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Exploring Machine Learning for Urban Green Space Mapping in Smart Cities: A Scoping Review

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Sustainable development within smart cities necessitates a comprehensive understanding of urban green spaces. This scoping review examines the growing possibilities of machine learning in automating and enhancing urban green space mapping. Through a systematic analysis of existing research, the study investigates the diverse machine learning techniques employed, the types of data utilized, and the level of accuracy of the machine learning techniques explored for urban green space mapping within smart city initiatives. By systematically analyzing twenty existing publications, the researchers explored that the machine learning techniques used for urban mapping analysis were convolutional neural networks (CNN), support vector machines (SVM), and random forests (RF). The researchers found that the most appropriate type of data to employ is remote sensing multispectral satellite imagery because it enables detailed information extraction and urban feature identification. Additionally, CNN demonstrated the highest level of accuracy for urban mapping analysis. By providing policymakers and urban planners with this knowledge, they can gain access to invaluable information that facilitates the enhancement of urban green space distribution, accessibility, and functionality.

Keywords: Urban green space, urban mapping, machine learning, scoping review.

1. Introduction

The notion of smart cities, characterized by abundant technology innovation and networked infrastructure [1], holds the potential for a future of highly efficient urban living. However, within the appeal of data-driven systems and intelligent networks, there is an important aspect that is often overlooked: the integration of nature [2]. One of the strategic outcomes for a smart city, based on the Association of Southeast Asian Nations (ASEAN) Smart Cities Framework, is a sustainable environment that entails assuring the long-term viability and accessibility of healthy ecosystems, as well as, enhancing disaster resilience and mitigating climate change impact. To be able to achieve this outcome, quality environment has been a development focus area through maintaining a clean and pleasant environment; advocating the sustainable use of ecosystems, natural resources, and biodiversity; and fortifying resilience against disaster risks and potential climate change impact [3].

Smart cities place a high importance on including urban green areas, acknowledging their capacity to enhance air quality, alleviate heat islands, enhance the welfare of residents, and establish a more environmentally sustainable urban setting. Urban green spaces serve a purpose beyond just adding aesthetics to the city. They function as the lungs [4] of these cities, playing a crucial part in environmental health, social well-being, and overall sustainability [5]. Urban green spaces are productive solution in the context of climate change, particularly in mitigating heat island effects and reduce flood risks. In the study of Zhou, W., et.al (2023) [6], the results demonstrated the cooling effect of urban green space in highly-urbanized area, as well as, protecting urban areas from the destructive effects of flooding. Effectively harnessing the potential of urban green space requires a detailed understanding of its distribution, characteristics, and accessibility. Mapping the urban green spaces is an invaluable tool in this context. By precisely identifying the location and characteristics of urban green space, we gain vital insights into its impact on the ecological health, social equity, and economic liveliness of the city [7], [8]. This insight enables legislators, urban planners, and landscape architects to make well-informed decisions regarding the preservation, expansion, and optimization of urban green spaces, resulting in creating a sustainable smart city.

Few enablers were identified in the ASEAN Smart Cities Framework in planning, implementing, and managing Southeast Asian smart cities such as the adoption of technological and digital solutions including geospatial databases and urban spatial data information systems [3]. Traditional mapping approaches can be time-consuming and resource-intensive [9]. Lahoti, S., et.al (2019) [10] discussed that the use of geographic information system for capturing, storing, retrieving, analyzing, and displaying spatial data, although effective and fast, is time-consuming due to its dependence on open source data, as well as, the manual mapping of polygons presented certain limitations such as overestimation of vegetation cover. Other approaches such as pixel-based image classification is limited to extracting information content in high-resolution data resulting to an inconsistent classification as mentioned by Amalisana, B., et.al (2017) [11]. Manually identifying and classifying green spaces from aerial photographs, satellite imagery, or even on-ground surveys can be extremely time-consuming and require a lot of manpower [12].

