Nexus Network Journal
https://doi.org/10.1007/s00004-023-00705-4

CONFERENCE PAPER

# Artificial Intelligence and Urban Block—Building the Common Language

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Accepted: 18 March 2023


**Abstract**
The research focuses on the application of AI in the field of urban morphology. The research takes urban blocks as a case study and treats urban block-related high-resolution images as data. The aim is to train an AI model to automatically detect urban block to conduct further quantitative analysis.

**Keywords** Urban block · Algorithm · Classification · Deep learning · Shape and size

## Introduction

The new vision of the implication of AI in architecture and urban studies covers an essential place in understanding the complex form of cities. Additionally, the accessibility of geographic data and mapping technologies created a shift from conventional methods to more automatic and data-driven methods. In this broad context, this study takes the urban block as the core to understand how a computer can learn to detect urban block types automatically. The study states that computers can learn and represent the role of an architect in analyzing and providing information on reading urban block types. The aim is to train the computer with urban block types based on shape and size to detect similar forms of urban blocks. The methodology comprises applying a deep learning model, defining the language between theory and machine in the context of input-tool-output. This study presents the preliminary algorithm of building language between machine and theory algorithm.

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Published online: 30 March 2023

Birkhäuser

## The Shift in Methodological Approaches

Moosavi (2017) demonstrate how the historical trend of different modelling capacities evolved and shifted over time. He clearly shows the shift from conventional methods to more automatic and data-driven approaches conducted since the 1950s. Similar paths have been followed in the field of urban morphology in the following years. The transformative and evolutionary ground provided by the protagonists of urban morphology studies, thus M.R.G. Conzen and S. Muratori, elaborated and developed from manifold perspectives. Based on the primary theories in the field of urban morphology, systematic and more quantitative approaches accelerated in recent years.

The most common methods of quantitative morphological analysis are conducted based on converting urban elements to numerical indexes (Chen et al. 2021). The wide range of studies devoted to quantifying urban form and its characters define the quantitative relationship among space, the definition of urban form indicators, etc. (Fleischmann et al. 2021; Marshall 2005). At the same time, morphological formation in terms of analysis tools is diverse in different levels of analysis (D'Acci and Batty 2019). As observed in the literature, the steps followed as, first, the defining a tool of analysis for the classification of urban form (Lehner and Blaschke 2019), second, automatically extracting the morphological properties, building footprints, and analysis of urban forms such as Lidar or neural networks (Ye and Van Nes 2014), and lastly, defining the tools to evaluate and analyze the results. GIS, as a platform for spatial analysis, is used widely to examine urban form. Moreover, recently, neural networks have become an essential tool in providing a comprehensive analysis of urban form (Chen et al. 2021; Ye and Van Nes 2014).

In recent years the attitude toward the complex form of cities created a ground for a new perception of considering cities as data. Following this new perception, an exchange can be observed in the role of architects, urban planners and tools of analysis. Rhee et al. interpret the city 'as the data from the viewpoint of urban architecture' and defines that 'AI can make design decisions through the context of information'. In his study, Rhee et al. questions whether a computer can learn rules to explain complex phenomena by taking the example of diagrammatic representation. According to Rhee, the role of computers shifted from being used as a tool to generate information.

## Building the Language and Urban Block

In this research, as a contemporary approach in the field of urban morphology, the implication of AI in the field is elaborated. The aim is to build the language between architectural components, the machine and tool. Teaching the computer the architectural language will lead the computer to recognize the architectural elements. This will help to construct the understanding of unnumerable relationships. As Rhee states, "*the possibilities of AI technologies in architectural design is amplified when thoroughly dealing with a data space called a city with complex and innumerable relationships*" (Rhee et al. 2019: 351 ).

Building the language between architectural analysis and computer is devoted to the logic behind the working mechanism of the computer, thus the definition of input-tool-output. As seen in Fig. 1 this study's input is constructed based on **urban blocks**, and the tool (machine) is identified as **a deep learning** model. Defining the input constituted from theory will make it easier to train the machine to read the urban form.

