Building Detection from Satellite Imagery Using Morphological Operations and Contour Analysis over Google Maps Roadmap Outlines

Arbab Sufyan Wadood[1], Ahthasham Sajid[2], Muhammad Mansoor Alam[3], Mazliham MohD Su'ud*[4], Arshad Mehmood[5], Inam Ullah Khan[6]
Department of Computer Science, Baluchistan University of Information Technology, Quetta, Pakistan[1]
Department of Information Security and Data Science, Riphah Institute of Systems Engineering, Riphah International University, Islamabad, Pakistan[2,5]
Faculty of Computing and Informatics, Multimedia University, Cyberjaya, Malaysia[3,4,6]

***Abstract*—One such research area is building detection, which has a high influence and potential impact in urban planning, disaster management, and construction development. Classifying buildings using satellite images is a difficult task due to building designs, shapes, and complex backgrounds which lead to occlusion between buildings. The current study introduces a new method for constructing recognition and classification globally based on Google Maps contour trace detection and an evolved image processing technique, seeking synergies with a systematic methodology. We first extract the building outlines by taking the image from the R̈oadmapv̈iew in Google Maps, converting it to gray scale, thresholding it to create binary boundaries,and finally applying morphological operations to facilitate noise removal and gap filling. These binary outlines are overlaid on colorful satellite imagery, which aids in identifying buildings. Machine learning techniques can also be used to improve aspect ratio analysis and improve overall detection accuracy and performance.**

***Keywords*—Building detection; satellite imagery; urban planning; disaster response; image processing; machine learning; morphological operations; contour detection; aspect ratio**

I. Introduction

Building detection in aerial images, a key and well-studied domain has recently drawn considerable attention. High-resolution satellite imagery is increasingly available, and thus necessitates automatic and accurate methods for building detection [1]. Building detection is an important task for urban planning, disaster response [2], change detection [3], construction and development activity monitoring [4].

However, several above-mentioned factors make the detection of buildings from satellite images a challenging and complex task. Buildings vary significantly in their shapes, sizes, and materials. That is, a building in a dense urban location may differ quite markedly from an equivalent suburban one in both form and scale [5].

Furthermore, it may be difficult to differentiate certain structures from their surroundings since they are made of materials that share spectral characteristics with the surrounding area [6], [7]. Other elements seen in metropolitan settings, such as streets, trees, and shadows, can also produce complicated backdrops that make it more difficult to identify buildings. It can also be complex to identify buildings from satellite photos since they can be partially or completely obscured by other objects, including trees or other structures [8]. The unpredictability of satellite imagery itself is another element that makes construction detection more difficult. Depending on the sensor, atmospheric conditions, and capture time, satellite imagery can differ greatly in terms of resolution, spectral bands, and quality [9].

It is difficult to create a general technique that can reliably identify structures because cities vary throughout time, from small adjustments to total demolition and reconstruction [10].

To overcome the difficulties caused by many elements and increase the precision and resilience of detection algorithms, advanced image processing [11], machine learning, and deep learning approaches can be applied. For the detection of buildings and urban areas from aerial photos, machine learning and deep learning approaches have demonstrated excellent results [2], [12], [13], [14]. Nevertheless, there are a number of restrictions on their use in this situation. First of all, the caliber and volume of training data are critical to these algorithms [15], [16].

The resulting model might not function well on fresh data if the training set is skewed toward particular building or area types or is not representative of real-world data. Large-scale training data collection and labelling can also be costly and time-consuming [17], [18].

Second, machine learning algorithms could find it difficult to generalize to various architectural styles and metropolitan regions [6].

