International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04664
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

AI-Powered Urban Green Space Detection and Analysis Using Deep Learning and GIS

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Abstract - In rapidly expanding cities, urban green areas are essential to maintaining environmental sustainability, public health, and general well-being. However, urban planners' capacity to make prompt and efficient decisions is limited by the manual, antiquated, and time-consuming nature of traditional ways of monitoring and administering these spaces. This research proposes an AI-driven system that combines sophisticated deep learning algorithms with high-resolution satellite and drone imagery and Geographic Information System (GIS) capabilities to automate the detection, mapping, and analysis of urban vegetation. The system uses Convolutional Neural Networks (CNNs) for semantic segmentation of green spaces, including parks, forests, and grasslands, ensuring high accuracy and adaptability. The distribution of green space in metropolitan areas is dynamically visualized by superimposing these identified areas on interactive GIS maps. Furthermore, a novel Green Space Accessibility Index is presented to assess how accessible and close green spaces are to the community, supporting equity-focused urban planning. Initial tests show that the system works well in various urban environments, with a detection accuracy of over 90%. The platform is designed to be scalable, affordable, and deployable in both large and small city settings, providing a potent instrument for real-time urban planning and environmental management.

Key Words: deep learning, urban green areas, accessibility index, GIS visualization, semantic segmentation, sustainable urban planning.

1.INTRODUCTION *(Size 11, Times New roman)*

Urban green spaces, including parks, community gardens, botanical regions, and tree-lined roadways, are vital for a healthy city. They provide ecological, social, and economic benefits such as reducing air pollution, mitigating urban heat islands, promoting physical activity, improving mental health, and enhancing the overall quality of urban life. As cities prioritize livability and climate resilience, the expansion and maintenance of green infrastructure become increasingly important.

However, rapid urbanization challenges the management and preservation of these spaces. The replacement of natural land cover with concrete structures reduces the extent and accessibility of green spaces, directly impacting the urban climate, biodiversity, and residents' well-being. The dynamic nature of urban landscapes requires frequent updates of green space statistics, which is difficult with traditional, resource-intensive, and spatially constrained monitoring methods. As a result, policymakers and urban planners often lack up-to-date, reliable information for sustainable urban growth and equitable green resource access.

This study proposes an AI-powered solution by integrating advanced deep learning techniques, GIS, and high-resolution satellite and drone imagery. Convolutional Neural Networks (CNNs) are used for the semantic segmentation and classification of green regions, enabling accurate and automated detection of urban vegetation. The end-to-end pipeline covers data collection, intelligent analysis, and GIS-based visualization. One of the key outputs is an interactive green space map with a Green Space Accessibility Index, which measures the availability and distribution of vegetation across urban districts. This index helps planners identify underserved areas and prioritize interventions where green space demand is highest. The system is designed for scalability, adaptability, and real-time updates, supporting smart city projects and sustainability goals.

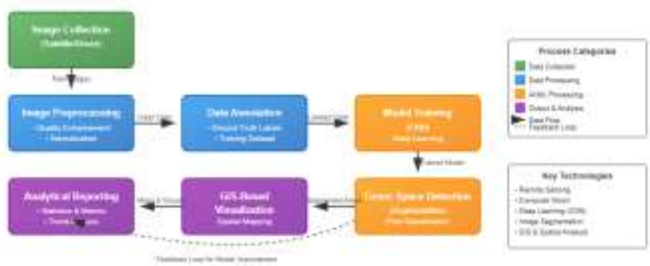

Figure 1: Overall System Workflow of Urban Green Space Detection & Analysis

2. Body of Paper

2.1 INTRODUCTION

A healthy city must have urban green spaces including parks, community gardens, botanical regions, and roadways lined with trees. Numerous ecological, social, and economic advantages are provided by them, such as lowering air pollution, lessening the effects of urban heat islands, promoting physical activity, boosting mental health, and improving the general standard of

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living for those living in cities. Green infrastructure expansion and maintenance are more important than ever in a time when communities are prioritizing livability and climate resilience.

