Utilization of Artificial Intelligence techniques in the development of City Information Models (CIM)

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Abstract. This paper presents an investigation into the application of computational intelligence techniques, optimization, and data modeling in the development of CIM models. CIM is a concept that seeks to integrate information and data related to a city into a three-dimensional digital model, allowing for a detailed and dynamic representation of the urban environment. However, dealing with large volumes of data and optimizing the efficiency of urban operations is a complex challenge. To address this challenge, this article proposes the use of artificial intelligence techniques, such as machine learning algorithms and artificial neural networks. These techniques are capable of handling large-scale problems, finding optimal or approximate solutions, and dealing with uncertain or imprecise data. The article explores the different applications of computational intelligence techniques in the optimization and data modeling of CIM through the development of a systematic literature review (SLR) and the application of the Design Science Research (DSR) method to discuss the relationship between these technologies and CIM.

Keywords: City Information Modeling, Artificial Intelligence, Image segmentation, Machine Learning.

1 Introduction

As urban environments become increasingly intricate and data-rich, the integration of Artificial Intelligence (AI) with City Information Models (CIM) opens up new avenues for urban city planning, analysis processes, and management. The demand for efficient and accurate methods of data integration, analysis, and decision-making is paramount, given the sheer volume of data flowing through and permeating cities. Artificial Intelligence (AI) techniques have emerged as potent tools to address these challenges, presenting innovative ways to harness and process the wealth of urban data.

City Information Models (CIM) are intricate systems that integrate multidisciplinary data from a city, including geospatial, socioeconomic, environmental, infrastructure, and other data. These models enable the creation of a detailed digital representation of the city, facilitating integrated analysis of information and supporting decision-making. By applying AI techniques such as machine learning, data mining, natural language processing, among others, valuable insights can be extracted from city data, leading to more effective urban governance actions and aiding in the development of smart cities [1].

AI refers to training computers to emulate thinking processes and, in some cases, simulate human behavior [2]. It is a branch of computer science aimed at simulating human intelligence processes and constitutes a data-driven system that enables a computer or software to perform tasks or make judgments.

Deep Reinforcement Learning (DRL) and Machine Learning (ML) are examples of advanced approaches that can be employed to analyze large volumes of data and achieve the most precise and effective conclusions possible. AI elevates cities to a more advanced level, empowering them to harness these data and insights to guide their choices. By 2025, it is estimated that AI will play a pivotal role in over 30% of smart city applications, ranging from urban transportation solutions to significantly enhancing resilience, sustainability, social well-being, and the vitality of urban life [3][4]. The majority of smart city initiatives and technologies aim primarily to generate data and gain new insights into the complexity and dynamics of a city [5].

Currently, smart city initiatives in leading countries have increasingly turned toward developing AI and IoT

(Internet of Things) based intelligent applications. The success of algorithms is intrinsically linked to access to large volumes of data, crucial for executing relevant tasks. This information is acquired through digital and mechanical technologies, which transfer, store, and process essential data, enabling the generation of satisfactory solutions for various problems [6].

This paper explores the concepts and applications of artificial intelligence applied to the development of City Information Models and how these techniques are capable of handling a large volume of data, primarily showcasing image segmentation techniques that can be a crucial tool in the development of these information models.

2 Terminologies

2.1 Artificial Intelligence applied to the development of City Information Models

Research in the field of AI opens up new possibilities for creating tools for digital Architecture and Urban Planning processes. The advancement of digital technologies and the integration of intelligence into planning and design tools are inherently linked to urban development.

The utilization of ML for analyzing large volumes of urban data has proven crucial in this scenario, allowing the creation of information models to be systematized for various purposes, from predictive to descriptive models. ML techniques have contributed to the digital transformation process of cities. Notably, with the evolution of computational power and the development of more efficient algorithms, ML is gaining ground in various sectors related to architecture, engineering, construction, and urban planning.

Whether in urban planning, urban design, or the life cycle of a building, the exchange of information takes complex and varying forms throughout phases. Much of this information is captured, exchanged, documented, and delivered through documents, serving as interfaces that grant access to this information [7].

Among the challenges encountered is the vast amount of data existing in this process, much of which is unstructured. On the other hand, Building Information Modeling (BIM) tends to alter part of this landscape, shifting the Architecture, Engineering, Construction, and Operations (AECO) sector toward a model-based approach, where development and information exchange occur through digital models [8]. City Information Modeling (CIM) reinforces part of this concept, considering the importance of information exchange for data to be shared and utilized more efficiently. However, since CIM involves GIS, BIM, and IoT processes, model-based exchanges remain complex, given the data volume inherent in this development [1].

