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Impact of Urban Vegetation in Sustainable Smart Cities Development: A Comprehensive Appraisal

Mr. Shadab Ali[1], Dr. Santosh Kumar Dwivedi[2], Mr. Ajeet Singh[3], Mr. Ashwin Kumar Shrivastava[4]

[1]Assistant Professor, Information Technology, SRMCEM, Lucknow, India
[2]Associate Professor, Computer Science, SRMCEM, Lucknow, India
[3, 4]Assistant Professor, Computer Application, SRMCEM, Lucknow, India

Correspondence should be addressed to Mr. Shadab Ali; shadab.alisir@gmail.com

ABSTRACT- Urban vegetation is the crucial need for the sustainable development of green smart cities. In the current green smart cities, absence of urban vegetation causes unusual high temperature and adverse effect of human health like heat stroke, headache, dehydration, cardiovascular, respiratory etc. This article offers an extensive examination of image processing methods employed in the assessment of urban vegetation. Urban environments often suffer from a scarcity of green areas, underscoring the importance of comprehending and tracking vegetation's condition and distribution for both environmental and human welfare. Notably, high-resolution aerial and satellite imagery, especially satellite images, serve as invaluable resources for evaluating urban vegetation. Within this paper, we delve into cutting-edge image processing techniques used in urban vegetation research, with a primary focus on classification, segmentation, and change detection algorithms. The study scrutinizes a range of approaches for feature extraction and classification, encompassing methodologies like texture analysis, spectral indices, and object-based analysis. Additionally, we explore machine learning and deep learning integration, multi-sensor data fusion, and the adoption of emerging technologies such as LiDAR and hyper spectral imaging as limitations and future avenues in urban vegetation analysis. The insights derived from this review will prove beneficial to researchers, practitioners, and policymakers involved in endeavors aimed at monitoring and enhancing green spaces within urban areas.

KEYWORDS- Urban Vegetation, Sustainable Smart Cities, Machine Learning, Artificial Neural Network, Fuzzy Classification, Decision Tree Classification, Deep Learning, Feature extraction.

I. INTRODUCTION

The speedy expansion of urban areas worldwide has led to significant changes in the landscape, with the proliferation of buildings, roads, and infrastructure often replacing natural vegetation. Urban vegetation plays a crucial role in enhancing the quality of life in cities by providing numerous environmental, social, and economic benefits. Therefore, understanding and monitoring the characteristics, health, and distribution of urban vegetation have become essential for urban planners, environmental scientists, and policymakers in sustainable smart cities development.The introduction provides an overview of the importance of urban vegetation and highlights the relevance of image processing techniques for its analysis. It emphasizes the need for accurate and efficient methodologies to assess the characteristics, health, and distribution of urban vegetation in the face of urbanization. Assessing and monitoring the condition of the Earth's surface is crucial for global change research. It is recognized as a fundamental requirement in various studies and reports [1]. One key aspect of this assessment is the classification and mapping of vegetation. This task is of great significance for the management of natural resources, as vegetation serves as the foundation for all living organisms and plays a vital role in influencing global climate change, including its impact on terrestrial CO2 levels [2]. Vegetation classification and mapping provide essential information for understanding ecological systems, monitoring land cover changes, and implementing effective measures to address environmental challenges. By studying vegetation patterns and dynamics, we can gain valuable insights into the functioning of ecosystems and their responses to environmental changes, ultimately aiding in the development of sustainable strategies for resource management and climate mitigation. Satellite Images is a valuable tool for studying land cover, as it allows for the measurement of surface-reflected radiation, enabling the assessment of various land surface properties [3]. The application of satellite images in the context of ecosystem services arises from its ability to characterize soil types, estimate biomass, analyze tree canopy properties derive Leaf Area Index (LAI) and monitor vegetation dynamics over space and time [4], among other applications. By employing models, spectral indices, data fusion techniques, and other processing methods, satellite images enables the identification and mapping of the contributions and losses of ecosystem services provided by natural elements on the Earth's surface [5]. This integration of satellite images and ecosystem service assessment facilitates the understanding of the spatial distribution and changes in ecosystem services, supporting decision-making processes for sustainable land management and conservation efforts. The assessment of ecosystem services often involves comparing ground-based assessments with satellite images approaches, a topic that has been frequently addressed in the literature