However, managing and preserving these green spaces is becoming more difficult due to the quickening rate of urbanization. The extent and accessibility of green spaces are diminished as cities continue to grow and natural land cover is regularly replaced by concrete buildings and asphalt highways. The urban climate, biodiversity, and inhabitants' well-being are all directly impacted by this loss of green space. Furthermore, in order to facilitate well-informed decision-making, green space statistics must be updated often due to the changing nature of urban landscapes. Manual field surveys and sporadic inspections are the mainstays of traditional green space monitoring techniques, which are frequently resource-intensive, time-consuming, and spatially constrained. Real-time, city-wide insights are difficult to obtain with these approaches, particularly in sizable or rapidly expanding urban areas. Because of this, politicians and urban planners frequently lack current, reliable information to direct sustainable urban growth and fair access to green resources.

The study offers an AI-powered solution to these problems by fusing sophisticated deep learning methods, Geographic Information Systems (GIS), and high-resolution satellite and drone data. Convolutional Neural Networks (CNNs), which are employed for the semantic segmentation and categorization of green regions, form the foundation of the system. This makes it possible to accurately and automatically identify urban vegetation, even in visually complicated cityscapes. This method's end-to-end pipeline, which includes data collection, intelligent analysis, and GIS-based display, is what makes it unique. A spatial analytics-layered interactive green space map with a Green Space Accessibility Index that measures the availability and distribution of vegetation in various urban districts is one of the processed outputs. Planners can use this index to pinpoint underprivileged areas and rank interventions according to the greatest demand for green space.

Scalability, adaptability to various towns and areas, and the ability to enable real-time changes are all features of the system's design. It could be an essential element in contemporary urban planning, supporting smart city projects and international sustainability goals.

2.2 RELATED WORK

In recent years, there has been a notable increase in the use of artificial intelligence (AI), especially deep learning, in the fields of environmental monitoring and urban green space analysis. Numerous research have shown how machine learning models can be used to automate the labor-intensive and manual process of assessing urban vegetation. In order to optimize the design and maintenance of green areas throughout time, Yu et al. (2023) investigated the usage of Long Short-Term Memory (LSTM) networks. Their research demonstrated how temporal data modeling, which forecasts changes in urban environments, can enhance accessibility and sustainability design. In a similar vein, Ghahramani et al. (2021) mined social media information and citizen input using Natural Language Processing (NLP) to assess public sentiment toward urban green areas. Although their method concentrated more on subjective viewpoints than on actual mapping, it allowed for a more citizen-centric understanding of how green spaces are used and perceived.

On the technical side, Huerta et al. (2021) mapped urban vegetation on a broad scale using deep learning approaches in conjunction with very high-resolution (VHR) satellite data. High classification accuracy was attained by their semantic segmentation framework in various urban areas. In order to promote targeted green infrastructure development, Pratiwi et al. (2022) integrated AI models with remote sensing data, underscoring the significance of accuracy in urban planning. Similarly, Burrewar et al. (2023) carried out an extensive analysis of deep learning-based techniques like DeepLabV3+ and U-Net and came to the conclusion that these models perform better than conventional classification techniques when it comes to recognizing intricate green structures from remote sensing data.

