and CNN) using true-orthoimage UAV and point clouds. We first apply photogrammetric processing through SfM pipelines to produce 3D point clouds and true-orthophoto. To extract DTM, CNN deep learning is implemented to classify point clouds into ground and non-ground objects. The detection of building footprint, as an important spatial information in the cadastral intelligence, is performed by implementing YOLO v8 deep-learning using custom trained data. To ensure that users, irrespective of their technical skill levels, can easily navigate and utilize those two algorithms, we build a GUI for a desktop application using Python, namely Geo-Carta (Geospatial-Cadastre with Artificial Intelligence for Generating LOD 3D City Model). It consists of four features dealing with the detection of building footprint from orthophotos, ground extraction from point clouds, land parcel editing feature, and generation of LOD-1 3D building models.
We tested the Geo-CARTA app for detecting building footprints across various building types (with different shapes and patterns) in several provinces in Indonesia, i.e., Papua, West Sulawesi, East Borneo, Riau, West Java, and Yogyakarta. The results show that the detection of building footprint reached the accuracies of 88.47%. For the accuracy assessment of ground extraction, we tested with the UAV dense clouds in West Java and Yogyakarta, achieved an accuracy of 0.969. The resulting building footprints, DTM, and DSM were then used for reconstructing 3D building models in LOD1 which were implemented automatically using Geo-CARTA app and exported the 3D model into cityjson format.

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1. INTRODUCTION

Accurately and rapidly extracting building footprint information from remote sensing imagery is an essential step for reconstructing 3D building model. The common approach for extracting building footprint is by implementing image segmentation, a procedure for detecting the roof outlines and the reconstruction approach of the buildings. The objective of segmentation is to cluster point clouds or partition a digital image with similar characteristics into homogenous regions [1]. In the past several decades, various image-segmentation algorithms have been proposed and developed. It is generally divided into four categories: thresholding, clustering, edge or contour detection and region extraction [2]. For detecting the building footprint, clustering and edge detection are commonly used. However, for complex and closed buildings, they are not fit to delineate the building boundaries individually. In addition, some proposed methods have difficulty separating the building boundary where dense vegetation partially obscures buildings.

The implementation of deep learning for building footprint extraction has shown significant advancements to solve those limitations. Various deep learning architectures like U-Net, ResUnet, and their variants have been successfully combined with multi-resolution segmentation techniques to enhance the accuracy and efficiency of building footprint extraction from high-resolution satellite images [3, 4] [5]. These approaches address challenges such as geometric inaccuracies and occlusions in building segmentation by leveraging binary semantic segmentation, regularization, and vectorization methods. Additionally, novel networks like MSA-UNET and MSA-ResUNET have been developed to aggregate multi-scale feature maps and improve robustness in cross-domain settings, showcasing superior performance in building footprint extraction tasks [5]. The proposed methodologies aim to provide accurate predictions with refined boundaries, essential for applications in urban planning, change detection, and population density estimation.

Object detection, a fundamental and challenging problem in computer vision, aims to identify object instances from a wide range of predefined categories within natural images. Deep learning techniques have become a powerful approach for learning feature representations directly from data, leading to significant advancements in the field of generic object detection [6]. One of the best and fastest of one-stage object detection networks was proposed by [7], which is able to process 45 frames per second while easily running the detection in real time. From its speed, it was called the You Only Look Once (YOLO) algorithm, then also been improving since it was introduced, by involving all its yolo variations [8]. YOLO offers strong real-time performance, reducing considerable time and effort in practical applications.

In this study we propose building footprint extraction based on YOLO-v8 network with custom trained data.

In the context of multipurpose cadastre, building footprint can be used to represent detailed land information together with the integration of land parcels and other spatial information such as terrain elevation and object height model (OHM) that represent building heights in 3D city models. Forming the foundation for constructing precise OHM, the ground extraction process is a critical component. This process is particularly challenging, especially when aiming for automation. Ground extraction methods are generally categorized into two approaches: (1) classic ground filtering, which relies on geometric features, and (2) learning-based pipelines that treat the process as a classification task [9]. Each method excels in different scenarios for extracting ground points. Common classic filters like Cloth Simulation Filter (CSF) [10, 11] and Progressive TIN Densification (PTD) [12, 13] are widely used across various applications. With advancements in Artificial Intelligence (AI), machine learning and deep learning algorithms, such as Random Forest [14], XGBoost [15], and PointNet/ PointNet++ [16, 17], have also been applied to ground extraction. In this study, we implement CNN with dynamic graph convolution (DG-CNN) that was originally proposed by [18]. This algorithm has demonstrated greater accuracy compared to traditional methods.

Ensuring the users can easily navigate and utilize those two algorithms (YOLO and CNN), we introduce a novel interface for a desktop application using Python, namely Geo-Carta (Geospatial-Cadastre with Artificial Intelligence for Generating LOD 3D City Model). Geo-carta has been established through a collaborative research between the Department of Geodetic Engineering, faculty of Engineering UGM with Indonesian Ministry of Agrarian and Spatial Planning / National Land Agency. It comprises four interconnected steps for generating LOD1-3D model automatically, i.e., generating building footprint based on true-orthoimage with YOLO v8 deep learning, extract ground objects with DG-CNN to produce DTM, and 3D reconstruction of LoD1 models **(Fig 1)**.

