

# Automatic extraction and quantification of Building footprints from Remote Sensing images by Deep Learning

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**Abbreviation:** *Deep Learning- DL, Convolution Neural Network – CNN, Generative Adversarial Network-GAN*

## Abstract

Detailed information about building footprints is required for most urban analyses and modelling. Our study aims at comparing the quality of outputs produced by deep learning to detect buildings footprints from Planetscope images (3m per pixel) and compare these to cadastral parcel data published by Belgian Land registry (here considered as ground truth). The building footprint detection is based on a combination of a CNN-based segmentation network with a GAN-based upsampling network for generating realistic building footprints. Our experiments show that our combined CNN-GAN model detects effectively building units in urban core areas of Brussels with a completeness of 36%, which shows a fair agreement with our cadastral data. As our training set is based on high density areas, the model tends to underestimate the number and cumulated area of buildings in peri-urban areas such as Leuven and Nivelles. Landscape metrics and statistical assessment are carried out at class and landscape level to measure the correlation and deviation between the output from deep learning and the original cadastral data. These results shows that the use of such system(deep learning ) to detect building footprint automatically over multiple years can be used to evaluate the changes in building footprints with accessibilities to amenities and green areas.

## 1. Introduction

Buildings are the basic "building block" of civilization in today's world. Building footprints are one of the major methods of analyzing the buildings. A building footprint captures the geofence of a building excluding the adjacent properties like parking lots and landscaping. For urban studies, building heights and footprints are of critical importance. For the past few decades, there has been many studies in order to find a method for automated building footprint extraction. Recent advances in remote sensing, such as airborne LiDAR, high-spatial resolution aerial photography, and object-based image analysis (OBIA) techniques([Zięba-Kulawik et al.,2020](#)), have made it possible to extract building footprint and height

information accurately and quickly at a low cost ([Zhang et al., 2020](#)).

Accurately identifying building footprints is one of the most difficult and important tasks in remote sensing imagery analysis ([Schuegraf and Bittner, 2019](#)). Dense, pixel-wise classification of images is now possible due to recent advances in repurposing CNNs(Convolution Neural Network)for semantic image segmentation.([Shelhamer et al.,2017](#)) This study aims to extract structured building information from satellite imagery due to its availability and applicability to various other applications and to make it available for countries or cities where there is a lack of plausible data.