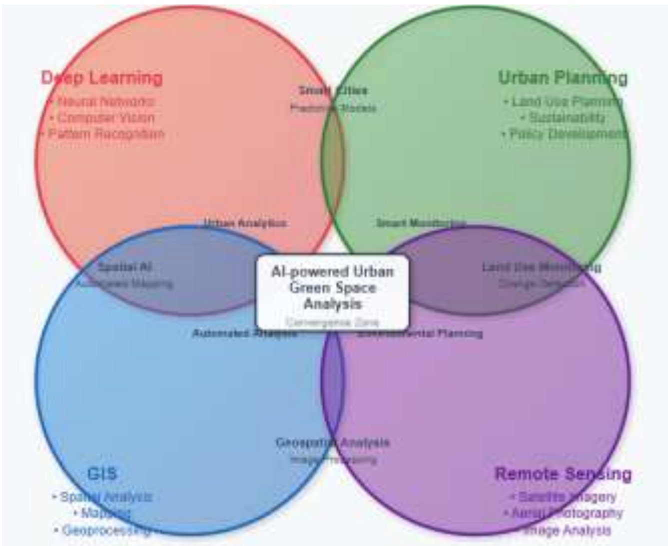

Figure 2:Research Focus Areas in Urban Green Space Analysis

There are still certain holes in the mechanisms in place, despite the encouraging results of these efforts. Many solutions lack capabilities for micro-level or neighborhood-specific analysis and instead concentrate mostly on large-scale municipal planning. Additionally, some models don't have dynamic visualization tools or easy-to-use reporting features, which restricts their applicability to decision-makers on the ground like city planners and municipal officials. The difficulty of differentiating between visually identical non-vegetated areas—like shaded concrete, green rooftops, or synthetic turf—and true green cover is another issue that has been brought to light in recent work. This difficulty results in false positives and decreased model reliability.

These drawbacks highlight the need for a more complete approach, one that blends the capabilities of deep learning with user-friendly tools for GIS research and visualization. Sustainable city planning may benefit greatly from a system that enables both precise green space designation and interactive, location-aware reporting. By putting forth an end-to-end AI-driven platform intended for high-precision detection, GIS-based visualization, and real-time analysis of urban green areas at both macro and micro levels, this study precisely meets those objectives.

2.3 PROBLEM STATEMENT

The growth of infrastructure is putting more and more strain on urban green spaces as cities grow quickly. These green spaces are essential for preserving the health of the environment, lowering urban temperatures, and improving people's quality of life. To monitor the amount of green space, the majority of urban planning organizations still use antiquated records and manual

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surveys. These conventional approaches lack the precision and regularity needed to enable contemporary, sustainable urban development, and they are time-consuming and labor-intensive. Further lowering the dependability of current automated methods are issues like incorrectly classifying non-vegetative green surfaces (such rooftops or artificial turf). Data-driven decision-making is hampered and the capacity to react to swift changes in the urban environment is constrained by the absence of real-time, scalable, and geographically detailed tools. In order to meet that demand, the study suggests an AI-based framework that combines GIS and deep learning to provide real-time insights for sustainable city planning.

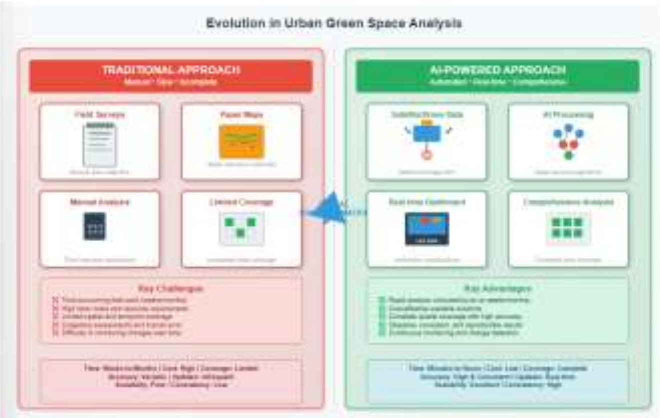

Figure 3:Green Space Monitoring Gap: Traditional vs. AI-Driven Approach

2.4 PROPOSED METHODOLOGY

The suggested approach makes use of GIS and deep learning technology to automatically identify and analyze urban green spaces. It consists of seven essential modules:

2.4.1 System Workflow

- **Image Collection:** Sentinel-2 and Google Earth are two publicly accessible sources of high-resolution satellite images. Drone-based imagery can also optionally be included for more in-depth study in nearby urban communities.
- **Image Preprocessing:** To improve the quality of the data, preprocessing is done before the photos are fed into the neural network. This entails denoising, scaling to a uniform dimension, normalization, and format conversion.
- **Data Annotation:** Training datasets are annotated with Roboflow and other tools. To differentiate vegetation zones from similar-looking non-vegetated regions, such as sports fields or green rooftops, annotators accurately draw lines around them. This phase improves the quality of model training and lowers the likelihood of false positives.
- **Model Training:** For both binary classification and semantic segmentation of green regions, a convolutional neural network (CNN) is used. Transfer learning is used in the training process to increase accuracy while reducing training time and processing demands by integrating pre-trained models such as ResNet or DeepLabV3+.
- **Green Space Detection:** New urban satellite photos are used to highlight and identify vegetation zones using the trained model. The output includes segmented or binary maps that identify green areas throughout the urban landscape.
- **GIS-Based Visualization:** An interactive GIS-based map is superimposed with the segmented green space data. Urban planners can use this visualization to evaluate the spatial distribution of green spaces and obtain specific metrics like the Green Space Accessibility Index and green space per capita.
- **Analytical Reporting:** Important criteria including the total area covered by green spaces, the building-to-green space ratio, and neighborhood-level accessibility studies are compiled into quantitative reports. The papers also offer strategic recommendations for enhancing urban greening based on identified gaps.