[6]. Satellite images have been found to be more practical and cost-effective for such assessments. However, there are identified gaps in the study, observation, and assessment of ecosystem services in urban areas using satellite images [7]. These challenges include the influence of physical conditions and properties of the urban environment on the scattering and emission of radiation from sensors, the need for integrating information from multiple sources to improve accuracy, image correction processes, data availability issues [8], among others. Over the past two decades, there has been a significant increase in the application of satellite images for studying and assessing ecosystem services. This growth is evident from the numerous studies published on this topic. The advancement of satellite imaging technology has played a crucial role in this progress, offering improvements in spatial, spectral, radiometric, and temporal resolution. These advancements enable the observation, classification, and monitoring of vegetation on the Earth's surface over space and time. However, despite these technological advancements, there are still methodological challenges that need to be addressed when assessing ecosystem services. These challenges arise due to the diverse applications of satellite images, the resources utilized, and the complexities associated with studying ecosystem services in urban environments. This systematic review aims to identify and analyze the various methods employed in satellite images for assessing ecosystem services provided by vegetation in cities. The review involves classifying these methods based on the data collection sources, which include passive sensors, passive and active sensors, and the fusion of other data sources with sensors. The selection of articles for analysis was based on a non-statistical meta-analysis approach, focusing on articles directly related to the topic of interest in indexed scientific databases. The results of the review highlight the different approaches found in each classified method, their relationship with geographical scales and image resolutions, as well as the advantages and limitations associated with the data processing steps involved in satellite images. Based on this analysis, three key factors emerge for consideration when selecting satellite images methods for assessing ecosystem services provided by urban vegetation: (1) defining the approach(es) to be used, (2) determining the urban scale to be assessed, and (3) considering the available image resolution. These factors should be carefully considered to ensure the appropriate selection and application of satellite images methods in assessing ecosystem services provided by urban vegetation. By addressing these factors, researchers and practitioners can enhance the accuracy and effectiveness of satellite images-based assessments in urban environments [9]. These gaps have led to the proposal of diverse methods in the literature [10], which may contribute to confusion in selecting an appropriate satellite images method or hinder the realization of the full potential that satellite images offers currently. Addressing these challenges and gaps is essential to advance the application of satellite images in assessing ecosystem services. Overcoming issues related to urban environmental conditions, integrating data from various sources, improving image correction processes, and enhancing data availability will enhance the accuracy and effectiveness of satellite images-based assessments. By addressing these challenges, satellite images can play a crucial role in understanding and managing ecosystem services in urban areas. In recent years, advancements in satellite images technologies, particularly high-resolution satellite and aerial imagery, have enabled researchers to employ image processing techniques for the analysis and assessment of urban vegetation. These techniques facilitate the extraction of valuable information from imagery, enabling detailed investigations into the spatial distribution, density, species composition, and health status of vegetation in urban environments. By harnessing the power of image processing, researchers can derive quantitative and qualitative metrics to support urban planning and management decisions. This review paper aims to provide an overview of the state-of-the-art image processing techniques employed in urban vegetation analysis. We will explore various methodologies and algorithms that have been developed for tasks such as vegetation detection, classification, segmentation, change detection, and health assessment. Furthermore, we will discuss the challenges and limitations associated with these techniques, along with potential avenues for future research and development. The structure of this review paper is organized as follows: first, we will present an overview of the importance of urban vegetation in enhancing urban environments and the key factors that influence its growth and distribution. Subsequently, we will delve into the different stages of image processing, including preprocessing, feature extraction, and classification, highlighting the specific techniques and algorithms. We will also explore the integration of machine learning and deep learning approaches to improve the accuracy and efficiency of vegetation analysis in urban areas. Additionally, we will discuss the wide range of data sources available for urban vegetation analysis, such as multispectral and hyper spectral imagery, LiDAR data, and aerial photographs. We will explore the strengths and limitations of each data source and discuss their suitability for specific analysis objectives. Moreover, we will address the challenges associated with data acquisition, including issues related to cloud cover, sensor resolution, and temporal availability. Finally, we have discussed the limitations, discussion and conclusion at the end of this study. By providing a comprehensive review of image processing techniques for urban vegetation analysis, this paper aims to contribute to the existing body of knowledge in this field. It is our hope that this review will serve as a valuable resource for researchers, practitioners, and policymakers seeking to leverage image processing approaches to better understand and manage urban vegetation in an increasingly urbanized world.

