DL-SLICER

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A novel artificial intelligence (AI)-driven city classification method which provides a homogeneous and unbiased result, employing visual and publicly accessible data focusing on factual circumstances and complex visual causalities. It offers a new perspective in the research domain by developing a deep learning (DL) tool that analyzes visual information from city satellite image patches.

Keywords: city identification ; city similarity ; urban planning ; satellite data

1. Introduction

Currently, the majority of the global population lives in cities, and urbanization rates are expected to continue rising [1]. Thus, cities play a significant role in shaping the sociological, economic, and environmental landscapes of the world. Their growing importance makes it vital to analyze and measure them accurately [2]. However, this is complicated by the unique identity and urban features of each city.

In general, spatial similarity refers to the extent to which two geographical entities share the same characteristics [3]. Cities can be compared based on different aspects, including, infrastructure, layout, societal and cultural peculiarities, historical background, economic situation, and even local user-generated content [3]. Moreover, understanding urban similarities could be important in shaping decisions that effectively improve the living conditions across cities with comparable features. In addition, analysis of the commonalities of cities can be helpful in the analysis of economic growth and understanding which features lead to the success of one city [4]. Furthermore, city commonality analyses can be used as data for further research, for example, index or ranking system development [3].

Identifying cities and developing knowledge about salient features can be used to guide the urban development of cities, for example, to keep or change their unique identity. In addition, such features can be useful in city categorization or analysis of city similarity [5]. Easy classification of city patterns can also aid in developing industrial solutions for natural resource management (air, water, and waste) [2]. Nevertheless, creating such a tool might be complicated because of rapid urbanization rates, which could change the urban typology and morphology.

While early research in measuring city similarity often relied on versatile data sources and distinct city features, there is limited evidence of dedicated efforts to identify cities based on satellite images. Analyzing separate features in isolation may offer a focused perspective on cities, but it can also lead to strong biases and an overwhelming reliance on them, potentially overlooking complex similarity patterns. In this regard, satellite images might serve as an integrated source capable of capturing a wealth of urban characteristics, including architectural patterns, transportation routes, geographical peculiarities, temporal and climatic conditions, and even air pollution rates. Several studies [2][6][7] have focused on classifying certain urban features based on satellite images, demonstrating the high accuracy of such models. This justifies considering satellite images as a reliable source for capturing various measurable traits, thereby integrating multiple features within themselves. Although these visual recognition methods prove highly accurate in specific cases, their use across multiple cities can be resource intensive and time consuming. Hence, a more adaptable methodology is needed to enable the development of more ubiquitous tools for the classification of cities.

2. City Similarity Tools

A comprehensive and uniform method to measure the similarity between cities does not exist. Frequently, cities are compared on the basis of certain characteristics such as basic indicators, including income distribution, costs, and ethnic composition. However, these characteristics only capture a small facet of the identity of a city, mostly related to economic and social dimensions. Earlier attempts at city clustering and identifying similar features can be found in the existing literature, and they use different data types and distinct methodologies.

Within academic research, the number of tools available for measuring city similarity is limited. For example, Saxena et al. developed a tool to identify cities similar to Delhi based on air quality metrics [8]. Cheng et al. (2022) developed an urban classification tool that aids in understanding and identifying urban environmental patterns [2]. This approach allowed them to measure the perception of city users through the photos they produced and shared. The researchers used certain city identity attributes for the image analysis, such as green areas, water resources, urban transportation systems, architectural forms, buildings, sports, and social activities.

In another study focusing on 385 European cities, researchers found that cities could be clustered according to their typology and environmental features [9]. A peer city identification tool was used for 960 cities in the United States (US), grouping them based on tabular data related various topics such as equity, resilience, outlook, and housing [10]. The authors of [11] conducted city map clustering using k-means of smart card data, aiding in the identification of city structures and clusters [11]. Costa and Tokuda (2022) investigated the similarity of 20 European cities based on their topology, utilizing a clustering method of street networks [4]. Seth et al. (2011) [12] found city similarities through query logs, suggesting that cities could be grouped not only by geographic location but also by the professional occupations of the populations (e.g., university students, high-tech companies, and defense contractors). For example, in their analysis of US cities, they found similarities among cities such as Boston, Brookline, New York, and Bethesda as well as Bethesda VA, Arlington VA, and Fort Myer VA [12].