This is where machine learning capabilities become apparent. Machine learning algorithms have the potential to revolutionize urban green space mapping. Through the analysis of large amounts of geospatial data including satellite imagery and sensor readings, machine learning can automate the process of identifying and describing urban green space with unprecedented accuracy and efficiency [12], [13]. Machine learning has emerged as a valuable technique for automating and improving the process of mapping urban green spaces. Smart cities utilize cutting-edge technology such as machine learning to generate comprehensive maps of urban green spaces. These maps provide data-driven decision-making to enhance the allocation, standard, and availability of these crucial areas, thereby promoting a healthier and more sustainable urban environment.

This scoping review employs a systematic analysis of existing research in exploring the use of machine learning in urban green space mapping within the context of smart city development. The research has undertaken a rigorous examination of how various machine learning techniques are being utilized to automate and enhance the mapping process. This paper aims to enumerate the diverse machine learning techniques used for urban green space mapping, examine the types of data employed, assess the levels of accuracy for urban green space mapping, and determine the most suitable machine learning algorithm for urban green space mapping. This undertaking paves the way for the development of smart cities that seamlessly integrate technological progress with the vital ecological benefits of urban green spaces, promoting a future where nature thrives alongside technology within the urban landscape.

2. Method

This research employed the scoping review methodology in order to explore machine learning techniques utilized in mapping urban green space and identifying data sources. A scoping review is used to map the landscape of existing literature on a particular topic as defined by Peters, M.D.J. (2020) [14]; which provides a broad survey aiming to identify the key features and characteristics of research in a specific field. A scoping review provides a valuable roadmap for navigating the existing literature on urban green space and its various mapping techniques. As the number of publications concerning the application of machine learning to urban analyses has increased substantially in recent years, a scoping review is particularly appropriate. The scoping review process is comprised of a three-step methodology [14]: (i) data extraction, particularly the formulation of eligibility criteria; (ii) data analysis, particularly identifying and screening literature from database searches; and (iii) data presentation, particularly executing the review and documenting of findings.

A. Data Extraction

This step involves developing a search strategy to find relevant studies which includes identifying relevant databases and crafting keyword searches. The researchers used the following criteria to select papers relevant to analyzing machine learning applications that utilize spatial information in urban areas: the papers had to primarily use machine learning techniques to address urban challenges, cover a range of urban scales from local communities to entire countries, and incorporate geospatial datasets. The researchers focused on papers that have been published in reputable peer-reviewed journals written in the English language. In order to collect the papers for this study, the researchers incorporated in the database searches the following terminologies: ‘urban green space’, ‘urban spatial analysis’, ‘urban environment’, ‘land use and land cover classification’, ‘urban environment’, and ‘machine learning’. The researchers sought papers published within the past five years specifically from 2018 to 2023 to revolve around the latest trends and advancements. The researchers used the Publish or Perish software to filter Google Scholar and Scopus-indexed articles with high h-index to uncover supplementary studies. The researchers examined a total of 28 papers and chose 20 studies that satisfied all the necessary requirements. The papers were gathered from October to December 2023.

B. Data Analysis

After applying the predetermined criteria, this step involves extracting key information from included studies and organizing it for analysis. The researchers extracted important details from the articles including the title, authors, keywords, publication year, problem statements, machine learning techniques employed, types of data used, and accuracy of mapping functionalities. In order to undertake the study's analysis of themes and mapping methods, the researchers carefully examined each paper publication and systematically organized the information into tables and charts. When a paper does not include any information about a certain detail, it is recorded as missing and is excluded from the analysis. The researchers' investigation encompassed different perspectives including the machine learning techniques employed, the types of data utilized, and the functionalities explored for urban green space mapping within smart city initiatives. Thereafter, the researchers identified the most prominent machine learning method in urban green space mapping from the results of testing the different machine learning techniques with the same dataset.