II. MATERIALS AND METHODS

While numerous review studies have explored the identification and classification of vegetation using satellite images, only a limited number have specifically focused on urban areas. A study is conducted on satellite images for urban green space analysis, examining various (potential) applications [11]. Their analysis revealed a rapid increase in studies on mapping the distribution of green spaces and tree species in recent years. The authors emphasized the need for a broader range of research, including different types of green spaces (e.g., private green spaces) and thematic applications (e.g., carbon mapping) using satellite images.

An analysis conducted on tree species identification in an urban setting, evaluating the added value of fusing spectral imagery with Light Detection and Ranging (LiDAR) data. They concluded that the fusion of these two data sources significantly improves tree species mapping results [12]. On the other hand, a review conducted on tree species classification without specifically focusing on urban areas. They found that many studies employed data-driven approaches but lacked a clear target in terms of anticipated applications or accuracy [13].This literature review aims to provide a comprehensive overview of state-of-the-art methods and approaches used for mapping different types of urban green spaces using high-resolution satellite images data. The focus is on spatially and thematically detailed mapping of urban vegetation and the various mapping methodologies employed.To compile the papers for this review study, a limited number of search queries were used, and the "snowballing" approach was applied to expand the database. The initial set of papers was collected from Web of Science and Google Scholar using keywords such as "satellite images," "urban green," "classification," "street view," and "terrestrial and laser scanning." The citations within the collected papers were then analyzed to identify additional relevant papers. This process was repeated until no new relevant papers meeting the criteria were found. All papers from Web of Science were analyzed, while only the first 300 returns from Google Scholar were considered.By conducting this review, the goal is to provide readers with a comprehensive overview of the current methods and approaches employed in mapping urban green spaces using high-resolution satellite images data.

In the selection process for this review study, all papers were evaluated based on following criteria:

1. Publication after 2000.
2. Focus on image processing and classifier for urban vegetation.

Following the initial search, snowballing, and selection, a total of 78 papers met these criteria and were included in the review study. The number of papers fulfilling the review criteria has shown a steady increase from 2000 to 2023. The majority of urban mapping studies included in the review were conducted in the USA, China, and Europe. Among the selected papers, a significant number focused on mapping tree species and image processing, while fewer studies focused on other taxonomic classes or functional vegetation types. The image processing of urban vegetation utilized various data sources such as spectral data and LiDAR, which were collected from different platforms including airborne, space borne, and terrestrial platforms. Additionally, different classifier approaches were employed for image analysis. Each of these dimensions will be explored in this review to provide a comprehensive overview of the field's evolution and current practices.

III. RESULTS: SATELLITE IMAGES WITH ACTIVE AND PASSIVE SENSORS

In the review of studies utilizing data from both passive and active sensors, the initial approach of Land Use and Land Cover (LULC) classification is identified, which was also mentioned in the previous method utilizing passive sensors. However, these studies delve deeper into the analysis of vegetation that has been classified within the LULC framework. By incorporating data from active sensors, such as LiDAR, Geographic-Object Based Image Analysis (GEOBIA) has been employed to identify specific aspects of vegetation, such as tree canopy, determine the typology of vegetated spaces, and assess the ecosystem services provided by individual plant species [14]. This integration of passive and active sensor data, combined with GEOBIA, enables a more detailed understanding of vegetation characteristics and its associated services in the urban environment.Apart from the in-depth study of vegetation, other conditions within the urban environment have been identified in the reviewed studies. For example, assessed the relationship between vegetation cover and temperatures on road surfaces, park interiors, and rooftops. They utilized hyper spectral and thermal imagery from Forward Looking InfraRed (FLIR), which captures the spatial distribution of different temperatures using a thermal camera that converts infrared (IR) radiation into an image. This data was combined with Light Detection and Ranging (LiDAR) for analysis. Another approach identified is the assessment of ecosystem services provided by invasive plants [15]. This approach is also linked to the detailed classification of existing vegetation.In the fusion of passive sensor and LiDAR imagery, a dependency between the two is identified for certain vegetation assessments. LiDAR dimensions can detect elements in the urban environment beyond vegetation, and thus merging with complementary spectral data is necessary for detailed mapping of these elements [16].