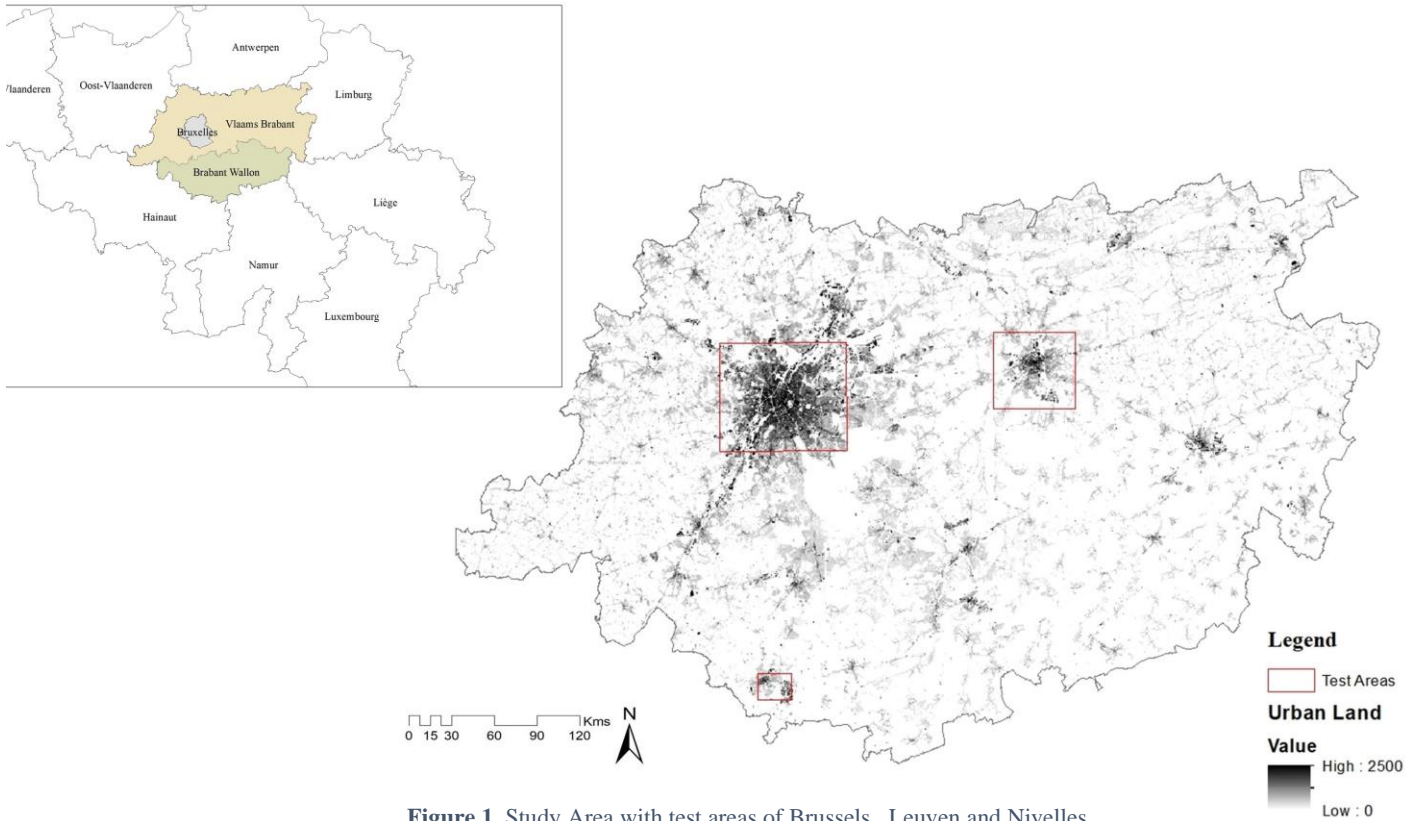


Figure 1. Study Area with test areas of Brussels , Leuven and Nivelles

## 2. Materials and Methods

### 2.1 Study Area

The study area comprises of the regions of Brussels, Vlaams Brabant and Walloon Brabant of Belgium (Figure 1). This study area occupies 3376 sq. km, which is approximately 11% of the total area covered by Belgium. In order to decrease the computational time taken for the automated extraction, three test areas were taken into consideration. With regards to better model efficiency and accuracy assessment, the test areas includes urban core like Brussels capital Region and Peri-urban areas like Leuven and Nivelles.