C. Data Presentation

After analyzing the extracted data, this step involves synthesis and reporting of findings to identify the machine learning techniques for urban mapping analysis, types of data employed, and the levels of accuracy of the machine learning techniques used for urban mapping analysis. Section 3 presents the results of the scoping review.

3. Results and Discussions

A. Machine Learning Techniques for Urban Mapping Analysis

The rise of machine learning offers a powerful toolkit for automating and enhancing urban green space mapping. This section explores the techniques employed in particular research themes within the domain of urban mapping.

Machine learning techniques offer a diverse toolkit for addressing urban mapping analysis. Supervised machine learning approaches, including support vector machines (SVM), random forest (RF), and convolutional neural networks (CNNs); unsupervised learning approaches including K-means clustering and ISODATA clustering; and integration with other techniques including object-based image analysis (OBIA), are all examples of the versatile toolkit that machine learning techniques provide for mapping of urban green spaces.

Supervised learning techniques, where algorithms are trained on labeled datasets of green spaces, offer a powerful approach for accurately identifying and classifying urban green spaces in maps. Kranjcic, N., et.al. (2019) [15] discussed that support vector machine (SVM) is highly effective for classifying urban green spaces from remote sensing data due to their ability to handle high-dimensional data and find optimal decision boundaries between green and non-green areas. Ismayilova, I. and Timpf, S. (2022) [16] explained that random forest is known for its robustness and accuracy, random forests create multiple decision trees from subsets of training data. These trees "vote" on the classification of new data points, leading to highly reliable results in identifying and characterizing green spaces. Tegegne, A.M. (2022) [17] discussed that convolutional neural networks (CNN) are particularly adept at extracting complex features from imagery data due to their convolutional layers. CNNs excel at identifying patterns in satellite and aerial photographs, making them ideal for automated green space detection and classification based on characteristics like vegetation type [17] or canopy density [18].

In unsupervised learning, machine learning algorithms act as students, learning to recognize urban green space features from pre-labeled examples, enabling them to accurately map green spaces in unseen data. Al-ghrairi, A.H.T., et.al (2018) [19] discussed that K-means clustering is a technique that groups pixels with similar spectral characteristics which are colors in satellite imagery into distinct clusters. By analyzing these clusters, researchers can identify areas likely to represent different green space types. Vimala, R., et.al. (2020) [20] discussed that ISODATA also known as Iterative Self-Organizing Data Analysis is an advanced clustering algorithm that builds upon K-means by dynamically determining the number of clusters based on data distribution. This allows for more nuanced segmentation of green spaces, potentially revealing variations within a specific type, like differentiating between highly managed parks and natural forests.

Machine learning techniques, when combined with approaches like object-based image analysis (OBIA), can leverage the strengths of both methods such as machine learning's ability to learn complex patterns and OBIA's focus on image segmentation for a more comprehensive and accurate mapping of urban green spaces. Machine learning algorithms can be combined with OBIA, which segments images into meaningful objects based on spectral and spatial information. This allows for a more holistic understanding of green spaces by considering not just their presence but also their size, shape, and relationship to surrounding features [21].