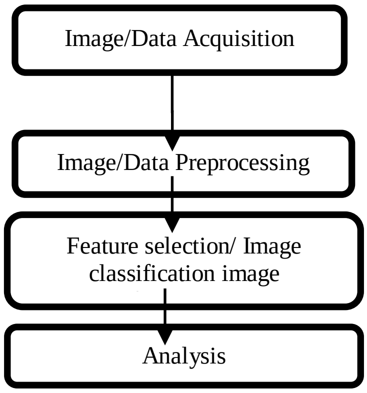

Figure 1: Steps involve in image processing analysis for urban vegetation

a) ***Data Acquisition:*** The first step in conducting urban vegetation analysis is the acquisition of suitable data. This typically involves obtaining high-resolution satellite imagery, aerial photographs, LiDAR data, or other relevant satellite images data sources. The choice of data depends on the analysis objectives, spatial resolution requirements, and availability. To demonstrate the impact of vegetation on psychological disorders and air pollution, investigated the association of tree canopy cover with childhood asthma, wheeze, rhinitis, and allergic sensitization. In these studies, various data sources were integrated, including ground-based measurements (GBM), vector maps, and interactive maps of environmental and socio-economic data combined with LiDAR [17].The integration of data extends beyond satellite images and includes other sources such as socio-economic information, weather and atmospheric data, social networks data, and demographic data. Cadastral data is combined with hyperspectral imagery and LiDAR data to map vegetation conditions at a local scale, as proposed in [18]. These approaches highlight the importance of incorporating diverse datasets and sensors to enhance the analysis and understanding of ecosystem services.

b) *Preprocessing:* Preprocessing is essential for enhancing the quality and usability of the acquired data. Common preprocessing steps include image calibration, atmospheric correction, geometric correction, and radiometric normalization. These steps aim to remove artifacts, correct geometric distortions, and ensure consistency across different data sources.

In image processing, key aspects include atmospheric correction, radiometric correction, topographic correction, geometric correction or orthorectification, and pan sharpening. These corrections are crucial to account for factors such as atmospheric conditions, radiometric accuracy, topographic variations, and spatial alignment of images. Additionally, there are processes to differentiate trees from buildings and other anthropogenic structures, as well as to address the influence of shadows cast by buildings and surface features on pixel values in the images.Data fusion poses challenges in land cover change (LCC) studies due to variations in image resolution over time. The use of different images with varying resolutions and information perceived by sensors can impact the processing and comparability of results. Multiple software tools may be required to process various factors studied, including socio-economic factors, while avoiding data redundancy [19]. Data fusion approaches can identify factors and dynamics associated with vegetation in cities, and the use of Geographical Information Systems (GIS) facilitates multisource data analysis.These considerations emphasize the importance of accurate image processing techniques, addressing challenges in data fusion, and utilizing appropriate software and GIS tools to enhance the reliability and comprehensiveness of the analysis.

Table 1: General approaches and Image processing of the studies reviewed

S.No	Approaches	Sensing methods	Processes
1	Identification and Classification of vegetation	Passive sensors	Analysis and collection of information
2	Assessing changes in vegetation	Passive sensors	Image correction
3	Quantification of vegetation	Passive sensors	Shadow exclusion or urban contamination
4	Socio-economic dynamics and vegetation	Passive sensors	Cross-check results (random or sampling etc.)