In the study context, urban block theories are considered as input to build the connection with the machine. Due to its contextual and physical relationship with the *plot, street and building*, the urban block is chosen as the core of the study. The study is conducted firstly to understand urban blocks and their morphogenesis, in other words, its evolutionary process to understand diversity in contemporary urban block forms and provide a classification for the machine (Tarbatt 2020; Sikna 1997). Secondly, literature is carefully examined to define the urban block and to build the same language with the machine. The literature studies show that the different combinations of urban block elements, *street, plot and building*, and changes in their configuration resulted in diversity in urban block types based on shape and size. In this study, therefore, a classification tree of the urban block is presented in order to present this diversity and to train the model with different types of urban blocks. Figure 2 shows the classification tree of urban block based on shape. The change in shape and size of the urban block led the study to identify the case study selection.

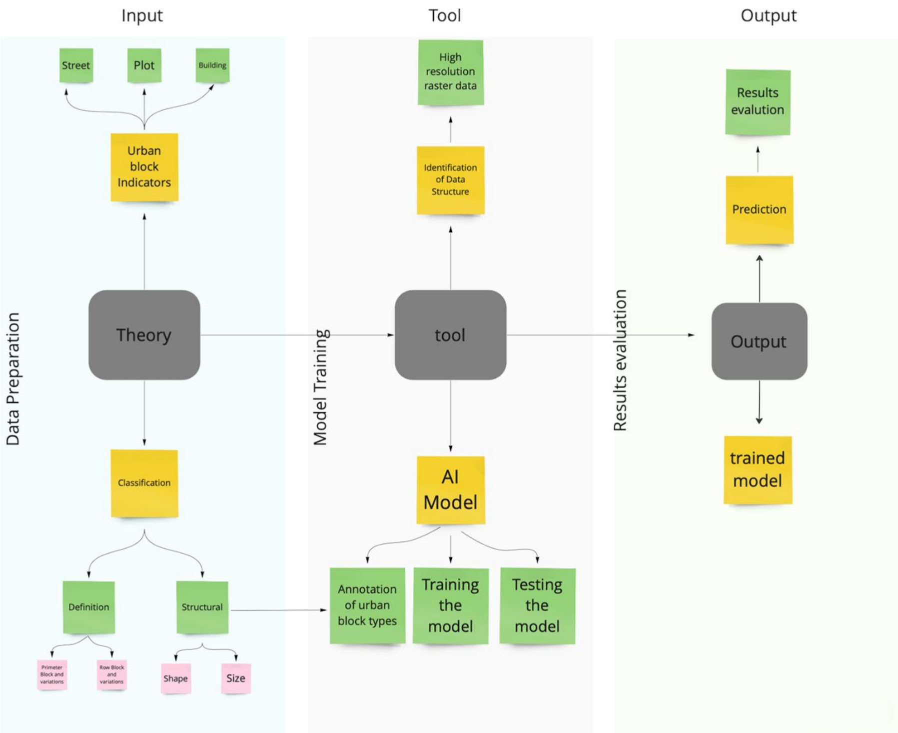


**Fig. 1** Algorithmic representation

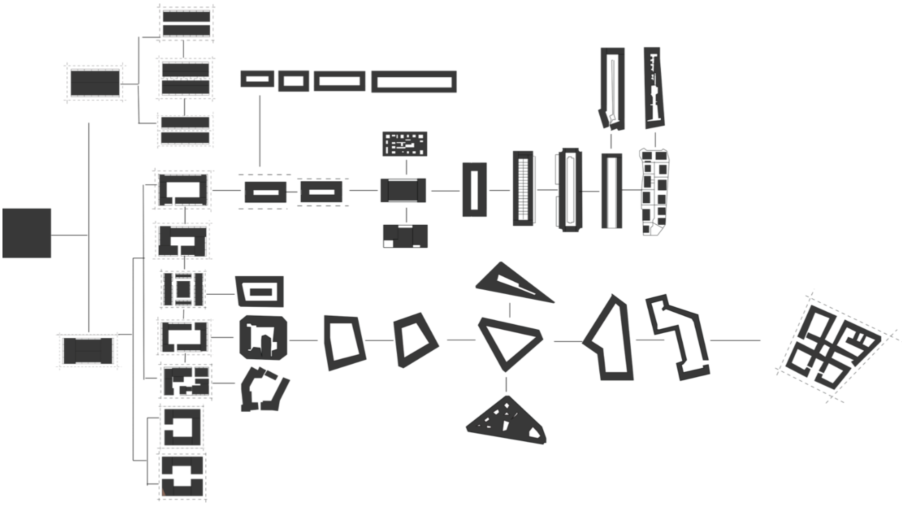

**Fig. 2** Urban block classification tree- diagrammatic representation

Additionally, this leads the study to identify data structure and format based on the selected machine learning model.