2.4.2 Novelty and Uniqueness

The suggested system distinguishes itself from other green space identification techniques by providing a highly flexible, modular, and integrated architecture that integrates several intelligent parts into a single, coherent pipeline. Our method improves the accuracy and contextual relevance of detection by combining manual annotation, AI-based segmentation, and GIS-enabled interactive visualization, whereas many existing systems just use automated classification using deep learning.

The manual data annotation procedure employed for model training is a significant distinction. Our annotated datasets are carefully selected to minimize false positives, in contrast to traditional models that frequently mistake artificial turf, green rooftops, or shaded surfaces for vegetation because of visual similarities. By teaching the algorithm to distinguish genuine green spaces from similar-looking but non-vegetative surfaces—a problem commonly noted in earlier studies—this step greatly increases model precision.

The addition of a GIS-based Green Space Accessibility Index (GSAI) is another novel element. Urban planners can assess not only the amount of green space but also who has access to it by using this index, which measures the availability and closeness of green spaces in relation to residential clusters. More fair and data-driven planning is made possible by this accessibility-focused statistic, which is frequently disregarded by large-scale mapping tools that solely display land cover percentages.

id	name	type	area (sq km)	location
1	Central Park	Urban Park	3.41	New York, USA
2	Hyde Park	Urban Park	1.42	London, UK
3	Botanical Garden	Botanical	0.55	Singapore
4	Golden Gate Park	Urban Park	4.12	San Francisco, USA
5	Tiergarten	Urban Park	2.10	Berlin, Germany

Figure 4:Overview of Sample Green Spaces

mapping_id	user_id	green_space_id	timestamp	notes
1	[illegible]	1	[illegible]	Verified boundaries
2	[illegible]	3	[illegible]	Area recalculated
3	[illegible]	2	[illegible]	Added walking trail
4	[illegible]	5	[illegible]	New playground [illegible]

Figure 5:User-Green Space Mapping Log

Additionally, our solution is built with local deployability in mind. Our lightweight, modular design enables it to be used efficiently in tier-2 and tier-3 cities—regions where such tools are generally lacking—whereas many solutions are designed for huge, resource-rich urban areas. Because of this, our approach is especially useful for cities with weak technology infrastructure but increasing urbanization issues.

Additionally, the modular architecture facilitates simple integration and scaling. It can be integrated into current municipal dashboards for real-time updates or expanded to additional cities with no modification. Data preprocessing, annotation, model inference, GIS mapping, and reporting are all loosely coupled components that may be upgraded and customized to meet local needs. When taken as a whole, these developments transform our system from a technical fix to a useful and socially significant instrument for managing urban green spaces.

2.5 RESULTS AND EXPECTED OUTCOMES

Preliminary tests of the constructed prototype have shown encouraging results. The system was able to identify green areas in test photographs with more than 90% accuracy by using CNN-based models and high-resolution data. In order to support data-driven actions, the GIS visualizer assisted urban planners in identifying areas with little green cover. A deployable desktop or web-based platform, analytical dashboards for city officials, possible integration with smart city infrastructure, and scholarly documentation that might aid in further study and development in AI-driven urban planning systems are among the anticipated results of the system.

2.6 CHALLENGES AND LIMITATIONS

The suggested system has certain drawbacks even if it automates the identification and evaluation of urban green spaces in a number of ways. Its performance and wider applicability are still impacted by a few major issues.

The availability of high-resolution, cloud-free satellite images is one of the main obstacles. Both the quality of model input and the frequency of updates can be impacted by the lack of good satellite photos in areas that are prone to prolonged cloud cover, particularly during the monsoon or winter seasons. This limits the system's capacity to provide timely insights in particular regions or at particular times of year.