A model trained on photos of contemporary high-rise structures in a crowded city, for instance, would not function as well when used to photos of low-rise, older structures in a rural region. Thirdly, variations in camera settings, illumination, and weather can have an impact on machine learning and deep learning models. Image processing techniques provide a number of benefits over machine learning techniques for more accurate and code-efficient building detection from satellite pictures. First off, compared to machine learning algorithms, image processing methods are less dependent on the caliber or volume of training data. Regardless of data variances, they are based on well-established rules and algorithms designed to detect particular features or patterns in the photographs. This saves time and money by doing away with the requirement for intensive data collecting and labelling [19]. Second, because image processing methods are not impacted by changes in lighting, weather, or camera settings, they may be used in a variety of metropolitan environments and building styles with little modification. This guarantees dependable and consistent outcomes in various settings. Finally, machine learning models are not as good at detecting buildings that are partially or completely blocked as image processing techniques. Even when building characteristics are completely or partially obscured by other objects, they can still be identified by using sophisticated algorithms like morphological filtering, edge identification, and texture analysis. This lowers the likelihood that the findings will contain false positives or false negatives. Creating trustworthy algorithms for identifying and categorizing buildings from high-resolution satellite data [20] has been the subject of numerous studies. But putting in place a system that can function globally presents other difficulties that need to be resolved, like the fact that different parts of the world have different kinds, sizes, and shapes of buildings, and that handling big datasets with different quality and resolution levels is necessary. A unique Roadmap-to-Satellite Building Detector (RSBD) method is put forth to overcome these obstacles. It makes use of outlines from Google Maps as well as other cutting-edge image processing techniques to create a highly effective and scalable system for building detection and classification on a worldwide basis. The Roadmap view image from Google Maps [21], which includes building outlines [22], is transformed to grayscale for this study. The final image is next subjected to a threshold, the value of which is established by the desired degree of building outline colour.

The threshold image is then enhanced and minor details are eliminated using morphological processes like dilation and erosion [23].

The contours in the threshold image are then determined by features like area or aspect ratio, and those that are not building outlines are filtered out. The identified buildings are then displayed once the filtered outlines have been put on a Google Maps satellite view image [24].

This research aims to solve issues like quality and resolution, as well as the variations in building kinds, sizes, and shapes across the globe, intended for global application. In this work, six distinct global locations with diverse building kinds, sizes, shapes, and picture resolution were used to test the Roadmap-to-Satellite Building Detector (RSBD). The experimental results and quantitative validation in this research indicate the promising potential of the developed approach.

The rest of this paper is organized as follows: Section II is the Literature Review where we discuss the related work. Section III explains the Methodology used by the authors. Section IV provides a Use Case Analysis that illustrates the usefulness of our work. Section V presents the Results of our experiments and evaluations. Section VI contains a detailed Discussion that interprets the results and their implications. Section VII discusses the Threshold Value Analysis, which sheds light on the essential counts that directly affect the output of our analysis. Finally Section VIII concludes the paper.

The major contributions of this article can be summarized as follows:

- Utilizes gray-colored building outlines found in Google Maps' "Roadmap" map type as a foundational element for building detection from satellite images.
- Introduces an adaptive thresholding technique to convert the grayscale Google Maps "Roadmap" view image into a binary representation.
- Morphological operations are applied to enhance the thresholded image, and contour filtering [25] is employed to remove non-building contours based on specific properties, such as area and aspect ratio, respectively.
- Presents a globally applicable methodology designed to address challenges related to variations in building types, sizes, shapes, image quality, and resolution across different regions worldwide, making it adaptable to diverse contexts.
- Validates the Roadmap-to-Satellite Building Detector (RSBD) through extensive testing on six distinct regions worldwide, encompassing diverse building characteristics and image resolutions. The experimental results and quantitative validation demonstrate the method's promise and potential for efficient and effective building detection.
- A comprehensive critical analysis of the existing work related to building detection in aerial images is presented providing insights into the strengths and weaknesses of the approaches.

II. Related Work

Numerous studies have been conducted on urban areas and building detection from aerial images using advanced image processing [26], [27], [28], [29] and machine learning techniques [2], [12], [13], [14]. In recent years, with the increasing availability of high-resolution satellite imagery, research on urban areas and building detection from aerial images using image processing techniques has been extensively explored due to its importance in various fields, including urban planning, disaster response, and monitoring of construction and development activities. Zerubia et al. presented one of the first studies in this area [26] . They developed a texture parameter that takes into account the image's local conditional variations by modelling the luminance field using chain-based models.

