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Machine Learning Approaches for Building Inventory Characterisation

A thesis submitted in partial fulfilment of the requirements for the Degree of Master of Science in Geospatial Technologies

by

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Abstract

Accurate building inventories and relevant information are essential for sustainable urban governance, thereby contributing to achieve the Sustainable Development Goal 11, which focuses on sustainable cities and communities. Acquiring building information manually in complex-built environment with densely populated buildings is impractical and may not guarantee the high thematic and spatial detail necessary for real world applications.

Recent advancements in remote sensing technology, coupled with the availability of high-resolution satellite and drone-based imagery through open access channels and as machine learning (ML) and deep learning (DL) continue to advance, showcasing their capability to recognise complex patterns, new opportunities for interpreting various surface features on the Earth are made possible. A growing body of literature emphasises the use of both traditional ML and DL for building footprint extraction, yet available and accessible literature reveal limited application of DL in urban building characterisation.

This study involves exploring and implementing Random Forest (RF) as machine learning model and dense neural network (DNN) as deep learning model in the context of multi-class building characterisation encompassing six classes. A total of 35 geometric and distribution features calculated using VHR imagery and OpenStreetMap data are used to train the model. The experiments show that overall accuracy of RF (79.9%) is higher than that of the DNN (71.9%). Upon closer examination and comparison of diagonal elements, representing the number of correctly classified samples for each class, it is found that the DNN outperforms RF in correctly classifying more instances for four classes. Further the recall rate using DNN is greater for four classes- ‘Building block in closed construction’, ‘Detached building block’, ‘Free standing individual building’, and ‘Garage’, in comparison to that of RF. Implementation of the DNN and comparison with traditional machine learning algorithm- RF provide additional scientific contribution, especially in situation where there is limited use of deep learning algorithms in the building characterisation.

Keywords: Building Footprints, Characterisation, Random Forest, Dense Neural Network

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List of Abbreviations

ADT	Aggregated Decision Tree
AI	Artificial Intelligence
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Dense Neural Network
DT	Decision Tree
GBDT	Gradient Boosted Decision Tree
GLCM	Grayscale Co-occurrence Matrix
kNN	k-Nearest Neighbours
LDA	Linear Discriminant Analysis
LiDAR	Light Detection and Ranging
MABI	Multi-Angular Built-up Index
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRF	Markov Random Field
NB	Naïve Bayes
NC	Nearest Centroid
OBIA	Object Based Image Analysis
OSM	OpenStreetMap
PGIS	Participatory Geographic Information Systems
POI	Point of Interests
RF	Random Forest
SAR	Synthetic Radar Aperture
SVM	Support Vector Machine
UN	United Nations
VHR	Very High Resolution
WM	Word Mining

Chapter 1
Introduction

1.1 Background

Over 55% of people worldwide live in cities, and the United Nations predicts that by 2050, about 70% of the global population will reside in urban areas (UN, 2019). As cities rapidly grow to accommodate this influx of population growth, they expand in three ways: more buildings (horizontal expansion), filling spaces between existing structures, and constructing taller buildings (Lall et al., 2021). This highlights the importance of buildings as primary living spaces of cities and integral components of urban morphology (Oliveira, 2016).

Accurate building inventories and relevant information are essential for various practical applications such as disaster management (Cerri et al., 2021; Geiss et al., 2015), climate and energy modelling (Anand & Deb, 2023; Masson et al., 2020), urban planning, and transport management (Grippa et al., 2018; Scorza & Fortunato, 2021). They also play significant role in sustainable urban governance (Wurm et al., 2010), thereby contributing to achieve the Sustainable Development Goal 11, which focuses on sustainable cities and communities (UN, 2023). Traditionally, gathering building information involves labour-intensive and time-consuming processes such as field surveys and manually digitizing aerial images (Geiss et al., 2017; Lu et al., 2014). However, these methods may not guarantee the high thematic and spatial detail necessary for real world applications (Hall, 2003). In addition, acquiring building information manually in complex-built environment with densely populated buildings is impractical (Zhou & Chang, 2021). Hence, there is a need for research into automated methods for identifying and characterising buildings.

"Citizen scientists" (Goodchild, 2007) and participatory geographic information systems (PGIS) have empowered the general public to actively contribute to the creation of data and participate in collaborative decision-making processes using spatial information (Balram & Dragicevic, 2006). OpenStreetMap (OSM), a well-known platform for PGIS established in 2014, has achieved approximately 80% global data coverage (Barrington-Leigh & Millard-Ball, 2017; Hecht et al., 2015). Nonetheless, concerns have arisen regarding the accuracy and quality of OSM data due to infrequent updates to the database (W. Chen et al., 2020). In the context of buildings, 82% of building polygons lack further information (Cerri et al., 2021). There are noticeable gaps in attribute information within OSM, specifically in building features such as occupancy, structural type, roofing materials, number of floors, and the age of houses. For example, the OSM consists of floor area information for only about 5% of building polygons in Germany (Wurm et al., 2021).