Machines can learn to detect similar urban forms using the learned vectors (Moosavi 2017). Therefore, to conduct teaching to the machine, a supervised machine learning model is identified to automatically extract the urban block features using convolutional neural networks. Convolutional Neural Networks can be used in image recognition and processing. These process is summarized in Fig. 3 starting from data preparation to detection and classification. This way, the detection of similar urban forms and comparison of detected urban forms become more accessible and efficient. Considering its applicability to the GIS platform and the adaptability of the model, the Mask-R CNN model is aimed to be used to train the model by labelling the urban blocks hinged on images. In this article, however, due to ongoing process, the application and results of the model will not be presented.

The aim is to demonstrate the data preparation process to build **an algorithm** that can be easily applied to different research contexts (**see** Fig. 1). Therefore, the model is carefully selected so the required data structure can be easily accessible. The model requires high-resolution satellite images to be trained. The primary aim is to access the open-access data to comply with the practicability of the methodological approach.

The creation of data for the model required specific steps. These steps for this research are identified as; the selection of case studies based on urban block, labelling of urban block types, creating the mask as shown in example in Fig. 4, splitting the data for training, validation and testing, and ultimately training the model based on created data. The satellite imagery annotation tool is used to annotate the urban block types and create the preliminary data. The preliminary labelling is done based on annotating the *perimeter block, row block, courtyard, and streets*. Based on the pure