To provide additional information on the likelihood that pixels would belong to a certain cluster, they created a modified fuzzy C-means method with an entropy term that does not require prior knowledge of the number of classes. This approach was tested on both simulated and real satellite images from CNES and ESA and was further applied to a Markovian segmentation model. Benediktsson et al. [27] suggested employing morphological and neural techniques to classify panchromatic high-resolution data from metropolitan regions. Three steps make up the method: feature extraction or selection, classification, and the creation of a differential morphological profile employing geodesic opening and closing operations. High-resolution Indian Remote Sensing 1C (IRS-1C) and IKONOS remote sensing data were used to test the suggested approach, which demonstrates better classification accuracy with comparatively few characteristics required. A technique for detecting buildings from low-contrast satellite pictures was presented by Aamir et al. [28].

The suggested technique uses a line-segment detection system to precisely identify building line segments and uses singular value decomposition based on the discrete wavelet transform to improve image contrast. The entire building's contours are then obtained by hierarchically grouping the identified line segments. The suggested technique performs better than current methods when applied to high-resolution images with sufficient contrast. In order to extract building rooftops from satellite pictures, Avudaiammal et al. [29] introduced MBION-SVM, a system that combines morphological, spectral, form, and geometrical features with an SVM classifier. The technique employs the Normalized Difference Vegetation Index (NDVI) and Otsu thresholding to remove mislabeled rooftops and the Morphological Building Index (MBI) to identify likely buildings.

An SVM is trained using geometrical features of recognized rooftops, and self-correction is utilized to eliminate rooftops that have been incorrectly categorized and provide surface area data. Kohli et al. [30] used object-oriented image analysis and expert knowledge to present a built environment morphology-based urban slum detection approach. For slum detection, the technique employed spatial measurements and the contrast of textural features. Compared to the land cover classification accuracy of 80.8%, the agreement percentage between the reference layer and slum classification was only 60%. According to the study's findings, the approach is practical and might be successfully used in related situations.

A novel approach to building extraction from high-resolution satellite data is presented by Liu et al. [7] utilizing the probabilistic Hough transform and multi-scale object-oriented categorization. Building roof extraction and shape reconfiguration are the two stages of the system. Building roofs are extracted using a fuzzy rule decision tree classifier after the multispectral and panchromatic pictures are fused and segmented at various space scales. After determining the building roof's dominant line using the probabilistic Hough transform, the building boundary is fitted using a building squaring algorithm.Experimental results show that the approach can precisely identify and extract rectangular building roofs. A new method for automatically extracting building footprints from HRS pan-sharpened IKONOS multispectral pictures was presented by Gavankar et al. [31]. In order to extract buildings and remove incorrectly categorized urban elements, the method mainly concentrates on optimizing segmentation and shape parameters. Completeness, accuracy, and quality indicators are used to assess the technique's suitability. Automatic building detection from pan-sharpened very high spatial resolution satellite data was the main focus of Dey et al. [32].