The researchers analyzed the machine learning techniques adopted for a particular research theme. The research themes have been identified to know which theme is the most common among the twenty studies analyzed. The top three research themes derived were urban green space mapping, vegetation mapping, and land use and land cover mapping. Urban green space mapping refers to the process of creating spatial representations of vegetation and other natural elements within urban areas such as parks, gardens, urban forests, woodlands, wetlands, green roofs, and vertical garden. These maps aim to identify, classify, and analyze the distribution, characteristics, and quality of urban green spaces which will provide a comprehensive overview of the existing green infrastructure within a city and identify areas with limited or lacking green spaces for targeted sustainability efforts. On the other hand, vegetation mapping is the process of creating a visual representation of the distribution and characteristics of plant life across a specific area. These maps can be created for various scales, ranging from detailed representations of a small park to regional or even global overviews, which will be used for identifying areas suitable for conservation, agriculture, forestry, distribution of green spaces within cities, and assessing the impact of climate change on vegetation patterns. Moreover, another research theme would be land use and land cover mapping which is referred to as the process of creating spatial representations that categorize and classify the human activities and physical features present on the Earth's surface within a specific timeframe. These maps provide a comprehensive overview of both the physical land cover and the way humans are utilizing the land within a specific area used for identifying areas suitable for development, infrastructure projects, and green space conservation; monitoring deforestation and other environmental concerns; and assessing the impact of climate change. To differentiate the research themes, urban green space mapping is a specialized vegetation mapping tailored to urban environments; vegetation mapping has a broader scope compared to urban green space mapping, encompassing all vegetation types; and land use and land cover mapping focuses on human activities and physical state of the land.

The researchers categorized the twenty studies into three research themes such as urban green space mapping, vegetation mapping, and land use and land cover mapping, thereafter, classified them into which machine learning was employed such as supervised learning, unsupervised learning, and integration with other techniques. The results showed that supervised learning methods dominate across the research themes, with land use and land cover classification studied prominently, followed by the urban green space mapping research theme.

Among the supervised learning methods, the convolutional neural network is the most prominent machine learning method used in the aforementioned research themes, followed by random forests, and support vector machines. Several studies explored the use of CNNs for land use and land cover classification and their results demonstrated the ability of CNNs to identify patterns making them well-suited for automated mapping and classification. Land use and land cover classification characterize the identification of functional areas in cities spatially. Among the twenty studies examined, 55% (11 papers) used the CNN machine learning technique. Specifically, Carranza-Garcia, M., et.al (2019) [22], Jagganathan, J., et.al (2021 [23], Tegegne, A. M. (2022) [17], and Yu, J., et.al. (2022) [24] were dedicated to land use and land cover mapping; on the other hand, Huerta, R., et. al (2021) [12], Chen,Y., et.al (2021) [13], Men, G., et.al (2021) [25], and Fayad, I., et.al (2021) [18], focused on urban green space mapping and extraction; while, Langford Z., et.al (2019) [26], Zhang, D., et.al (2020) [27], and Shao, Y., et.al (2021) [28] were centered around vegetation mapping. Some studies such as Huerta, R., et. al (2021) [12], Jagganathan, J., et.al (2021 [23], Yu, J., et.al. (2022) [24] and Shao, Y., et.al (2021) [28] specifically discussed U-Net and VGG16 architecture to deploy CNNs in land use and land cover classification. Thus, CNN provides a promising and accurate method for categorizing land use and land cover.

On the other hand, 15% (3 papers) demonstrated the effectiveness of SVMs for land use and urban green space mapping by Hasan, H., et.al (2019) [29] , Shirmard, H.,et.al (2022) [30], and Kranjcic, N., et.al (2019) [15]. Similarly, 15% (3 papers) successfully employed random forests to map urban green space within cities by Lian, Z., et.al (2022) [31], Wang, W., et.al (2022) [32], and Ismayilova, I., et.al (2022) [16]. Few studies (15%) employed unsupervised learning by Al-Ghrairi, A.H.T., et.al (2018) [19] and Vimala, R., et.al (2020) [20] and integration with other techniques by Norman, M., et.al (2021) [21] for the abovementioned research themes. Table I shows the machine learning used in urban mapping analysis.