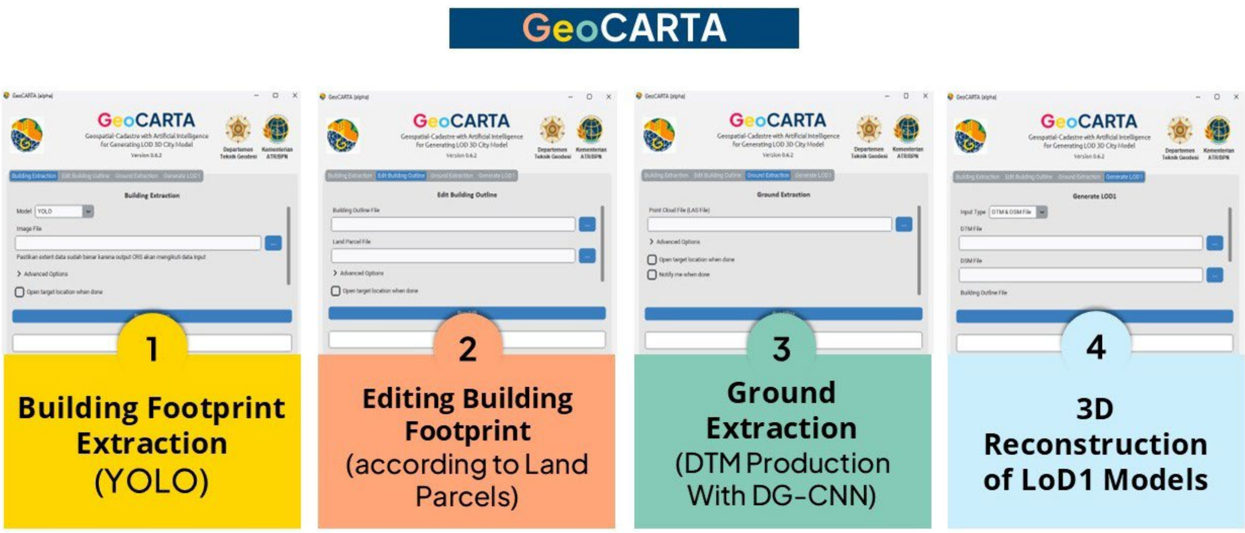

Figure 1. Interconnected steps for generating LOD1-3D in Geo-Carta App

1.1 Building footprint

A building footprint is a polygon or set of polygons in vector format representation of the base of a building or structure (https://www.lawinsider.com/dictionary/building-footprint). This base is defined as where the walls intersect with the ground (**Fig 2**). Several approaches can be implemented for extracting building footprint, including segmentation-based, classification-based, or hybrid method [19]. Building footprint play significant role in the generating 3D building model. Extruding the building footprint according to the height of the building will generate a LoD1 building model. In the generating LoD2, building footprint must be integrated with roof structure, thus, the type of building roofs plays a crucial role in fitting a 3D model to each building [20].

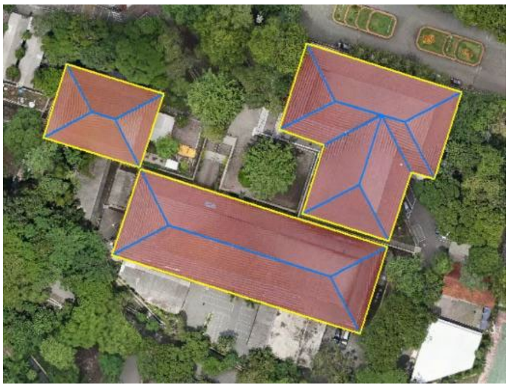

Figure 2. Building footprint (yellow polygons)

1.2 Digital Terrain Model

The automated generation of the LOD-1 building model required the DSM and DTM data. DSM represents the elevation surface of buildings and other objects which can be produced by creating TIN surfaces of original point clouds data. Point clouds data need to be classified as ground and non-ground to generate DTM. The generation of ground point cloud as a surface represents the elevation of ground/terrain object/DTM (**Fig 3**). An accurate estimation of building footprint and DTM is a key step toward 3D city modeling both in model-driven and data driven approaches which directly affects the final precision of the LoD1 3D building model. Building height can be extracted by subtracting the DSM with DTM. LoD1 building model was then generated by extruding building footprint according to this height.

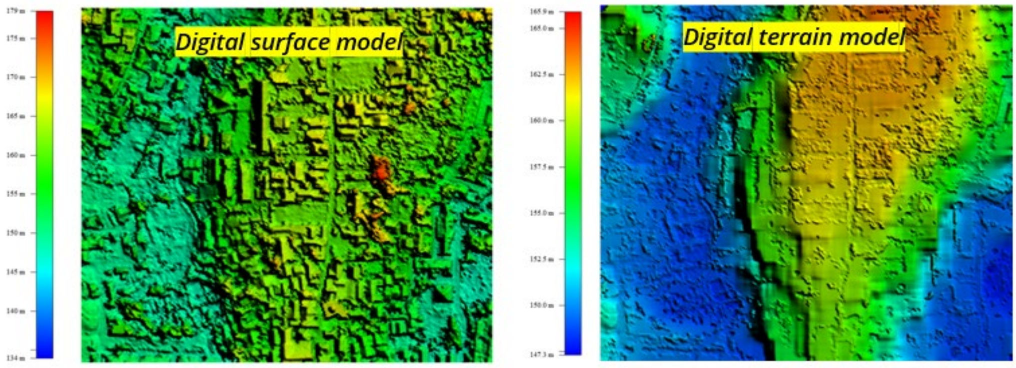

Figure 3. DSM and DTM

2. RESEARCH METHOD

2.1 Study area and datasets

The study areas of this research are part of six provinces in Indonesia, i.e., Papua, West Sulawesi, East Borneo, Riau, West Java, and Yogyakarta (**Fig 4**). The entire images were captured by using UAV platform with the ground sampling distance of 10 cm.