The escalating complexity of urban environments presents diverse challenges to architects and urban planners, as well as urban designers reflecting on the necessity of designing and intervening in these spaces to make them more resilient, sustainable, and intelligent [9]. Despite technological advancements, sources of unstructured information, like text documents, remain essential components in construction projects [10], as well as urban projects and urban planning processes.

It's noteworthy that one of the issues in AI and the creation of these intelligent "environments" is that a significant portion of developments still occurs within the realm of computer science and information technology, reinforcing the need for discussion by architects and urban planners about development associated with the construction sector, such as creating smart houses, smart cities, autonomous transportation systems, AI assistants, and even cognitive simulators.

Despite significant advances in digital technologies related to urban planning, cities still face significant challenges in achieving comprehensive systematization. Among these are the lack of data standardization, interoperability of geospatial data, ethical and data privacy concerns. There are also issues related to politics and technology, as many municipalities, particularly in Brazil, are not equipped to support and process certain systems, either due to technical or operational capabilities. Given this, the development of scalable and efficient solutions is necessary, considering that cities need to deal with vast volumes of urban data [1].

2.2 Image Segmentation for Urban Analysis

By capturing high-resolution images of an area, it is possible to utilize this data to train algorithms for automated segmentation and classification. This is crucial in applications such as constructing information models.

Additionally, remote sensing allows for data acquisition repeatedly over time, enabling long-term monitoring of territorial changes. It provides detailed information about a wide geographic area at once, proving useful for monitoring changes in land use, vegetation cover, urban expansion, water resources, and more.

Currently, the most successful tools for semantic segmentation are neural networks [11]. Unlike traditional methods where features of interest are manually extracted using detectors, neural networks have the capability to automatically learn the most suitable detectors for the given task.

Image segmentation involves partitioning a digital image into multiple regions [12]. The field of image processing involves subdividing an image into significant regions or segments based on specific characteristics such as color, intensity, texture, shape, or other attributes. The aim of image segmentation is to separate different parts of an image to facilitate analysis, interpretation, and understanding.

Image segmentation serves various purposes and applications, from facial recognition processes to city traffic control systems, as well as urban issue mapping. Frequent use cases include land use and land cover mapping (LULC). It's possible to identify and detect urban changes using satellite images, establishing land use/cover maps based on differences in the city's land usage, segmenting urban areas, green spaces, or industrial zones [13][14][15].

Numerous satellites offer historical images that enable the analysis of evolution over time, encompassing human impact and other factors [16][17]. These images provide a unique view of transformations resulting from human influence on urban space. Through the analysis of temporal series of satellite images, it's possible to track and quantify a variety of processes and phenomena. This extends to making decisions related to disaster management, population density analysis, evaluating neighborhood impact studies, and developing urban infrastructure planning strategies.

2.3 Applications of Image Segmentation in the Creation of CIM Models

In recent years, there has been a significant increase in interest in concepts associated with CIM. Despite being a recent concept, CIM presents a new paradigm for the fields of architecture, engineering, and urban planning, particularly influencing planning and urban design processes. CIM offers substantial advantages for stakeholders involved in the process, optimizing services for public administration and facilitating the development of intelligent digital platforms for urban management and data control [18][19].

The integration of Geographic Information Systems (GIS) and Building Information Modeling (BIM) becomes an effective approach to promoting the development of City Information Models (CIM) [20]. It emphasizes the importance of including Internet of Things (IoT) systems in this integration, considering that the city comprises complex and dynamic systems that static data alone would not be able to address or represent the dynamism present in these scenarios [1]. GIS models are developed to represent geographic and geometric data, while BIM models allow for the description of semantic and topological information within a building's model [19].

The creation of digital city models involves a series of steps and technologies, some of which can capture, process, and represent the array of geospatial and urban information a city presents. The utilization of remote sensing data acquisition tools, such as Light Detection and Ranging (LiDAR) systems, Terrestrial Laser Scanning (TLS) systems, photogrammetry, and field surveys, allows for the collection of topographical information and, particularly, geometric data that can be enriched with specific semantic information [21].

Through TLS models, the utilization of image segmentation techniques becomes possible. Since TLS provides crucial input data for segmentation processes, it can capture high-resolution three-dimensional data of the urban environment. From this 3D data, it can be used for segmenting specific areas, enabling more precise segmentation based on the real geometry of the space [21].

The development of point clouds has become increasingly common in BIM processes and developments, as well as a valuable resource in the GIS field. Point clouds accurately represent three-dimensional information from the "real world." Remote sensing uses aerial or ground-based sensors to capture data that can be used to create Digital Surface Models (DSM).