Many non-academic methods for comparing and assessing cities focus on the cost of living. Examples include “Numbeo” [13], “Forbes Calculator” [14], and others [15][16]. The Urban Observatory, on the other hand, offers city comparisons across a variety of topics, including the type of work, transportation, and population density [17]. The ArcGIS Similarity Search tool allows for city comparisons based on attributes such as population, crime, and education [18]. ArcGIS developers emphasize the utility of this tool for various stakeholders, including retailers, policymakers, human resource specialists, law enforcement agencies, and academia. Shell has developed a tool that compares cities by considering such factors as the population density, the use of energy, and the need for energy resources [19].

3. Use of AI and Satellite Images in Urban Planning

AI techniques have been applied to analyze urban designs and city characteristics. These include fuzzy logic (FL), genetic algorithms (GA), neural networks (NNs), and simulated annealing (SA) [20]. NNs have been commonly used to predict land pollution (noise, air, water, waste) and changes in land use and form [21]. One of the stirring applications has been forecasting extreme temperatures and possible droughts in urban environments [22]. AI prospects in the field of urban construction and building design are also promising. Applications include the design of sustainable structures, structural health monitoring, soil analysis, and energy efficiency enhancements (e.g., variable heat flow and efficient use of solar panels) [20][23].

The combination of satellite imagery and AI has become increasingly prevalent, facilitating the analysis of parking, agricultural crops, and geological implications. Despite its increasing accessibility thanks to technological advancements, this approach is challenging due to imprecisions and artifacts in satellite imagery [24][25]. Convolutional NNs, namely U-Net and Mask R-CNN, have proven successful in satellite image understanding for building detection [24]. Other research has demonstrated the utility of deep neural networks (DNNs) for clustering urban land images even in low-resolution aerial photos [26]. In another study, Google Earth data were used to train an AI model to categorize cities by their formality level [2].

AI applications in geography extend to recognizing terrain features and land classification [27]. In one case, satellite images of green spaces in Colombo helped to predict air quality in the city [28]. Researchers also studied how a city grows using satellite images and applying NN algorithms as well as maximum likelihood and shortest distance methods [29]. Researchers have also studied urban growth using satellite images and NN algorithms algorithms as well as maximum likelihood and shortest distance methods [29]. Object-based image analysis (OBIA) and a SVM have been employed to understand urban expansion using satellite imagery from different regions (e.g., Canada, Sweden, and China) [30]. In another study, satellite images were processed to identify poor urban regions, which are also indexed by ten categories, from slums to more structured neighborhoods [31].

Overall, DL methods are frequently employed for land classification with satellite imagery. They are instrumental in mapping urban areas over different years using high-resolution satellite images for further analysis of urban development [32]. Pixel-based satellite images are commonly preferred over object-based ones for city mapping because of their efficiency [33]. However, the existing literature suggests a research gap concerning the use of satellite images and urban plans for city indexing, rating, or ranking, particularly for purposes such as sustainability assessment or district similarities, thus warranting further investigation. This limitation indicates a gap in the development of a more adaptable and efficient methodology. Such a methodology is essential for enabling broader application of tools in the classification of cities, reducing the need for extensive resources and time commitment. The research gap, therefore, lies in creating a scalable and less resource-intensive approach that maintains accuracy while being applicable to a diverse range of urban environments across multiple cities. Furthermore, there is a notable deficiency in the comprehensive analysis of Central Asian cities within the existing literature on urban studies.

Analyzing Central Asian cities has been a missed opportunity in the global spectrum of urban patterns that can be extracted from satellite data. The region is often overlooked in literature, including city knowledge databases, owing to its historical background and barriers imposed by socio-economic development levels. Nevertheless, the region holds significant interest for audiences thanks to the intersection of unique cultural and historical traits in Central Asia, rooted in Turkic groups, and echoing the Soviet Era through city infrastructure and architecture. Central Asia comprises Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. After the collapse of the Soviet Union in 1991, these countries emerged as separate entities, often omitted in most geographic-related studies.

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