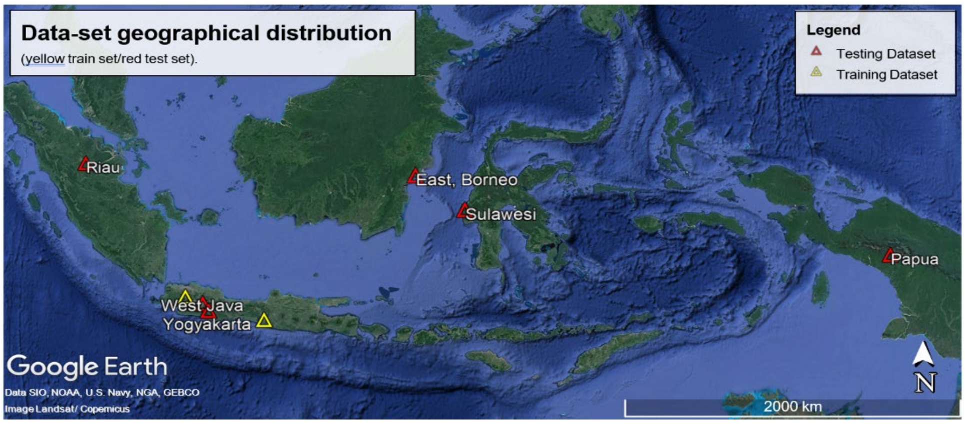

Figure 4. The study areas over six provinces in Indonesia

The images were processed by implementing structure from motion – multi view stereo (SfM-MVS) algorithm through Metashape software to produce dense clouds and true-orthophoto. **Fig 5** shows the visualization of true-orthophoto in six provinces.

Figure 5. True-orthophoto on the six provinces in Indonesia

2.2 Proposed Method

The general workflow of the proposed application is described in **Fig 6**. The first phase focuses on building footprint extraction through YOLO algorithm utilizing true-orthoimage UAV. Here, orthophoto was generated through SfM-MVS pipelines from UAV imagery. This orthophoto was used as input data for the YOLO algorithms. For the training dataset, an area of 20 Ha in West Java was used for the training sample. We created, trained, and deployed YOLO v8 models in a Jupyter notebook. YOLO algorithm works by reframing object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. A single neural network is then deployed to predict bounding boxes and class probabilities directly from full images in one evaluation [7]. YOLO uses the entire image as input for the network, allowing a neural network to determine both the location of bounding boxes and their corresponding categories [21]. The process creates an extremely fast process, due to not using a complex pipeline. With its rapid object detection capabilities, we have selected and trained YOLO algorithms in this paper to detect building footprints, thereby developing an automated method for segmenting building outlines.

The second step was generating DSM and DTM by implementing CNN deep learning based on UAV dense clouds. CNN has been utilized for ground filtering from airborne LiDAR data, offering a local topological information-aware deep learning method [22]. The model incorporates a local topological information mining module and modified graph convolutional networks for improved ground filtering performance. Using custom data, we split into validation and actual training data for training the CNN model and testing it using the validation set. We use the Pytorch framework to build the model, originally from [18], then modified into ground classification problems. The algorithm has been proven to attain the new state of the art performance in solving point cloud classification and segmentation tasks [23].

The CNN model, especially dynamic graph CNN leverage local geometric structures by building a local neighborhood graph and performing convolution-like operations on the edges connecting adjacent points, following the principles of graph neural networks [18]. DGCNN's key component, EdgeConv, captures the local geometric structure of the point cloud while maintaining permutation invariance. Combined with the dynamically updated K-NN algorithm, which considers geometrically distant points, EdgeConv enabled DGCNN to capture both local and global information effectively [24]. Since CNN deep learning aims to extract ground objects to produce DTM, we classify the point cloud data into two classes, i.e., ground and non-ground point.

Based on the building footprint and DTM, we calculate the difference between the DSM and the DTM to generate the normalized digital surface model (nDSM) or object height model (OHM). The last step of the proposed method was generating the LOD1 building model by extruding building footprint according to UHM. The resulting 3D model was then stored and exported into cityjson format.