In multi-level segmentation-based building detection, the suggested method makes use of shadow context, color tone, size, edge features, structural and geometric features, and prior information. Although the results are encouraging, they require modifications for real-world applications. Additionally, the study demonstrates the effectiveness of the UNB pan sharpening method in applications that make use of spectral and spatial data. A region-based level set segmentation technique was presented by Karantzalos et al. [33] for the automatic identification of artificial items in satellite and aerial photos. The method measures information within regions according to their statistical description, optimizing the position and shape of an evolving geometric curve.Because of its rapid convergence and complete automation, the technique is appropriate for real-time applications. The algorithm was tested on various aerial and satellite photos. It correctly identified roads, buildings, and other man-made features, demonstrating its efficacy through both qualitative and quantitative evaluation. In order to create normalized Digital Surface Models (nDSM) and differentiate between ground and non-ground points, Cao et al. [34] used point cloud data processing techniques such as noise removal and point reduction. They then created a technique that uses characteristics including flatness, normal direction variance, and nDSM texture to designate structures at an object scale. A graph-cut technique was utilized to fuse and normalize these features. The impact of varying grid sizes on parameter correctness and detail was also investigated. In conclusion, the authors thoroughly examined point cloud data in order to construct labeling and characterization. Farhadi et al. [15] use satellite imagery to extract building footprints (BF) in order to address the difficult challenge of tracking the expansion of urbanization. They suggest a novel unsupervised method dubbed Feature-Based Building Footprint Extraction (F2BFE), which makes use of a Digital Elevation Model (DEM) and Sentinel-1 and 2 satellite photos. The process uses sophisticated thresholding techniques for feature extraction and generates a radar index (NRI) from Sentinel-1 data to extract main building footprints (PBF). Furthermore, spectral indices associated with various land cover categories are extracted from Sentinel-2 photos. In order to create precise and effective ways for identifying buildings in satellite data [35], machine learning approaches have recently gained popularity. Support vector machines (SVMs) are a common machine learning method for object detection. SVMs are binary classifiers that have been effectively used for a number of pattern recognition tasks, such as identifying objects in aerial photos. The suggested approach in a paper by Turker et al. [36] uses SVM classification to identify building patches in the image and sequential processing of edge detection, Hough transformation, and perceptual grouping to extract building boundaries.

The developed method is validated through experiments conducted on pan-sharpened and panchromatic Ikonos imagery, which demonstrate high accuracy in detecting industrial and residential buildings,achieving average detection rates of 93.45% for industrial and 95.34% for residential buildings. Cao et al. [14], addressed the challenge of accurately detecting changes in built-up areas (BAs) for a comprehensive understanding of urban development. They introduced a multi-scale weakly supervised learning approach that utilized image-level labels and high-resolution images. Creating multi-scale Class Activation Maps (CAM) for BA pseudo labels, reducing noise in the pseudo labels, and producing trustworthy pseudo labels for BA change detection were the three main components of the approach. Additionally, they used ZY-3 satellite pictures to create multi-view datasets that covered China's largest cities. This method, which uses multi-scale CAM and temporal correlations for increased accuracy, was beneficial because it was economical and efficient in situations with few labels. One machine learning method that has become more and more prominent in building detection is random forests (RFs).

RFs are an ensemble learning technique based on decision trees that has been effectively used for a variety of remote sensing tasks. The efficiency of machine learning techniques in mapping Jeddah, Saudi Arabia's informal settlements using very-high resolution imagery and terrain data was investigated in a study by Fallatah et al. [13]. The study used an object-based RF technique to map 14 markers of settlement features. With an overall accuracy of 91%, the object-based RF method was found to be more successful than object-based image analysis. Building detection in satellite images has also made extensive use of artificial neural networks (ANNs) [37], in addition to SVMs and RFs. Large datasets can be used to teach ANNs, which are strong machine learning models, intricate patterns, and correlations. Building traits were automatically extracted from high-resolution Pleiades data using machine learning methods in a work by Idris et al. [38]. Building footprints were extracted using the Artificial Neural Network (ANN) with an accuracy rate of 80.13%, proving its efficacy and excellent computational efficiency. The findings of the study offer an automated method for building extraction that can streamline database and map updates for planning and decision-making.

Building detection in satellite photography has been accomplished through the use of convolutional neural networks (CNNs). One kind of deep learning model that is capable of extracting hierarchical features from huge datasets is CNN. A damaged building detection technique based on CNNs optimized with the Bayesian optimization approach was proposed by Ekici et al. [39]. The effectiveness of the improved CNN model is confirmed by performance evaluation metrics derived from balanced and unbalanced testing datasets, and testing and validation results demonstrate the robustness of the suggested approach. UNet-AP, a unique CNN architecture, was presented by Rastogi et al. [40] for the automatic extraction of building footprints from satellite data. The architecture was evaluated using multispectral satellite images and contrasted with the UNet and SegNet baseline implementations. The findings demonstrate that the suggested architecture consistently improves performance across various urban settlement classes, surpassing both UNet and SegNet.