Preprocessing of satellite images is crucial prior to vegetation extraction in order to eliminate noise and enhance the interpretability of the image data. This becomes especially important when working with a time series of imagery or when dealing with multiple images covering a specific area, as it is essential to ensure spatial and spectral compatibility among them. The goal of image preprocessing is to make all the images appear as if they were acquired from the same sensor [20]. However, it is worth noting that not all preprocessing procedures may be necessary, as some of them might have already been performed by image distribution agencies. Therefore, it is recommended to consult with the image distributor to determine the level of preprocessing that has been applied to the imagery before making a purchase. For instance, different levels of preprocessing, such as level 0, 1A, 1B, 2A, 2B, 3A, 3B, may indicate varying degrees of image quality improvement, including radiometric correction, geometric correction, and orthorectification. Common operations involved in image preprocessing include replacing bad lines, radiometric correction, geometric correction, image enhancement, and masking (e.g., for clouds, water, and irrelevant features). It is important to note that the specific preprocessing steps may vary depending on the sensor used to acquire the images. Geometric correction is a crucial step in image preprocessing that aims to rectify geometric distortions present in satellite images. This process involves establishing the relationship between the image coordinate system and the geographic coordinate system by utilizing calibration data from the sensor, measured position and altitude data, and ground control points. The main objectives of geometric correction are to select a suitable map projection system and to co-register the satellite image data with other reference data for calibration purposes. The desired outcome of geometric correction is to achieve an error within plus or minus one pixel of the true position, enabling accurate spatial assessments and measurements of the data derived from the satellite imagery. Image enhancement techniques are employed to improve the visual clarity and highlight specific features within satellite images, such as distinct vegetation species, for better interpretation. Traditional image enhancement methods include gray scale conversion, histogram adjustment, color composition, color space transformations (e.g., RGB to HSI), and other techniques that are commonly applied to enhance the output images for visual analysis. However, these traditional methods have certain limitations. The drawbacks of traditional image enhancement approaches and proposed a more effective method based on genetic algorithms [21].When mapping vegetation cover using satellite images images, particularly over large regions, clouds pose a significant challenge as they can obscure vegetation information. Therefore, it becomes necessary to remove or mask the cloud cover. A neural network-based approach for cloud detection in SPOT VEGETATION images used in [22]. Similarly, Walton and Morgan (1998) utilized cloud-free space shuttle photographs to identify and mask unwanted cloud cover in Landsat TM scenes. These techniques enable the extraction of vegetation information by eliminating the interference caused by clouds.

***Feature Extraction*:** In many cases, researchers opt to derive a set of features from the original spectral data instead of directly using it as input for classifiers. This approach aims to extract the most relevant information from the available data, reduce noise, and address the challenges associated with high-dimensional feature spaces. Feature extraction involves quantifying relevant information from the segmented regions. Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), or Leaf Area Index (LAI), are commonly computed to assess vegetation health and density. Feature extraction happens in two ways shows in figure 2. Texture features, such as Haralick or Gabor features, may also be calculated to capture spatial patterns and heterogeneity within the vegetation.

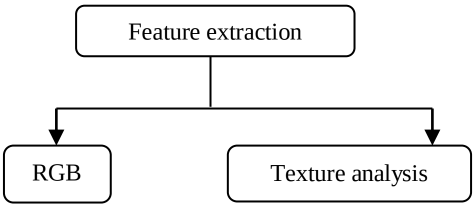

Figure 2: Feature extraction types

Textural features capture the spectral variation in the vicinity of a pixel or within a predefined object, providing valuable information. In many studies, texture measures have been utilized to distinguish between high and low vegetation, as well as to identify different vegetation types or species. However, their significance diminishes when aiming for finer levels of vegetation differentiation. When it comes to mapping tree species, textural information related to tree crown structure becomes relevant only when the spatial resolution of the imagery is adequately high, which depends on the size of the tree crown [23].

Classification/ Analysis: Classification aims to assign predefined classes or categories to the extracted features. Supervised and unsupervised classification techniques are commonly employed. Supervised classification utilizes training samples with known class labels to train a classifier, such as Support Vector Machines (SVM), identifies natural groupings in the data without prior class information [25]. Image classification refers to the process of identifying and differentiating various classes or themes, such as land use categories or vegetation species, from raw satellite imagery. While image classification encompasses the entire workflow, including image preprocessing, we will specifically focus on the classification process that occurs after the preprocessing stage shown in figure 3.