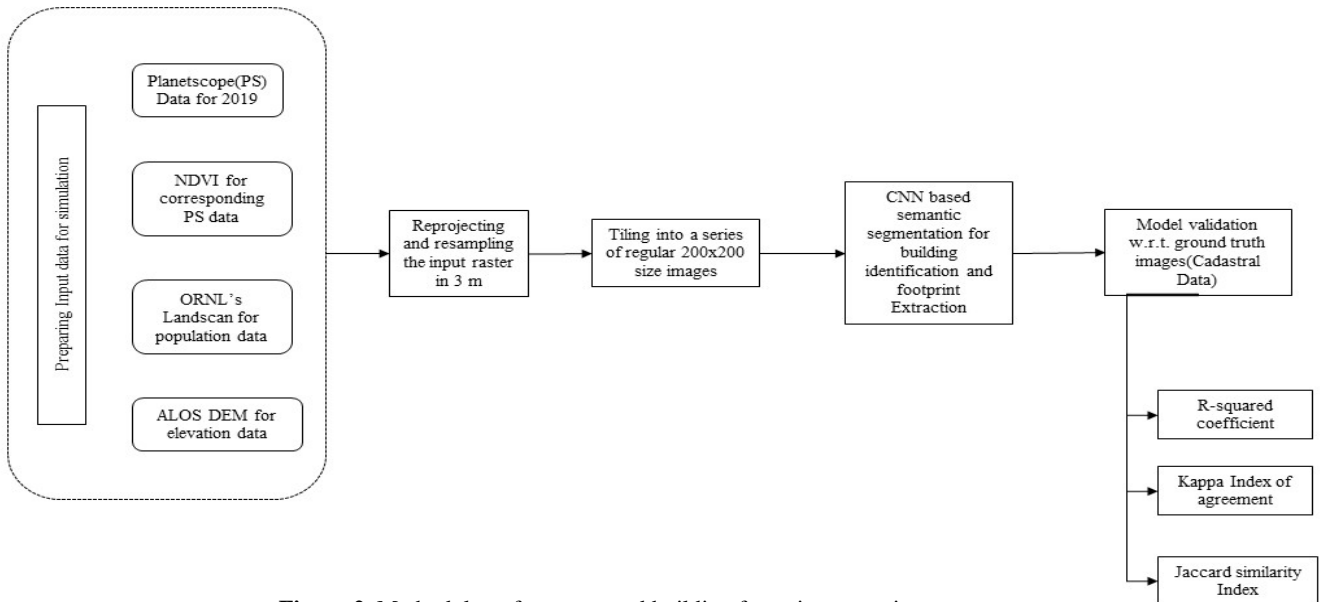
### 2.2 Methodology

Three inputs were selected for training the model in order to extract the building footprints. A medium resolution PlanetScope image was acquired for 2019 from PlanetScope with a resolution of 3m. Normalized vegetation Index (NDVI) were calculated for corresponding images using python code . The other associated data includes landscan population data and Also DEM was prepared and resampled at the same scale of PlanetScope image in order to

gain a efficient results. Once the data were prepared, a DL algorithm based on CNN-GAN was developed taking 10% of brussels dataset and considering 100% area as urban. In order to avoid the disparity in results, especially in peri-urban areas, multiple runs were simulated in various combination of training and testing dataset. With course of several runs, the final output were made which could detect the building footprints in both urban and rural area better than the initial runs.

## 3. Result and discussion:

A CNN-GAN based segmentation was performed taking 10% of Brussels as the training sets. The main objective of the work was to establish a realistic automation process for building footprint extraction which will facilitate cities across the world with user ready data and help them for further studies. The first run, however showed a very low level of kappa agreement for peri urban areas. This was due to the selection of training set which only considered a 500 by 500 pixel patches with only buildings inside it .The rural areas



**Figure 2.** Methodology for automated building footprint extraction

were mostly not been taken as it could lead perfectly showed zero prediction for rural patches. However, with multiple runs and consideration of 50% urban and 50% rural areas , the final result shows a fair agreement level based on Kappa coefficient on both urban and peri urban areas. The output were rescaled into multiple scale level (100,200,400,800m).

To further amplify the validation between the simulated output with ground truth, we cross checked the result using two others methods. The Jaccard index, also known as the Jaccard similarity coefficient is a statistic used for gauging the similarity and diversity of sample sets. This index again shows a better level of similarity between the initial run (11%) and final run (35%). The R-squared values is a measure of goodness of fit and indicates the percentage of variance in the dependent variable to the independent variable. The R-squared shows a significant variation at each level of scaling as shown in (Table 1). It mostly conclude that it is at 800m level that the model fits the best while omitting the zero values and setting a minimum threshold for each scale level to consider each footprints as built-up.

**Table 1.** R-squared values for different cell size

Scale(in meters)	R-Squared value		
	Brussels	Leuven	Nivelles
100	0,71	0,62	0,65
200	0,95	0,94	0,94
400	0,99	0,99	0,99
800	0,99	0,99	0,99

#### 4. Conclusion

We conclude from the various analysis and validation that has been made through this automation result that the parameters of every segmentation process shall vary with their geographical area of interest. Places such as Brussels act differently than Chicago and California. Availability of proper ground truth data that can be used for validation of the model is also imperative to study. The transposability of such models over time and across space can vary with their parameters and lack efficient ground truth. So training and testing data based on such parameters might not be sufficient for creating automated building extraction. That is why even after multiple runs, the result could be slightly better but still not sufficient. Such anomaly can be avoided if intense research can be done through different case studies and thus deciding upon a set of optimized parameters and efficient selection of training and testing sets.

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