Point clouds are digital three-dimensional representations of objects or environments, typically captured through technologies like LiDAR systems, TLS, Aerial Laser Scanning (ALS) systems, and photogrammetric processes. From the capture of three-dimensional points (X, Y, and Z), each point is represented in a specific space, creating a three-dimensional point model. Each point can contain additional information beyond geographical position, such as attributes like color, intensity, and more [22].

Developing point cloud models requires data capture from various sources, ranging from aerial and ground-based sensors to drones. Sensors emit signals, like lasers or light pulses, which, upon interacting with object surfaces, return information about the distance and location of each point. When these points are processed and combined, they form a 3D point cloud [21]. Figure 1 illustrates a point cloud developed for urban space analysis using photogrammetric processes.

Figure 1. Image of a 3D point cloud of a square.

Point cloud models can be used for various purposes, ranging from building documentation, As-built models, digital topography and geomatics models, rapid prototyping, digital preservation processes, volumetric analysis, simulations, and monitoring. Due to the high point density that TLS can capture and its ability to ensure excellent geometric precision in point clouds, TLS has become one of the most commonly used systems for constructing CIM information models. Precision and the quantity of geometric information are essential for such developments [21][22][23].

TLS has the capability to efficiently gather information from the scanned scene image, ensuring integration of visual and spatial data, contributing to a more comprehensive and detailed representation of the captured environment. After the laser scanning process, TLS is able to capture RGB color information from the scene. This process involves a coordinate transformation matrix that facilitates the direct mapping of RGB color values to corresponding laser points.

3 Methods

For the development of this study, the image segmentation (SI) method was proposed with the aim of identifying elements in urban space and performing segmentation of satellite images and georeferenced orthophotos to extract footprints or georeferenced points for the construction of digital models and CIM models. The study area images underwent a data pre-processing process to generate training and test data.

For the AI-based testing developments, the open-source python package Segment-Geospatial (Samgeo) was employed. Its purpose is to simplify the segmentation process of geospatial data using the Segment Anything model. This package utilizes popular Python libraries such as leafmap, ipywidgets, rasterio, geopandas, and segment-anything-py, offering users a direct interface to segment remote sensing images. It also allows exporting results in various formats, including both vector and raster data [24].

Finally, some post-processing methodologies were used to improve semantic segmentation results. The supervised image classification method, a well-established approach, was utilized to categorize Land Use Land Cover (LULC) identified from satellite images. The procedure involved pixel supervision through image analysis, using a specific algorithm.

4 Results and Discussions

The Meta research team recently introduced the "Segment Anything" project, presenting a model called the Segment Anything Model (SAM) [25]. SAM performs segmentation based on prompts, which differs from semantic segmentation. Semantic segmentation is the task of classifying each pixel in an image into classes. However, it's important to emphasize that segmentation is different from classification. In segmentation, a class is assigned to each pixel in the image, while in classification, a single class is assigned to the entire image.

In the case of SAM segmentation, the generated masks are not labeled, and SAM relies on prompts [26]. In the context of artificial intelligence and natural language processing, prompts are instructions or inputs given to a model to request a specific task or response. They are used to guide the behavior or output of a language model or other types of AI models. In the case of the SAM model for image segmentation, prompts are used to guide the model in the task of cutting out objects from an image.

SAM cuts out objects from the image without assigning labels, and the objects that are cut out depend on the provided prompt. According to Zhang et al. [26], SAM's training is carried out with a dataset called SA-1B, which covers over one billion masks from 11 million images, making it the largest segmentation dataset ever released.

As stated by Kirillov et al. [25], SAM can be used to segment an object of interest and achieve strong generalization for unseen objects in 3D reconstruction from a single RGB-D image (these images combine color (red, green, blue) and depth information). This combination allows for the capture of not only the visual appearance of the scene but also the distance or depth of each point in the scene relative to a reference point.

The depth information provided by RGB-D images allows for the creation of more accurate 3D maps of the city. This can be used to represent the geometry of buildings, streets, squares, and other urban elements in a more realistic manner, as well as enable more accurate and efficient detection of objects like cars, pedestrians, trees, and urban furniture. Thus, with this combination of color and depth information, they can assist in object segmentation with greater reliability.

The figure 2 represents the analysis performed with Samgeo on a square in Goiânia, Goiás, Brazil. High-resolution image sets captured from satellite images and orthophotos taken from drone-captured images were utilized. The initial segmentation attempted to separate all elements of the square, followed by the segmentation of trees using an approach based on the Meta AI's SAM algorithm. The algorithm combines image processing techniques, such as adaptive thresholding and mathematical morphology, to effectively identify regions of interest, in this initial analysis, the tree canopies.

Figure 2. Satellite images of a segmented square using the Samgeo algorithm.