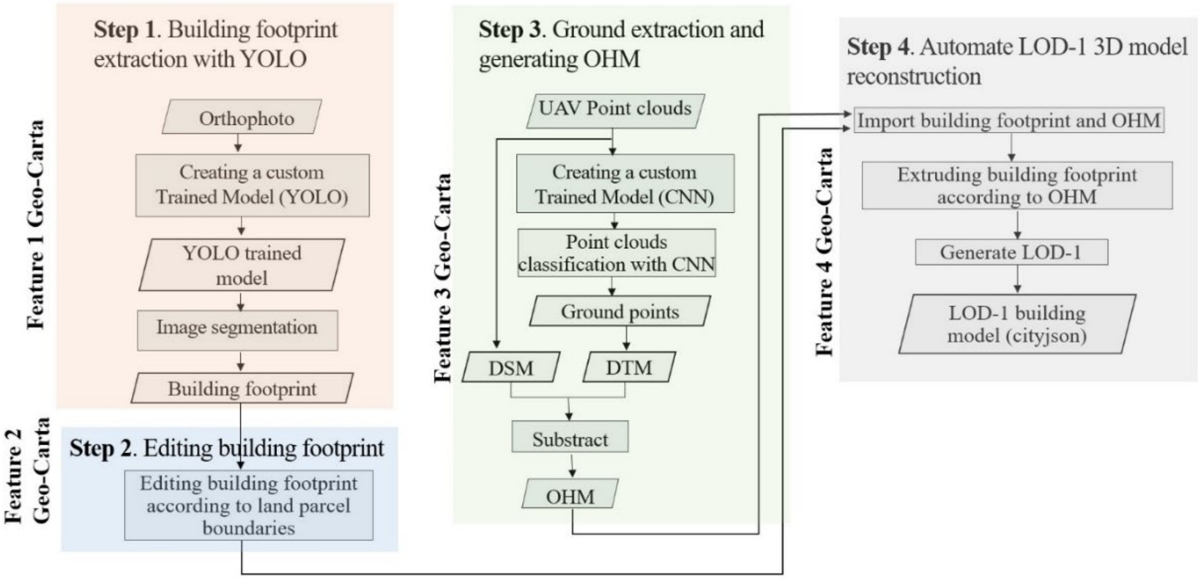

Figure 6. General workflow

2.3 Geo-Carta App

Geo-Carta app comprises four features that integrate several steps in the automate generation of LOD1-3D model. The first feature is building footprint extraction. Here users can select deep learning models of the two designated deep learning models, i.e., YOLO v8 and Modified Vision Transformer (MVT). MVT represents a deep learning framework predicated on the CSwin transformer architecture, which endeavors to implement the foundational principles inherent to transformer models. Given that YOLO deep learning exhibits a good performance in delineating building outlines and is more aptly suited for deployment within the Indonesian context, this study accentuates the utilization of YOLO v8. Furthermore, users may select the desired detections level in the predefined YOLO type, i.e., rapid, medium, highest. Those levels indicate the different levels in the detection, the higher level type the higher detail of the resulting segmentation. As shown in **Fig 7**, users can extract building footprint beginning from import true-orthoimage (square image with tiff format) then execute "run prediction" according to the predefined trained model.

The performance of Geo-Carta to segment the building footprint indeed depends on the quality of the trained model. It is advisable to revise and enhance the trained model in specific regions where it exhibits divergent characteristics relative to our model. To facilitate this, Geo-Carta provides users with the capability to substitute and update the trained model in accordance with their building characteristics. This process can be accomplished by selecting the model path within the advanced options and inputting the new trained model file in Pytorch model format (.pt).

Figure 7. The window of feature #1 in Geo-Carta

The second feature is a tool for editing the building footprint according to the land parcel boundary (**Fig 8**b). This feature comes from the fact that the generated building footprint in the complex and closed buildings are not fit to delineate the building boundaries individually (**Fig 8**a). To recover this condition, users can apply this tool to edit or modify the original building footprint and get a refined one (**Fig 8**c). For more detailed illustration, the process can be seen in **Fig 8**. The red polygons are the extracted building footprint, the green polygons are the land parcel boundaries, and the yellow polygons represent the refined building footprint separated by land parcels.

(a) (b) (c)

Figure 8. The process of editing building footprint according to the land parcel boundary

The third feature aims to extract ground point from a set of point clouds. The input data for this task is point clouds file in .las format (**Fig 9a**). DG-CNN uses six statistical features to determine the class of ground and non-ground, i.e., coordinates of points in x,y,z, and color

RGB channels. Prior to the ground prediction, users need to determine “batch size” and “predict area” in the window. Batch size indicates the size of point feed into the deep learning model, while the predicted area represents ID or order to choose which area wants to process. The current version of Geo-Carta allows classification of both point clouds from photogrammetry and Lidar, however the intensity value was not used as a feature in the statistical model. We consider incorporating the intensity value in the further version. The last feature of Geo-Carta is an interface for generating LOD-1 models based on three input data, i.e., building footprint, DSM, and DTM (**Fig 9b**). We also facilitate the generating LOD-1 model directly from classified point cloud files together with building footprint.

(a) Ground extraction menu (feature #3) (b) Generating LOD-1 menu (feature #4)