A new model called SG-EPUNet was introduced by Geo et al. [14] for updating building footprints in bitemporal remote sensing pictures. Change detection, building extraction, and edge preservation are all combined into one framework in this approach. It uses a gated attention module (GAM) to improve building edges and an Edge-preservation building extraction network (EPUNet) for accurate building footprint extraction. By using semi-supervised self-training, SG-EPUNet overcomes the problem of limited post-change labels by updating building footprints using pre-change and post-change picture attributes along with a change saliency map.

The proposed approach leverages deep learning [41] and transfer learning to improve model robustness and generalization, making it suitable for automating building footprint updates in remote sensing imagery. However, the proposed SG-EPUNet show limitations in updating the small newly-built buildings, especially when the image resolution is low.

Zheng et al. [2] addresses the critical issue of rapid and accurate building damage assessment in the aftermath of sudden-onset natural and man-made disasters. the study introduces a novel framework called ChangeOS. In ChangeOS, a deep object localization network replaces the conventional superpixel segmentation in OBIA to generate precise building objects. These objects are then integrated into a unified semantic change detection network along with a deep damage classification network, facilitating end-to-end building damage assessment. This approach not only ensures semantic consistency but also provides deep object features for more coherent feature representation. Ding et al. [42] introduce the Semi-LCD method to enhance Binary Change Detection (BCD) performance when labeled samples are limited. Semi-LCD combines sample perturbation, consistency regularization, and pseudo-labeling. It comprises a supervised module for labeled data and an unsupervised module for unlabeled data. They also propose a lightweight change detection network, LCD-Net, designed to maintain high performance while reducing model complexity. During training, a combined loss function balances supervised and unsupervised components. In testing, the unsupervised module is not used, and change probabilities are binarized to obtain BCD results.

This approach aims to improve BCD with limited labeled data and address model complexity issues.

Wang et al. [43]proposed a deep learning-based approach to detect structured building rooflines from satellite images. The proposed approach uses CNNs to detect corner and line segment primitives, and a collaborative branch of semantic annotation information to obtain the building segmentation map. Experiments on the SpaceNet dataset show that the proposed approach improves the accuracy of building extraction, and the planar graph representation promotes 3D reconstruction and other subsequent applications.

Mohammadian et al. [44] focus on building detection and change detection using remote sensing images, the authors propose a novel siamese model called SiamixFormer. This model utilizes both pre- and post-disaster images as inputs and features a hierarchical transformer architecture with two encoders. In SiamixFormer, each stage of both encoders contributes to a temporal transformer for feature fusion. This fusion involves generating a query from pre-disaster images and (key, value) pairs from post-disaster images, considering temporal features for enhanced performance.

The use of temporal transformers in feature fusion allows the model to maintain large receptive fields effectively, outperforming CNN-based approaches. Finally, the output from the temporal transformer is passed through a simple MLP decoder at each stage.

Although machine learning techniques have shown promise in detecting buildings in urban areas from aerial images, they have limitations. These limitations include heavy dependence on the quality and quantity of training data [16], difficulty in generalizing to different types of urban areas and building styles [6], and challenges in detecting partially or fully obstructed buildings [7]. Furthermore, gathering and classifying training data can be costly and time-consuming [17], [18].

On the other hand, image processing methods can get around these restrictions when it comes to detecting buildings in satellite photos. In order to overcome the aforementioned constraints, image processing techniques are employed in this study. A thorough critical evaluation of the corpus of research on building detection in aerial photos is provided in Table I. To address the problem of detecting buildings in high-resolution satellite data, the research that are part of this investigation use a variety of approaches, such as image processing techniques, deep learning, and machine learning algorithms. For each study, its advantages and limitations are highlighted, providing insights into the strengths and weaknesses of the respective approaches. This critical assessment serves as a valuable reference for researchers, practitioners, and decision-makers in the fields of urban planning, disaster response, and construction monitoring, helping them make informed choices when selecting methodologies for building detection tasks.