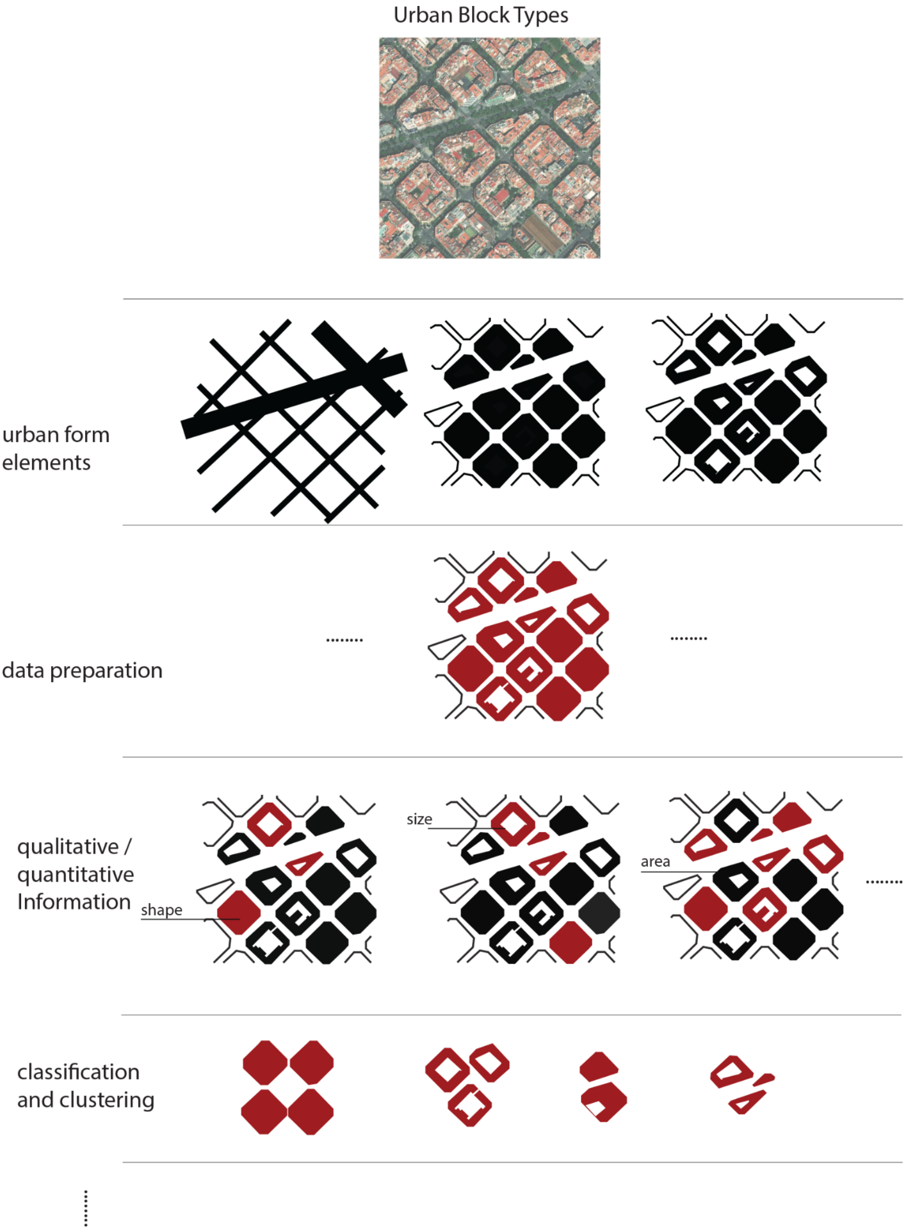


**Fig. 3** Data preparation and extraction

and most representative urban block types, Barcelona is chosen as the first case study to train the model for perimeter block types. Taking into consideration the diversity in shape and size, Paris, London, and Copenhagen are chosen as other case studies in the early stage.

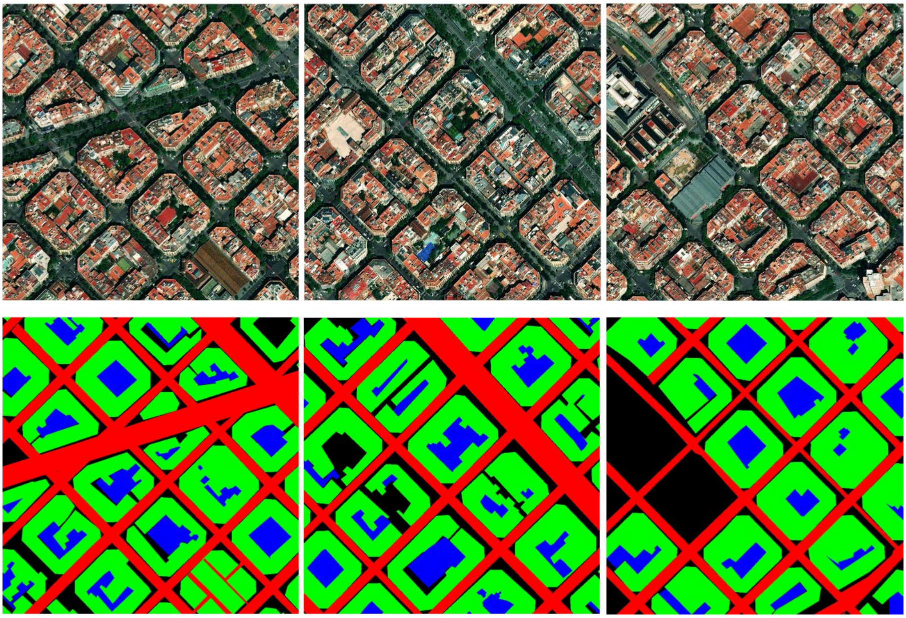

**Fig. 4** Conversion of images to data for tool/ mask creation

## Conclusion

The study presents the shift from conventional methods to the usage of automatic tools. The process of building the language between theory and machine is presented in systematic steps in the case of the urban block. As the study's outcome, a classification three of urban block and conversion steps of transferring the classification tree to data are presented. The paper presents the process of building the language between theory and machine. The results show that although outcomes are promising, the process requires oversimplification in defining urban block types. Further quantitative analysis can be conducted based on retrieved urban block types. The process requires further analysis and development to understand the complex relationship of urban form elements.

**Funding** Ongoing PhD research under supervision of Prof. Marco Trisciuoglio, Francesca Frassoldati, Matteo Robiglio- In collaboration of Transitional Morphologies Joint Research Unit and Future Urban Legacy Lab (FULL) – Research grant is funded by FULL.
Open access funding provided by Politecnico di Torino within the CRUI-CARE Agreement.

## Declarations

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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