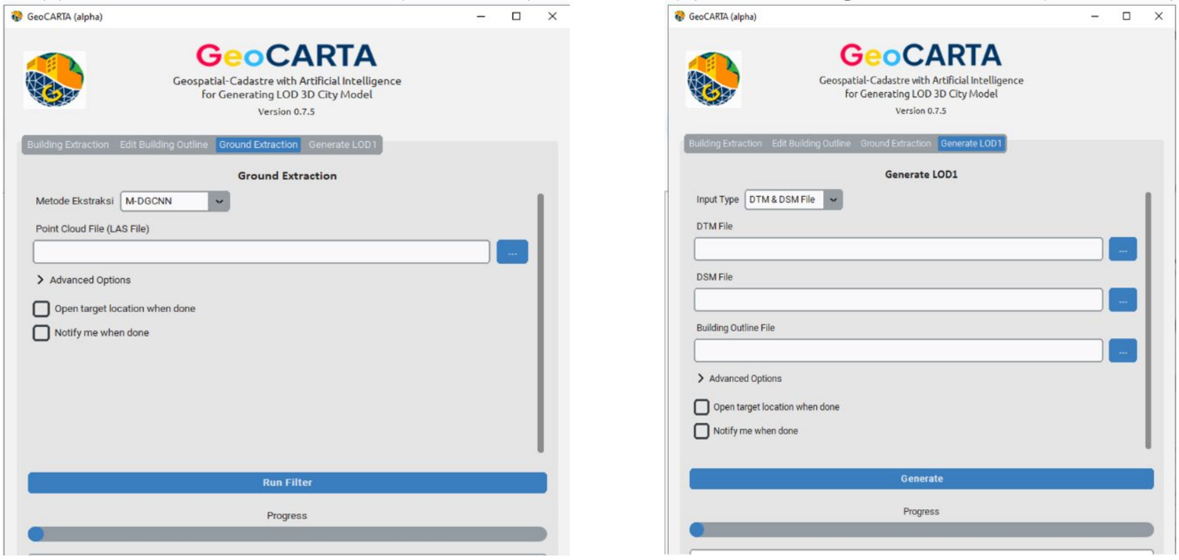

Figure 9. Window menu of feature #3 and #4 in Geo-Carta

Geo-Carta App can be downloaded from the website www.geocarta.id. However, right now only users who have an account in the geo-kkp BPN RI can install and utilize these features.

2.4 Reconstruction of LOD-1 3D building model

The 3D model resulted in Geo-carta represented by BREP (boundary representation) format as a collection of NURBS surfaces. Each individual face within this model is encompassed by a closed loop structure, composed of one or multiple edges. This sophisticated representation of the 3D model through the BREP format highlights the complex interplay between surfaces, edges, and vertices, illustrating the advanced principles of computational geometry. The reconstruction of BREP 3D model starts from the building footprint (vector 2D), which then extrudes the height of every surface (roof, wall, and ground) according to the OHM. The reconstruction process of BREP 3D models are illustrated in **Fig 10**. For example, the green wall is reconstructed by creating a face between four edges (1,2,6,5). The elevation of 1,2,3 and 4 are determined by calculating the average of height in every edge according to the OHM. The model then stores and exports into CityJSON format, an alternative to the GML encoding of CityGML, which can be verbose and complex to read and manipulate.

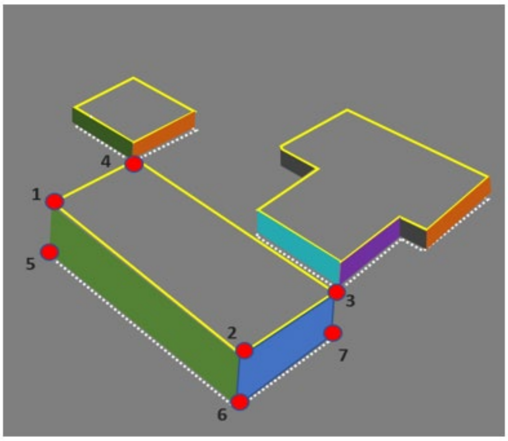

Figure 10. Reconstruction of BREP 3D model

3. RESULT AND DISCUSSION

Three experimental results of the proposed approach (i.e., building footprint extraction, ground extraction, and 3D BREP LOD1 generation) across various building shapes and patterns in six provinces in Indonesia are presented in this section. The trained model of YOLO was built over 40 Ha in some areas in West Java, whereas the DG-CNN model was trained over 55 Ha of urban and suburban areas in West Java and Yogyakarta province.