III. Methodology

As shown in Fig. 1, Google Maps building outlines are the graphical representation of buildings on a map. These belong to the "Roadmap" map type of Google Maps which is intended to show the road network and various geographical features like building footprints. These outlines are lines that outline the shape of a footprint for buildings, and they're typically presented in light gray or beige. Note that the building outlines shown in Google Maps are not precise: Google's machine learning algorithms identify and extract building outlines from satellite and aerial images, an image processing technique [31]. These techniques are not always foolproof and often misidentify building footprints, mistaking them with shadows, vegetation or other features [45]. Building outlines are helpful for getting a high-level sense of the general area and so navigating in Google Maps, but they are likely not detailed enough to support urban planning, disaster response or construction tracking efforts. But still, those outlines of buildings can help kick-start the automated process of building detection using satellite images. In this research, several image processing operations are applied to the Roadmap image to extract and clean up the building boundaries. You then get an overlaid image, which you can also lay down on a color satellite image and see the structures. The Roadmap-to-Satellite Building Detector (RSBD) flowchart is in Fig. 2 and the articles below explain each step in detail.

Figure 1. Google map roadmap view with building outlines.

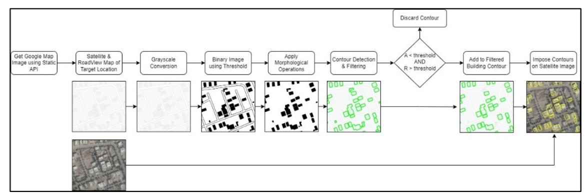


Figure 2. Flow diagram of the Roadmap-to-Satellite Building Detector (RSBD) process.

A. Converting Google Maps Images to Grayscale for Simplified Image Processing

Let $I_q(r,c)$ represent the "Roadmap" image where $q \in \{1\}$ and pixel value at row r and column c. The I_q image of the target location is obtained by passing the parameters like coordinates, zoom level, and size to the Google Maps Static API [22]. To simplify the image processing operations and reduce the amount of data that needs to be processed [46], the image I_q is converted to grayscale using the Eq. (1):

$$G_q(r,c) = 0.114 \cdot I(r,c,0) + 0.587 \cdot I(r,c,1) + 0.299 \cdot I(r,c,2) \quad (1)$$

where $I(r,c,0)$, $I(r,c,1)$, and $I(r,c,2)$ represent the values of the respective color channels of each pixel, and $G_q(r,c)$ is the resulting grayscale image. The choice of weights used in Eq. (1) was motivated by the well-established phenomenon that the human eye is more sensitive to green light compared to red or blue light [47]. Therefore, the green channel was given a higher weight in the computation, followed by the red and blue channels.

B. Thresholding Technique for Building Outline Extraction from Grayscale Images

Thresholding is a commonly used technique for converting a grayscale image into a binary image, where each pixel is classified as either foreground or background. Its goal is to make it easier to do additional picture analysis by separating the object of interest—in this case, building outlines—from the background. This study employed a binary thresholding approach, which allocates zero to all pixel values below the threshold and the maximum value to all pixel values above it. The maximum value of 255 and the empirically determined threshold value of 243 in Eq. (2) are based on the features of the building outlines in the grayscale image that was produced from Eq. (1). The following formula is used to apply the thresholding:

$$T(r,c) = \begin{cases} \text{maxval} & \text{if } G_q(r,c) > \text{thresh} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $G_q(r,c)$ is the intensity value of the grayscale image at pixel (r,c), thresh is the threshold value 243, maxval is the maximum value 255, and $T(r,c)$ is the resulting threshold image.