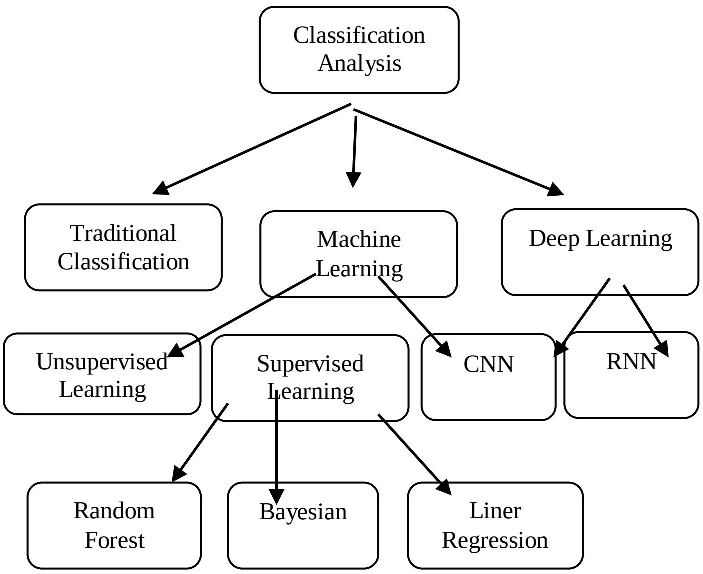

Figure 3: Image classifier

Vegetation extraction techniques can be categorized into three types: traditional and machine learning and deep learning methods. Traditional methods are established techniques commonly used in satellite images, while improved methods involve innovative approaches that have demonstrated enhanced performance in vegetation extraction.

Traditional Classifier

Traditional methods for vegetation extraction often rely on classical image classification algorithms. For unsupervised classification, popular techniques include the K-means and ISODATA clustering algorithms. These methods are commonly used for thematic mapping, including vegetation cover mapping, and are readily available in image processing and statistical software packages. In the K-means algorithm, an initial set of cluster centroids is randomly assigned, and each pixel is then assigned to the closest cluster based on its spectral characteristics. The algorithm iteratively updates the cluster centroids until convergence is reached.

The advantage of using unsupervised classification methods is that they can automatically transform raw image data into useful information, as long as they achieve high classification accuracy. However, unsupervised methods have limitations. For instance, if new data or samples are added, the classification process needs to be repeated from the beginning.

To address the limitations of purely spectral unsupervised methods, researchers have explored incorporating both spectral and contextual information. For example, a framework proposed based on Hidden Markov Models that incorporates both types of information, leading to improvements in classification accuracy and visual quality.

Machine learning classifiers

Investigated and compared different unsupervised classification algorithms in terms of their ability to reproduce ground data in complex areas. While unsupervised classification methods are relatively easy to apply, the need for repetition when new data is added is considered a disadvantage.