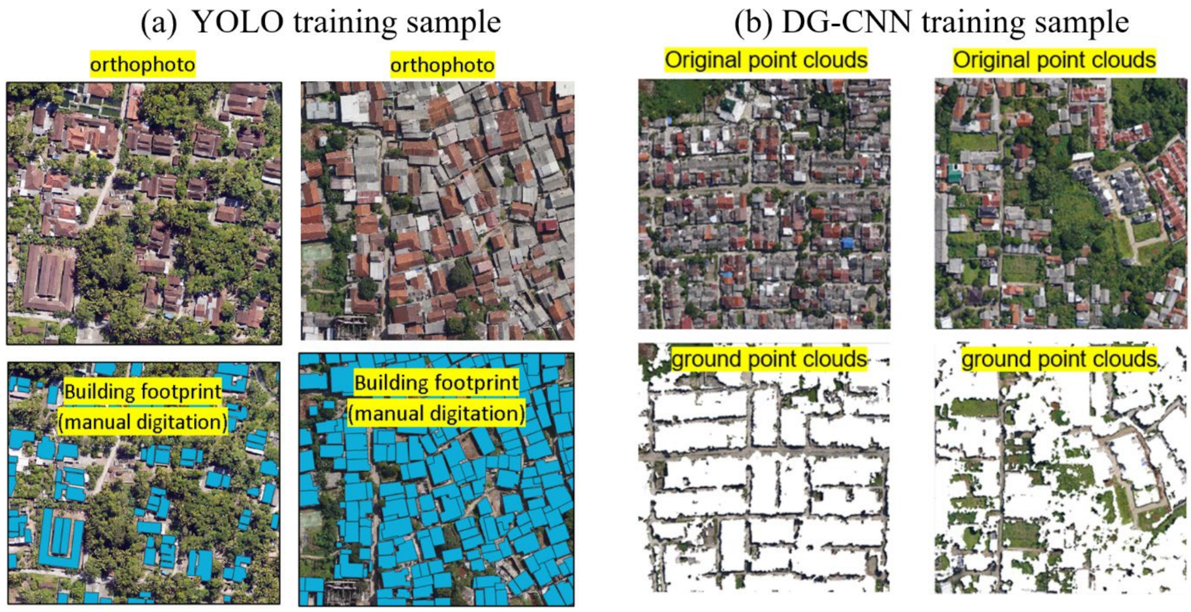

Figure 11. Training sample of YOLO and DG-CNN

3.1 Generated building footprint and accuracy assessment

According to the YOLO trained model (**Fig 11**a.), we implement Geo-Carta App for generating building footprint. Through the YOLO deep learning with a custom trained model, our program can recognize and separate each building precisely. The final results of building footprint of six datasets were illustrated in **Fig 12**. However, some buildings are not properly segmented, particularly at the flat, dense and connected buildings.

Figure 12. The resulting building footprint by YOLO deep learning with a custom trained model

According to the ground truth data formed by manual digitization, we compare and analyze the accuracy of the detected building footprint. We use F1 score to evaluate the deep learning model that measures a model's accuracy. It combines the precision and recall scores of a model, yielding the score of 93.88%. The overall accuracy as indicated that the predicted values match the actual values (ground truth) yielded an accuracy of 88.47%. We also compare the detection building footprint by Geo-Carta with the Mapflow, a QGIS python plugins repository by Geoalert to extract real-world objects from satellite imagery. In the area with connected buildings, Geo-Carta can recognize and separate each building more precisely (yellow circles in **Fig 13**). We also found the resulting building footprint with Mapflow has inaccurate orientation (black circles in **Fig 13**), while the detected building footprint with Geo-Carta demonstrates correct shape and orientation.

Table 1. Accuracy of detected building footprint

Indicators	Score
Accuracy	88.47 %
Precision	90.59 %
F1 Score	93.88 %
Commission Error	9.32 %
Omission Error	2.58 %