Table 1. Machine Learning Used in Urban Mapping Analysis

Study	Research Theme	Pattern in Methods	Machine Learning Technique
Huerta, R., et. al (2021) [12]	Urban Green Space Mapping, Land Use, Urban Vegetation	Supervised Learning	Convolutional Neural Network (CNN)
Chen,Y., et.al (2021) [13]	Automatic Mapping, Urban Green Space, Geospatial Big Data	Supervised Learning	Convolutional Neural Network (CNN)
Kranjcic, N., et.al (2019) [15]	Urban Green Space Extraction, Urban Planning	Supervised Learning	Support Vector Machine (SVM)
Ismayilova, I., et.al (2022) [16]	Urban Green Space Mapping, Land Use, Land Use Classification	Supervised Learning	Random Forest (RF)
Tegegne, A. M. (2022) [17]	Land Use, Land Cover Change, Groundwater Potentiality	Supervised Learning	Convolutional Neural Network (CNN)
Fayad, I., et.al (2021) [18]	Urban Greenery, Canopy Density, Wood Volume	Supervised Learning	Convolutional Neural Network (CNN)

Al-Ghrairi, A.H.T., et.al (2018) [19]	Land Cover Mapping	Unsupervised Learning	K-Means Clustering
Vimala, R., et.al (2020) [20]	Land Cover Change, Urban Expansion, Urban Sprawl	Unsupervised Learning	ISODATA Algorithm
Norman, M., et.al (2021) [21]	Land Use Mapping, Urban Building Detection	Integration with Other Techniques	Object-based Image Analysis with Support Vector Machine (SVM) and Decision Tree (DT)
Carranza-Garcia, M., et.al (2019) [22]	Land Use, Land Cover Mapping	Supervised Learning	Convolutional Neural Network (CNN)
Jagannathan, J., et.al (2021) [23]	Land Use, Land Cover Mapping	Supervised Learning	Deep Convolutional Neural Network (DCNN)
Yu, J., et.al. (2022) [24]	Land Use Classification, Land Use Mapping	Supervised Learning	Deep Convolutional Neural Network (DCNN)
Men, G., et.al (2021) [25]	Urban Green Space Extraction	Supervised Learning	Convolutional Neural Network (CNN)
Langford Z., et.al (2019) [26]	Arctic Vegetation Mapping	Supervised Learning	Convolutional Neural Network (CNN)
Zhang, D., et.al (2020) [27]	Cropland Mapping, Land Use Mapping	Supervised Learning	Deep Convolutional Neural Network (DCNN)
Shao, Y., et.al (2021) [28]	Urban Mapping, Vegetation Mapping, Object Detection Performance	Supervised Learning	Deep Convolutional Neural Network (DCNN)
Hasan, H., et.al (2019) [29]	Land Use, Land Cover Mapping	Supervised Learning	Support Vector Machine (SVM)
Shirmard, H.,et.al (2022) [30]	Lithological Mapping, Geological Features mapping, Land Use	Supervised Learning	Support Vector Machine (SVM)
Lian, Z., et.al (2022) [31]	Urban Green Space Pattern, Morphological Spatial Pattern Analysis, Environmental Impact of Urban Green Space	Supervised Learning	Random Forest (RF)
Wang, W., et.al (2022) [32]	Urban Green Cover Mapping	Supervised Learning	Random Forest (RF)

B. Types of Data for Urban Mapping Analysis

Machine learning studies reveal critical information in the type of data utilized. To examine the underlying type of data, the researchers provided the frequency at which various categories of data were employed.

Remote sensing data is used in all the papers examined. Remote sensing is the method of acquiring data about things, regions, or events from a distance, usually using aircraft or satellites. Satellite remote sensing involves the utilization of sensor technology on satellites or aircraft to identify and categorize items on the Earth's surface, as well as in the atmosphere and oceans. Kranjcic, N., et.al (2019) [15] discussed that satellite imagery is the fastest method for data collection for urban planning. The majority of remotely sensed data utilized for mapping and geographical analysis is obtained through the capture of reflected electromagnetic radiation which is then converted into a digital image. The data collected by the satellite is typically tailored to its mission, taking into account both the type and resolution of the information which are classified as visible, infrared, multispectral or hyperspectral data. Visible data is

represented by pixels that contain color values for red, green, and blue, resulting in three separate bands of data on a raster image. Infrared data often comprises images that encompass both the visible channels and a specific range of the infrared spectrum. Multispectral data typically consists of 7-12 channels of data, while hyperspectral data might include 50 or more bands recorded over specific bandwidths of the electromagnetic spectrum. Another type of remote sensing is LiDAR (Light Detection and Ranging) technology which is used for capturing geospatial data that uses laser scanning to create three-dimensional point clouds of geographic features.