Artificial Neural Network (ANN) and fuzzy logic approaches have been explored in the literature for vegetation classification. ANN is a versatile method suitable for analyzing various types of data, regardless of their statistical properties. It proves valuable in extracting vegetation-type information in complex vegetation mapping problems. However, the interpretability of the results is compromised because ANN adopts a black-box approach that conceals the underlying prediction process [31]. Berberoglu et al. (2000) combined ANN and texture analysis on a per-field basis to classify land cover, achieving accuracy 15% higher than a standard per-pixel Maximum Likelihood (ML) classification.One drawback of ANN is its computational demand, especially when dealing with large datasets for training the network. In some cases, even with extensive computation, no result may be obtained due to local minima (e.g., in back-propagation ANN).Fuzzy classification approaches have proven useful in various applications, such as the classification of suburban land cover from satellite images imagery, the study of medium-to-long term vegetation changes, and biotic-based grassland classification [32].Decision Tree (DT) classification is another approach for vegetation classification that involves matching spectral features or combinations of spectral features from images with possible end members of vegetation types at the community or species level. DT is computationally efficient, does not make statistical assumptions, and can handle data represented on different measurement scales. Hansen et al. (2006) produced a global land cover map using a DT approach with 41 metrics generated from five spectral channels and NDVI as input, derived from AVHRR imagery. The agreement for all classes varied from an average of 65% when considering all pixels to an average of 82% when considering only 1 km pixels consisting of over 90% of a single class within high-resolution datasets.Other studies have combined soft classification with the DT approach. They compared the performance of DT classifiers with that of Artificial Neural Network (ANN) and Maximum Likelihood (ML) classifiers, considering factors such as training data size, attribute selection measures, pruning methods, and boosting. Their findings indicated that the use of DT classifiers with high-dimensional hyperspectral data is limited, while good results were achieved with multispectral data.In certain circumstances, DT can be particularly useful when vegetation types are strongly associated with other natural conditions, such as soil type or topography. For example, certain vegetation species may only thrive in areas with elevations above a specific threshold. If ancillary data regarding such conditions are available, they can be integrated into the DT to enhance the classification process using imagery.In the study of monitoring natural vegetation in the Mediterranean, investigated various vegetation classification methods for satellite images imagery. Firstly, the study explored the random forests and support vector machines methods, which demonstrated better performance compared to traditional classification techniques. Secondly, instead of relying solely on per-pixel spectral information, Sluiter utilized both per-pixel spectral information and the spectral information of neighboring pixels in the spatial domain to analyze and classify satellite images imagery. The implementation of a contextual technique called SPARK (SPAtial Reclassification Kernel) successfully detected vegetation classes that could not be distinguished using conventional per-pixel-based methods.There are numerous classification methods and algorithms developed for image classification in various specific applications. In some cases, combining multiple methods or algorithms can enhance the quality of classification results. For instance, a hybrid method proposed that incorporated the advantages of supervised and unsupervised approaches, as well as hard and soft classifications, to map land cover in the Atlanta Metropolitan Area using Landsat 7 ETM+ data. However, caution should be exercised when applying improved classifiers as these methods are often designed to address specific challenges and solve unique problems.Furthermore, the discrimination of vegetation species from single imagery is only possible when a combination of leaf chemistry, structure, and moisture content results in a distinctive spectral signature. Therefore, successful imagery classification relies on accurately extracting pure spectral signatures for each species, which is influenced by the spatial resolution of the sensor and the timing of observations [34]. In summary, the search for improved image classification algorithms remains an active field in satellite images applications because there is no universally applicable super classification method.Random Forest is a well-known machine learning algorithm from the supervised learning technique. It can be applied to both classification and regression issues in machine learning. It is built on the notion of ensemble learning, which is a method that involves integrating numerous classifiers to solve a complex problem and improve the model's performance."Random Forest" is a classifier that "contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead than relying on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority vote of predictions.Deep learning refers to neural network architectures with multiple hidden layers, and it can be applied to supervised, unsupervised, or semi-supervised learning. Deep learning techniques excel in creating feature representations that enhance class separability. Few studies have utilized deep learning for urban green classification. These studies employed three types of deep learning algorithms: Boltzmann machines, multi-layer perceptron (MLP) with multiple hidden layers, and convolutional neural networks (CNNs). An MLP with three hidden layers used to classify 17 tree species using hyperspectral imagery captured by a terrestrial sensor across different seasons. The MLP achieved high prediction accuracy ranging from 84% to 96% for different seasons. An MLP with four hidden layers employed to differentiate between high and low vegetation using high-resolution RGB images.

IV. CHALLENGES AND LIMITATIONS

One limitation of this review paper is the focus on image processing and classification techniques for urban vegetation analysis, which may overlook other relevant approaches or methodologies for studying urban vegetation. While image processing techniques are undoubtedly important and widely used, there may be alternative methods, such as LiDAR or field-based surveys and machine learning classifiers that were not thoroughly discussed in this review.Another limitation is the potential bias towards deep learning methods, as the review highlights their advantages and growing popularity. This bias may overshadow the potential benefits of other image processing techniques or neglect to thoroughly explore their comparative strengths and weaknesses.Additionally, the review primarily emphasizes the technical aspects of image processing techniques, such as classifier performance and accuracy. However, it may not fully address the limitations related to data availability, such as the challenges of acquiring high-resolution imagery or obtaining ground truth data for validation. These practical constraints can significantly impact the applicability and generalizability of the image processing techniques discussed.Furthermore, the review may not cover the latest advancements or emerging trends in the field of image processing for urban vegetation analysis. As the field is rapidly evolving, new techniques, algorithms, and data sources may have emerged since the literature search was conducted for this review.Lastly, while the review acknowledges the importance of urban vegetation in providing ecosystem services, it may not extensively address the broader ecological and socio-economic implications of urban vegetation mapping.