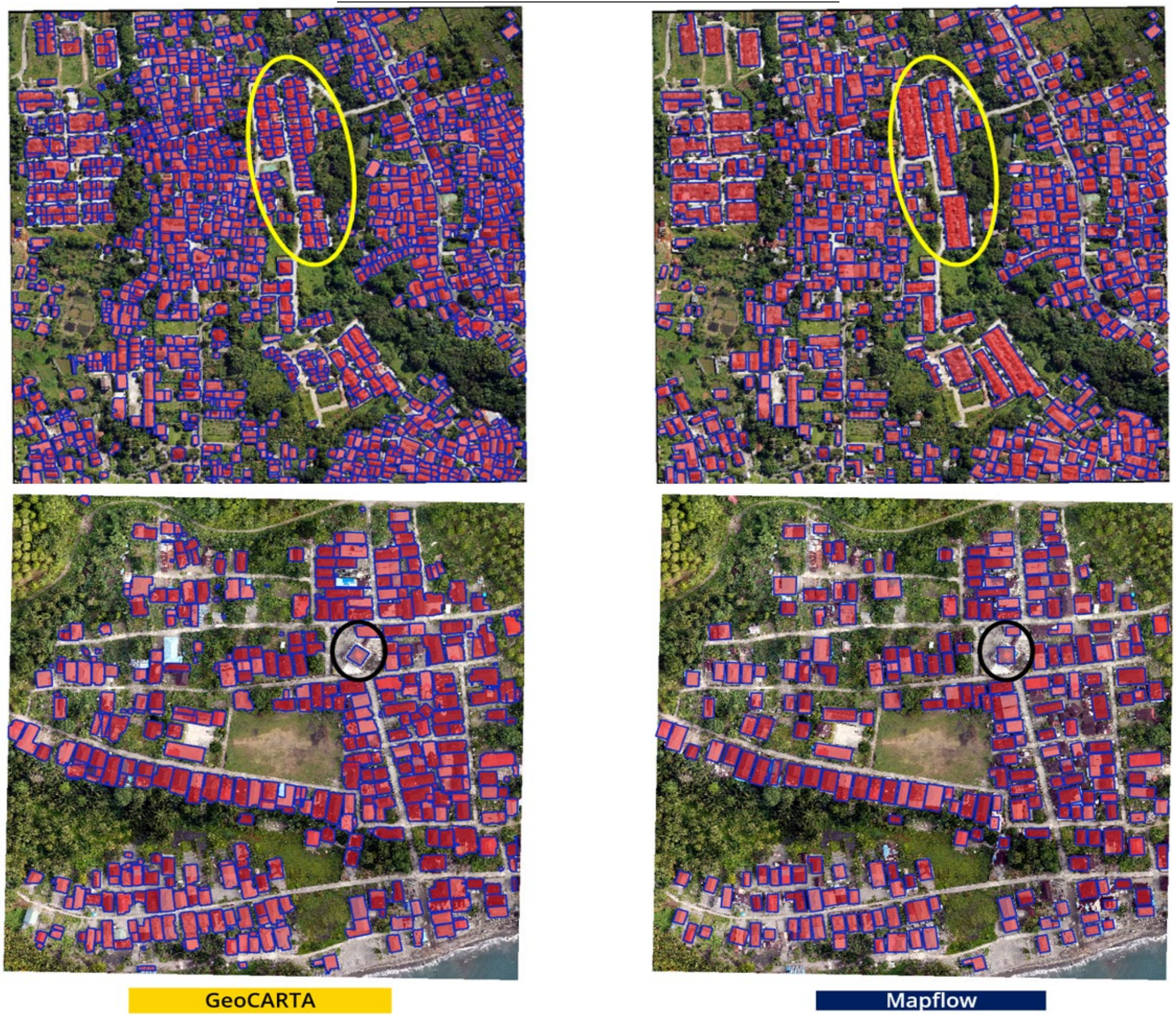

Figure 13. Comparative results between Geo-Carta and Mapflow

3.2 Generated DTM and accuracy assessment

The term DTM refers to a model in which the elevations are referred to the bare ground. DTM can be formed based on point clouds (photogrammetry and Lidar) or other spatial data sources like terrestrial survey, satellite imagery, etc, The third feature of Geo-Carta app is an application to extract ground features from unclassified points. It means that the input data source is a set of object points (vegetation, building, car, water body, etc). In the context of multipurpose cadastre, the land parcels data need to be referred with terrain elevation on the same coordinate system. Therefore, the referred land parcels can be integrated with other spatial information.

We have built a custom DG-CNN trained model and are available to use in the Geo-carta App. However, to the best of our understanding, our trained dataset is not adequately suited for the prediction and extraction of ground points across the Indonesian archipelago. Consequently, it is imperative to implement updates or modifications to the trained models to achieve enhanced accuracy in ground prediction. We have facilitated for users to build, import and implement their own trained model in the prediction process. By using our trained model, we have tested some point clouds data generated from UAV photogrammetry in West Java and Yogyakarta. The result can be seen in **Fig 14**. According to the extracted ground points, we have evaluated the accuracy of Geo-Carta prediction compared with the ground truth. It yielded the intersection over union (IoU) score and overall accuracy of 0.906 and 0.969, respectively.