Generally, 75% of the studies used remote sensing, multispectral satellite imagery such as Sentinel 2, Sentinel 2-A, Landsat 8, Gaofen-1, and Gaofen-2. Multispectral satellite imagery is the most common dataset used in urban green space mapping (35%), land use mapping (30%), and vegetation mapping (20%). Hyperspectral satellite imagery is used in land use mapping (10%) and vegetation mapping (5%). Infrared satellite imagery is used in land use mapping (5%). On the other hand, only 5% of the studies used LiDAR remote sensing imagery for urban green space mapping.

Chen,Y., et.al (2021) [13] employed Sentinel-2A multispectral satellite images to automate the mapping of urban green space in Wuhan City, China while Huerta, R., et. al (2021) [12] utilized WorldView-2 multispectral satellite images to evaluate two automated methods using U-Net architecture to detect the patterns of all types of urban green space in the metropolitan level of Mexico. Men, G., et.al (2021) [25] used Gaofen-1 remote sensing images providing reliable data support for accurately extracting urban green space in Shenzhen City, China. Lian, Z., et.al (2022) [31] employed Sentinal-2A remote sensing images to assess the spatial pattern and type of urban green space at the neighborhood, district, and city scales providing a reference for the integration and optimization of green space system and sustainable urban development in Guangdong–Hong Kong–Macao Greater Bay Area (GBA) in China. Wang, W., et.al (2022) [32] used Sentinel-2A multispectral satellite imagery for evaluating multi-training method in the recognition of urban green space in Nanjing City, Jiangsu province, China. Ismayilova, I., et.al (2022) [16] reported that the outcome of the study showed that greenery in large and homogeneous areas such as forests and parks could be very accurately identified using Sentinel-2 data.

Multispectral imagery proved to be the most utilized type of data among the examined papers. Multispectral imagery, which captures data at wavelengths beyond the visible spectrum, enables researchers to identify and distinguish between diverse urban features. Near-infrared reflectance, for instance, can be utilized to differentiate vegetation from buildings. This detailed spectral data facilitates the identification and classification of various urban characteristics, including buildings, roadways, vegetation, and bodies of water [33], [34]. Hence, the use of multispectral satellite imagery is the most appropriate type of data to use for mapping urban green space and for land use classification. Fig.1 shows the number of studies using remote sensing data in each research theme for urban mapping analysis.