The SAM model is a base model, also known as a reference model, in which a machine learning model is pre-trained on a large amount of unlabeled data before being fine-tuned for specific tasks. In this case, these models are designed to capture rich and generalized data representations and can later be adapted to more specific tasks through additional training.

For the development of the following tests, the segment-geospatial package was used to simplify the process of utilizing SAM for geospatial data analysis. These tools were developed to streamline the processing of spatial data (GeoTIFF and TMS) with the Meta AI Segment Anything models using sliding window algorithms for large files.

The figure 3 represents the use of the same algorithm with the input of an orthophoto and a Digital Elevation Model (DEM), which represents a surface model as a regular grid of height values. This allows for identifying specific depths in the image for segmentation. Subsequently, GIS systems (Q-GIS software) were used to identify each segmented quadrant as a point with georeferenced coordinates, pinpointing the exact location of each tree present in the square.

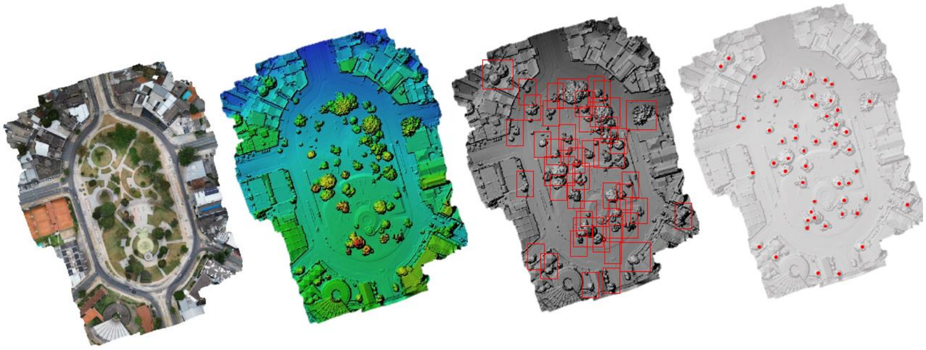

Figure 3. Digital elevation model of a segmented square using the Samgeo algorithm.

Our experiments demonstrated that the approach based on the SAM algorithm was able to successfully segment trees in urban square images. The average accuracy rate was measured at 90%, considering a manual validation dataset. The total area of tree canopies and their spatial distribution were accurately calculated. This revealed its effectiveness in isolating regions of interest and properly separating vegetation from the background and other urban elements.

Some difficulties were observed in differentiating images of low-growing plant species. Identifying ground-level plant species can be a challenging task for the algorithm due to various reasons, including the variety and morphological diversity, as well as color variations. This challenge is particularly prominent during certain times of the year when the foliage among species can make them difficult to distinguish, especially when compared to larger species. Dense growth patterns can also hinder species distinction and subsequently affect algorithm detection. This is especially problematic when the goal is to identify individual characteristics or growth patterns of each species.

Furthermore, the acquired data is being applied to construct models of square information using Visual Programming Language (VPL) - with software like Dynamo and Grasshopper (Visual programming platforms used to create parametric workflows, especially in the context of Building Information Modeling - BIM). These models should include the location, species, and density of trees, allowing for a detailed representation of vegetation characteristics in the square. These models can be used for biodiversity analyses, landscape planning, and assessment of environmental benefits in urban spaces.

However, the analysis of urban squares through image segmentation and the construction of information models has proven to be a promising approach. The obtained results reveal the potential of this methodology to guide more sustainable, informed, and community-centered urban planning, while also respecting the environment. As a result, it is expected that this research will inspire the adoption of similar strategies in other areas of study related to urban analysis and design.

5 Conclusions

Undoubtedly, the samgeo package presents itself as a valuable solution for professionals and researchers who need to utilize geospatial data segmentation, streamlining the process, especially due to the lack of necessity for deep learning model training, which remains a time-consuming and labor-intensive task. This enables users to focus their efforts on analyzing and interpreting results, facilitating and expediting processes and projects related to remote sensing, as well as the construction of city information models.

The integration of various artificial intelligence techniques associated with CIM development represents promising solutions for addressing contemporary urban challenges. City information models driven by AI-associated processes can play a pivotal role in building smart and sustainable cities.

The "Segment Anything" model (SAM) is one of the first models that can "mimic" the human eye for understanding the world, utilizing image segmentation tasks with the use of prompts. This model has transformed the computer vision community.

It's important to note that SAM is not perfect; despite its high performance, it might miss certain fine structures, hallucinate with small components, and produce edges that are not as sharp. Undoubtedly, this could pose challenges for developing footprints of specific objects for the geometric construction of city information models. Continued research and development of AI techniques specifically tailored for city modeling represent an opportunity for advancing solutions for smart cities. Our main contribution is that SAM models, in combination with a dataset, can assist and optimize the development of City Information Models.

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