The trained model's generalizability is another issue. The accuracy of the system may decline when applied to new places with distinct architectural styles, plant patterns, or landscape elements, even while it performs well on the cities that were part of the training data. Disparities that the model would not have experienced during training can be introduced by variations in urban layouts, building materials, or vegetation density.

Furthermore, in intricate urban environments, false positives continue to be a problem. In satellite photography, green rooftops, shaded patches, or artificial turf frequently mimic natural vegetation, particularly when there are overlapping structures or inadequate daylight. Even though model adjustment and manual annotation lessen these errors, misclassifications might still happen occasionally and affect accuracy in crucial applications.

The incorporation of multi-spectral and temporal images, which can more effectively differentiate vegetation from non-vegetative surfaces, is one of the continuous advancements made to address these problems. In order to improve adaptability and resilience, efforts are also being made to broaden the training dataset across various regions. Additionally, the segmentation pipeline is being improved to reduce noise and enhance object boundaries, particularly in urban areas with high population density.

These restrictions offer legitimate difficulties, but they also point to areas that could use more study and improvement to make the system more reliable and widely applicable.

2.7 CONCLUSIONS

The work offers a scalable and reliable framework for autonomously identifying, mapping, and analyzing urban green spaces using deep learning methods in combination with Geographic Information Systems (GIS). The system increases monitoring frequency, provides real-time, actionable insights to policymakers and urban planners, and drastically reduces reliance on manual field surveys by combining sophisticated Convolutional Neural Networks (CNNs) with high-resolution satellite imagery and GIS-based visualization.

The end-to-end automated pipeline of the suggested system, which includes everything from data pretreatment and model training to geographic analysis and reporting, is one of its main advantages. In addition to increasing detection accuracy through hand annotation, it also presents new metrics, such as the Green Space Accessibility Index, to evaluate how evenly green spaces are distributed throughout neighborhoods. Because of these characteristics, the system is positioned as a significant improvement over traditional urban surveillance technologies, which frequently lack interactivity, granularity, and adaptability.

The system has a lot of potential to spread into tier-2 and tier-3 cities, where there are currently few technologically advanced urban planning tools, thanks to its modular design and emphasis on local deployability. It is appropriate for larger smart city ecosystems because to its scalability and compatibility with current municipal dashboards. Its accuracy and generalization can be improved in the future by adding multi-spectral imaging, enlarging training datasets to include a wider range of geographical locations, and improving segmentation algorithms. Furthermore, the system can be made into a potent instrument for long-term environmental sustainability and participatory planning by combining it with citizen feedback systems or urban development policies.

3. CONCLUSIONS

This study demonstrates the transformative potential of integrating deep learning and Geographic Information Systems (GIS) for the automated detection, mapping, and analysis of urban green spaces. By leveraging Convolutional Neural Networks (CNNs) and high-resolution satellite and drone imagery, the proposed system achieves high accuracy in identifying diverse green areas, including parks, forests, and grasslands, even within visually complex urban environments. The end-to-end pipeline—from image acquisition and preprocessing to intelligent analysis and GIS-based visualization—enables real-time, scalable, and adaptable monitoring that significantly surpasses the limitations of traditional manual surveys and static records.

A key innovation of this work is the introduction of the Green Space Accessibility Index, which not only quantifies the presence of green spaces but also evaluates their accessibility and distribution relative to urban populations. This metric supports equity-focused urban planning, allowing policymakers to identify underserved neighborhoods and prioritize interventions that enhance environmental sustainability and public well-being.

Figure 6:GIS-based green space accessibility interface

ACKNOWLEDGEMENT

The authors would like to thank the faculty and staff of RV College of Engineering (RVCE), Bengaluru, for their invaluable support and guidance throughout this research. We are grateful to the Department of Artificial Intelligence and Machine Learning, Department of Cyber Security, Department of Computer Science and Engineering, and Department of Information Science and Engineering at RVCE for providing the necessary resources and infrastructure. Special thanks are extended to our mentors and peers for their constructive feedback and encouragement during the development of this project.

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