Nevertheless, these attributes are crucial for developing practical models for real world applications. For instance, building features such as footprint area, floor area, and building use type are crucial for urban energy models (Anand & Deb, 2023; Wurm et al., 2021).

Recent advancements in remote sensing technology, coupled with the availability of high-resolution satellite and drone-based imagery through open access channels, offer new opportunities for interpreting various surface features on the Earth (Guo et al., 2018; Yuan et al., 2021). Multispectral optical imagery (W. Li et al., 2019), synthetic aperture radar (SAR) data (Pasquali et al., 2019), light detection and ranging (LiDAR) data (J. Wang & Shan, 2009) and drone-derived imagery (Wouters et al., 2021) have been leveraged to extract building footprints and compute additional features essential for characterising buildings (Bandam et al., 2022). Further, as machine learning (ML) and deep learning (DL) continue to advance, showcasing their capability to recognise complex patterns, there is increasing interest in research that employs artificial intelligence to automatically delineate building footprints and define their characteristics (Lu et al., 2014; Maxwell et al., 2018; Zhou & Chang, 2021).

1.2 Research Gap and Scientific Significance

Building characterisation involves two processes- outlining the boundary of building footprints and classifying these footprints into one or more classes based on attribute information. However, there are challenges in obtaining attribute information. Firstly, the OSM attribute information on building function or typology is incomplete (Cerri et al., 2021; Wurm et al., 2021). Secondly, governmental geodatabase, while accessible (may be challenging in developing country context), might lack consistent and required building information (W. Chen et al., 2020). Thirdly, buildings of different classes might have similar geometric and spectral characteristics, making solely remote sensing-based building classification quite challenging (Lu et al., 2014). This complexity necessitates the computation of additional features to numerically encapsulate building characteristics (Labetski et al., 2023) and identify the most significant features that contribute to data-driven building characterisation.

A growing body of literature emphasises the use of both traditional ML and DL for building footprint extraction. Notably, conventional machine learning models like Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), as well as deep learning models such as convolutional neural network (CNN), and U-Net algorithm, have been widely applied in building footprint extraction (Neupane et al., 2023; Shrestha & Vanneschi, 2018; Thottolil & Kumar, 2022; Virtriana et al., 2023; Wurm et al., 2021; Yuan et al., 2021). In the realm of building characterisation, traditional ML algorithms such as RF and SVM have been used (Geiss et al., 2015; Hecht et al., 2015), but there have been limited efforts in application of deep learning models (Pelizari et al., 2021; Taoufiq et al., 2020). In addition, it is important to acknowledge that performance for ML and DL algorithms is specific to a domain, making it challenging to identify a single best algorithm across various datasets and applications (Ben-David et al., 2010; Sebastiani, 2002). Hence, further research and experimentation are necessary to find potentially more effective algorithm for building characterisation (Zhou & Chang, 2021).

To address above-mentioned gaps and limitations, the proposed research involves exploring and implementing Random Forest (refer to section 3.1.1) as machine learning model and dense neural network (refer to section 3.1.2) as deep learning model in the context of multi-class building characterisation encompassing six classes. Dataset comprises 152 features (refer to section 3.2.1) consisting of both 2D and 3D geometric indices, and spectral indices, computed using a very high-resolution satellite imagery. The indices are available in three spatial levels- individual buildings, aggregated buildings, and building blocks and are integrated into building polygons from the OSM dataset for city of Cologne, Germany. Subsequently, 215660 building data samples are used to train and test the models and their performances are compared. This research contributes to automated classification in the built environment. Given that this research is initial effort to implement both machine learning and deep learning for building characterisation, the results obtained are potentially significant for benchmarking model performance in similar future studies.

1.3 Objectives and Research Questions

The primary aim is the automated characterisation of building inventories using high-resolution multispectral satellite imagery and OpenStreetMap data. The following objectives and corresponding research questions are designed to achieve this goal:

Objective 1: To design and implement the Random Forest machine learning algorithm for building inventories characterisation.

Research questions:

a. How are the most significant features distributed across three spatial level- individual building, aggregated building, and building block- in characterising building inventories?

b. What is the performance of Random Forest in characterising building across six classes?

Objective 2: To design and implement the Dense Neural Network, deep learning algorithm, for building inventories characterisation.

Research questions:

a. How does Dense Neural Network perform in characterising buildings across six classes?

b. What difference exist in the model performance compared to Random Forest in characterising buildings across six classes?

1.4 Thesis structure

This thesis comprises of five chapters. Following the introductory chapter, **Chapter 2** reviews relevant literature to assess “state of the art” on application of artificial intelligence (both ML and DL) in building type characterisation. **Chapter 3** describes the study area, data, and provides conceptual background on Random Forest and Dense Neural Network. It further explains experimental set up for data preparation and preprocessing and for implementing RF and DNN. **Chapters 4** describes the results on implementation of models and their performance. It further discusses comparative analysis of RF and DNN model and the implications of the results on building characterisation. Finally, **Chapter 5** summarises the limitation of the study and provides recommendation for future work and summarises key findings and contributions of this study.

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