Further exploration of the relationships between vegetation characteristics, ecosystem services, and human well-being could enhance the understanding of the practical implications of these image processing techniques.

V. DISCUSSION

The review conducted by Stroud, Peacock, and Hassall (2022) highlights that the most commonly used methods for assessing ecosystem services provided by urban vegetation involve the utilization of passive and active sensors, as well as the fusion of these sensors with other data sources. However, the review also identifies existing gaps, particularly in terms of geographical discrepancies and available information, especially at the local urban scale.Through the analysis of the classified methods, their relationships with geographical scale, image resolutions, and image processing, a discussion has been generated to address the lack of specifically defined remote sensing methods for assessing ecosystem services provided by urban vegetation.In the review, the limitations of this review paper include a potential narrow focus on image processing techniques, a bias towards deep learning methods, potential oversight of alternative methodologies, potential neglect of practical limitations related to data availability, potential out datedness in terms of recent advancements, and limited discussion on the broader implications of urban vegetation mapping beyond technical aspects.

VI. CONCLUSION

This review paper provides an overview of image processing techniques for urban vegetation analysis. The most widely used method for mapping vegetation in an urban setting continues to be traditional supervised learning. Nonparametric classifiers typically outperform parametric classifiers when enough reference data is available; the most popular mapping techniques are SVM and decision tree classifiers. However, in recent years, deep learning methods have gained popularity due to their ability to handle high-resolution imagery and integrate diverse data sources, offering improved accuracy and detailed mapping and classifying capabilities.The reviewed studies demonstrate the added value of deep learning techniques for thematically detailed vegetation mapping, classification and the integration of different data types. These methods hold great promise for advancing the analysis of urban vegetation and its role in providing multiple ecosystem services. As the awareness of the importance of urban vegetation grows and more complementary data sources become available, we anticipate a rapid increase in the application of these techniques in the field of urban vegetation mapping and classification of images.In this review highlights the progress and potential of image processing techniques, particularly deep learning, for urban vegetation analysis. To improve the existing methodologies in past researches in future, we applied deep learning techniques with features extraction techniques which provide better results. Further research and advancements in this field are expected to refine and expand these techniques, enabling more comprehensive and accurate assessments of urban vegetation and its associated benefits.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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ABOUT THE AUTHORS

Shadab Ali (Correspondence Author), Assistant Prof. Computer Application Deptt, SRMCEM and Research Scholar, Integral Univ. Lucknow. He has 15 years of teaching experience and his research area in image processing. In his Teaching-Learning journey, he also acquired M.Phil (CS) and M. Tech(IT) Degrees. He has guided/published more than 20 research papers at International forums including UGC Care approved Journals

Dr. Santosh Kumar Dwivedi is working as Head of Department and an Associate Professor in the department of Computer Application serving academic field for the last 15 years. He has completed his doctoral degree in Computer science in 2013. In his Teaching-Learning journey, he also acquired M.Phil(CS) and M. Tech(IT) Degrees. He has published more than 9 research papers at International forums including UGC Care approved Journals and SPRINGER. His academic area includes Data Structures and algorithms, Computer Networks, Software Engineering, OOPs, DBMS etc. As a Head of the Department, His objective is to maintain high academic standards and innovative learning.

Mr. Ajeet Singh is currently working as an Assistant Professor at SRMCEM, Lucknow in BCA department. Mr Ajeet has acquired degrees of MCA and MSc. Mathematics. He has more than 8 years of teaching experience. He has also qualified UGC-NET and believes in imparting value education to students. His academic area includes computer graphics, image processing and databases,etc.

Mr. Ashwin Kumar Shrivastava is currently working as an Assistant Professor at SRMCEM, Lucknow in BCA department. He passed out MCA in 2023 and is an early bird in the field of education. He believes in bridging the gap between traditional education system and the current demands of the industry. He has expertise in the area of Machine Leaning, Neural Network, Model building, Algorithms, Operating System, etc.