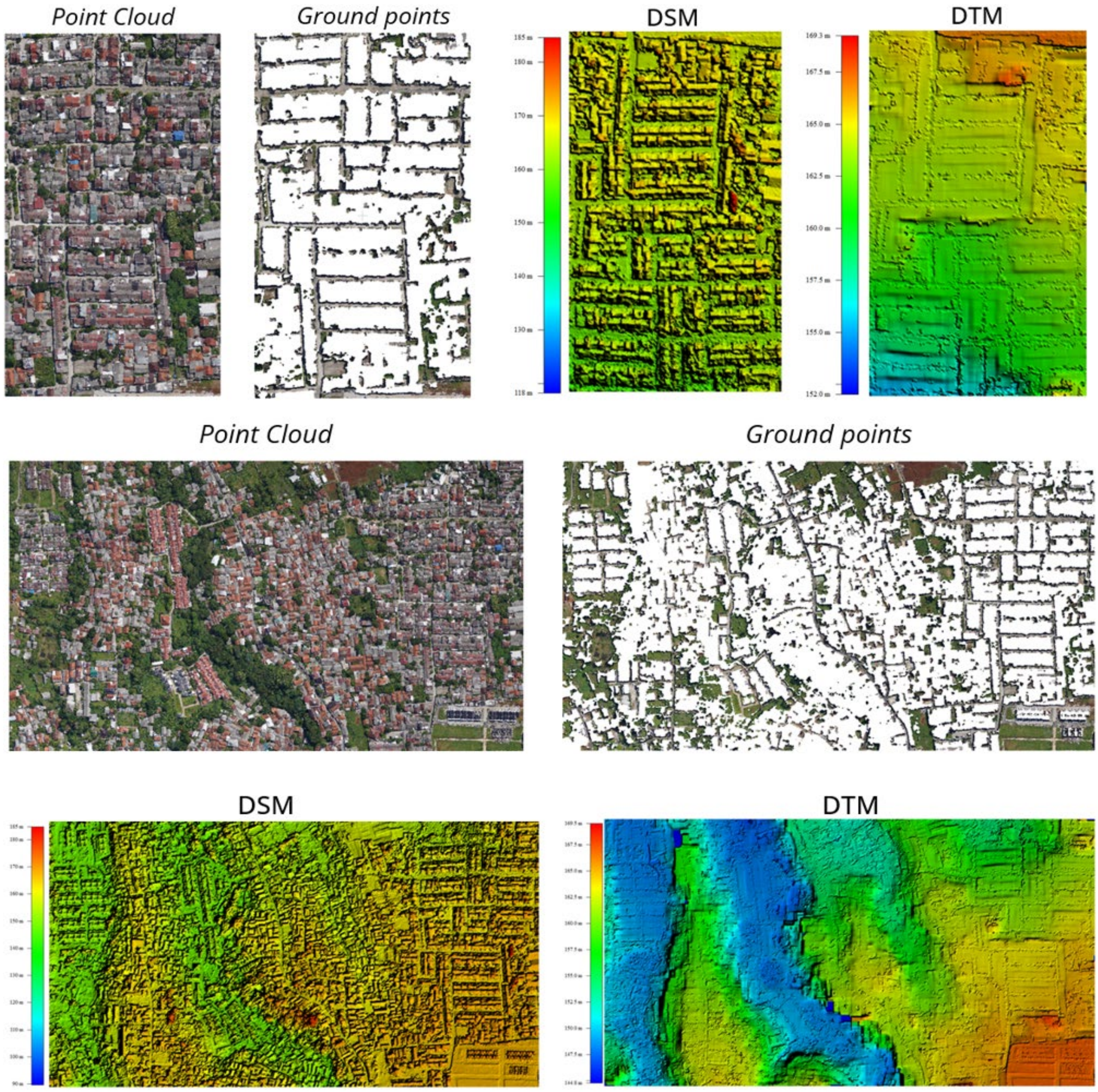

Figure 14. Original point clouds, extracted ground point and generated DTM by implementing Geo-Carta

3.3 Generated LOD-1 3D building model and accuracy assessment

The generation of BREP 3D LOD1 model can be applied by two input data options, as a point cloud that has been classified into ground and non-ground or in raster data including DSM and DTM. We have implemented Geo-Carta for the 3D model reconstruction over four locations in three provinces, i.e., Yogyakarta (UGM campus), West Java (Bogor icon building), and DKI Jakarta (Trunojoyo). The results of LOD1 models were illustrated in **Fig 15**. Those 3D models were built automatically, beginning with the detection of building footprint followed by extracting ground points and generating DSM and DTM. Once those data are available, the generation 3D model can be performed automatically.

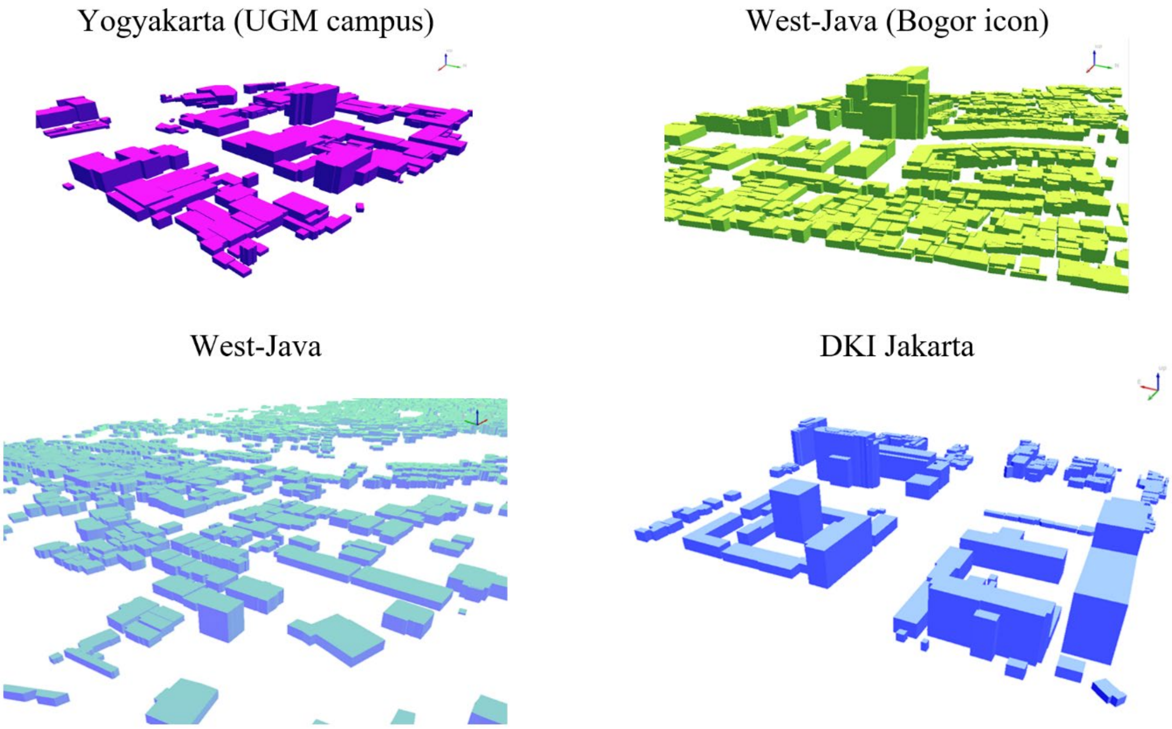

Figure 15. The generated 3D LOD-1 model in city-JSON format

4. CONCLUSIONS

This paper presents an automatic method for detecting building footprint, ground point extraction and 3D model in LOD-1 based on UAV orthophoto and point clouds. Those steps were integrated into a single interface application, namely Geo-Carta, a desktop application using Python. The building footprints are extracted from orthophoto through YOLO deep learning and the ground points as an input data to produce DTM is extracted from UAV point clouds by implementing DG-CNN algorithm. Results show that the building footprint can be well recognized and it can separate each building precisely. However, in the dense and connected buildings, they are not properly segmented, introducing irregular patterns. Therefore, editing building footprint with land parcel should be performed.

In the context of multipurpose cadastre, it is essential to reference land parcel data with terrain elevation within a uniform coordinate system to facilitate its integration with other spatial information, including land parcel height, building information, and three-dimensional models. Through the utilization of Geo-Carta, these procedures can be executed in a straightforward manner, delivering high accuracy in the geometric components involved.

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BIOGRAPHICAL NOTES

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