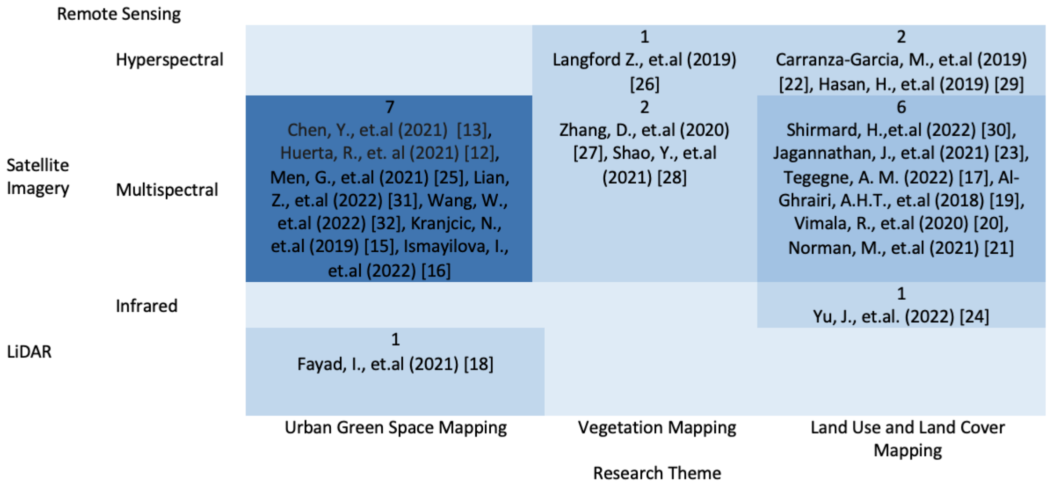

Fig. 1. Heatmap of remote sensing data. The figure shows the type of remote sensing data used with the number of papers by each research theme in urban mapping analysis.

C. Mapping Accuracy of Machine Learning Techniques

Accuracy assessment allows for comparing different machine learning techniques to identify the best-performing model for specific applications. Understanding the mapping accuracy of machine learning techniques allows for the assessment of its reliability and effectiveness. A highly accurate map inspires confidence in its results, while a map with lower accuracy might require additional verification or alternative data sources. Reporting the accuracy of mapping builds trust and transparency in the results and identifying accuracy issues helps in pinpointing areas where the machine learning model needs refinement.

The use of Convolutional Neural Networks (CNN) in research themes such as urban green space mapping and land use classification demonstrated a high level of accuracy. Similarly, Support Vector Machines (SVM) were also effective for these types of research themes. The usage of CNN for vegetation mapping research theme led to a reduced level of accuracy. The use of Random Forests (RF) and integration with Object-based Image Analysis (OBIA) for urban green space mapping and land use classification themes resulted in a lesser level of accuracy. Figure 2 shows the accuracy level of the machine learning technique used in each research theme.

Using CNN for the urban green space mapping research theme, Huerta, R., et.al (2021) [12] and Men, G., et.al (2019) [25] demonstrated a high level of accuracy with 97 % and 97.34 %, respectively, while Chen,Y., et.al (2021) [13] reported a 94.6% accuracy. CNN's high level of accuracy is comparably evident in the land use and land cover research theme as Carranza-Garcia, M., et.al (2019) [22] and Jagannathan, J., et.al (2021) [23] demonstrated a high level of 98.7% and 98.5% mapping accuracy, respectively, while Tegegne, A. M. (2022) [17] and Yu, J., et.al (2021) [24] reported 80% and 89.9% level of accuracy. Men, G., et.al (2021) [25] experimental results showed that using CNN specifically CRAUNet architecture achieved the best performance dealing with less susceptibility to noise and preserving complete segmented edge details. Using SVM for the urban green space mapping research theme, Kranjcic, N., et.al (2019) [15] reported 97% accuracy, while for the land use and land cover mapping research theme, Hasan H., et.al (2022) [29] and Shirmard, H., et.al (2022) [30] showed 97.4% and 99% level of mapping accuracy. Using RF for the urban green space mapping research theme, Lian, Z., et.al (2019) [31], Wang, W., et.al (2022) [32], and Ismayilova, I., et.al (2022) [16] reported 85.2%, 90.6%, and 97% mapping accuracy. Integration with other techniques such as OBIA is evident in the land use and land cover mapping research theme with Al-ghrairi, A.H.T., et.al (2018) [19], Vimala, R., et.al (2020) [20], and Norman, M., et.al (2021) [21] reporting 92.1%, 87%, and 93% mapping accuracy. Fig. 2 shows the level of accuracy using CNN, SVM, and RF in each research theme.

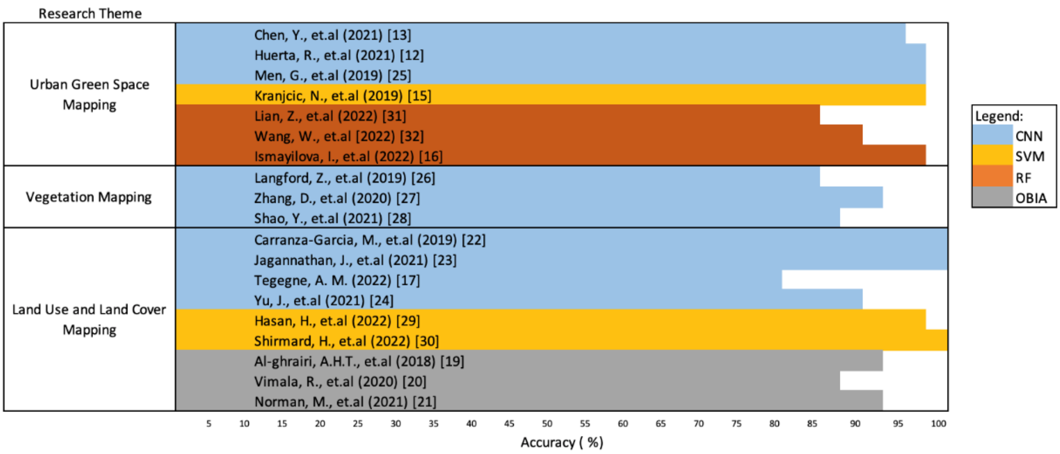

Fig. 2. The figure shows the level of accuracy using CNN, SVM, RF and OBIA in each research theme.

Several research studies have recommended that in addition to examining the level of accuracy, it would be beneficial to investigate other indicators in order to efficiently detect green spaces in urban settings. Kranjcic, N., et.al (2019) [15] showed the combination of parameters that fit best for extracting urban areas using a kappa coefficient index of 0.87 and 0.89 demonstrating a very high classification accuracy. Men, G., et.al (2019) [25] evaluated the accuracy of urban green space mapping using CNN through several evaluation indices, including pixel accuracy, precision, recall, F1-score, and mean intersection over union (MIoU). Pixel accuracy is the ratio of the correctly classified number of pixels and the total number of pixels, precision is the ratio of the number of classified pixels and the number of the labeled pixels, recall is the ratio of the number of correctly classified pixels and the number of the actual target feature pixels, F1-score is the harmonic means for precision and recall, and mean intersection over union or MIoU is the average ratio of the intersection and union of the ground truth and the predicted area. The indicators of 97.34% PA and 94.77% MIoU in the study [25] demonstrated that CNN machine learning has strong feature extraction and high-resolution detail recovery capabilities for remote sensing images.

4. Conclusions

This scoping review has delved with the use of machine learning in urban green space mapping within smart cities. By systematically analyzing twenty existing literature, the researchers have explored the diverse machine learning techniques such as convolutional neural networks (CNN), support vector machines (SVM) and random forests (RF) in the following research themes such as urban green space mapping including urban green cover and urban greenery, vegetation mapping including arctic and cropland mapping, and land use classification including geological features mapping. The most suitable machine learning for urban green space mapping, vegetation mapping, and land use classification is the convolutional neural network (CNN). The scoping review unveiled the types of data used for the abovementioned research themes. Remote sensing data using satellites is classified into infrared, multispectral, and hyperspectral imagery. The researchers found that the most appropriate type of data to employ is remote sensing multispectral satellite imagery because it enables detailed information extraction and urban feature identification. The use of convolutional neural networks (CNN) in research themes such as urban green space mapping and land use classification demonstrates a high level of accuracy compared to support vector machines (SVM) and random forests (RF). Thus, this scoping review provided a compelling discussion on the use of machine learning in urban green space mapping which will pave the way for the creation of ecologically balanced urban environments fostering a future where nature and technology thrive in harmony with the smart city landscape. The findings of this scoping review will serve as the backbone in the development of a system for urban green space mapping in a smart city and will be extended to further study on the usability of the mapping system to intended stakeholders.

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