TABLE I. CRITICAL ANALYSIS OF EXISTING STUDIES ON BUILDING DETECTION IN AERIAL IMAGES

Year	Author	Method	Advantages	Limitations
2000	Zerubia et al. [26]	Chain-based models, fuzzy C-means algorithm, Markovian model.	• Texture parameter for luminance field. • No prior knowledge of classes required. • Tested on real satellite images.	• Limited to texture-based features. • May not generalize well to all urban areas. • Specific to certain satellite images.
2003	Benediktsson et al. [23]	Morphological and neural approaches	• Improved classification accuracy. • Few features needed. • Tested on high-resolution data.	• Specific to certain data sources (IRS-1C, IKONOS).
2018	Aamir et al. [28]	Singular value decomposition, line-segment detection	• Works with low contrast satellite images. • Accurate building line segment detection.	• Focuses on line segments, not complete building shapes.
2020	Avudaiammal et al. [29]	Morphological Building Index (MBI), SVM classifier	• Integrates multiple features. • Eliminates mislabeled rooftops. • Geometrical features used.	• Relies on multiple preprocessing steps. • Requires a labeled dataset for SVM training.
2016	Kohli et al. [[30]]	Object-oriented image analysis, textural feature contrast, spatial metrics	• Suitable for urban slum detection. • Qualitative and quantitative evaluation.	• Lower accuracy compared to land cover classification.
2005	Liu et al. [7]	Multi-scale object-oriented classification, probabilistic Hough transform, building squaring algorithm	• Accurate detection and extraction of rectangular building roofs.	• Specific to certain image types. • Multi-scale segmentation may be computationally expensive.
2019	Gavankar et al. [31]	Optimization of segmentation and shape parameters	• Focuses on building footprint extraction. • Evaluates completeness and correctness.	• Specific to HRS pansharpened IKONOS images.
2011	Dey et al. [32]	Shadow context, color tone, size, edge features, structural and geometric features, multi-level segmentation	• Utilizes various spectral and spatial features. • Shows promising results.	• Requires modifications for real-world applications. • Performance may vary with image quality.
2009	Karantzalos et al. [33]	Region-based level set segmentation	• Automated and converges quickly. • Detects roads, buildings, and man-made objects.	• Effectiveness may depend on image content and quality.
2020	Cao et al. [34]	Point cloud data processing, feature fusion	• Comprehensive analysis of point cloud data. • Addresses building characterization and labeling.	• Sensitivity to parameter settings. • May require careful tuning for different scenarios.
2023	Farhadi et al. [15]	Feature-Based Building Footprint Extraction (F2BFE)	• Focuses on monitoring urbanization growth. • Utilizes Sentinel-1 and 2 satellite images. • Automated approach.	• Dependent on Sentinel satellite data availability. • Effectiveness may vary with disaster types.
2015	Turker et al. [36]	SVM classification, edge detection, Hough transformation, perceptual grouping	• High accuracy in detecting industrial and residential buildings. • Sequential processing.	• Specific to certain imagery (Ikonos).
2023	Cao et al. [12]	Multi-scale weakly supervised learning, Class Activation Maps (CAM), pseudo labels	• Cost-effective approach. • Leverages multi-scale CAM and temporal correlations.	• Effectiveness may depend on label availability and quality. • May require large-scale datasets.
2020	Fallatah et al. [13]]	Object-based RF approach	• Effective in mapping informal settlements. • High overall accuracy.	• May not generalize well to different regions.
2021	Idris et al. [38]	Artificial Neural Network (ANN)	• High accuracy in building footprint extraction. • High computational efficiency.	• Performance may vary with dataset and model complexity.
2021	Ekici et al. [39]	Convolutional Neural Networks (CNNs)	• Robust damaged building detection method. • Optimized using Bayesian optimization.	• Effectiveness may depend on dataset and model optimization.
2022	Rastogi et al. [40]	UNet-AP architecture	• Improved building footprint extraction. • Outperforms baseline implementations.	• Specific to multispectral satellite imagery.
2021	Geo et al. [14]	SG-EPUNet model	• Updates building footprints in bi-temporal remote sensing images. • Incorporates deep learning and transfer learning. • Addresses limited post-change labels.	• May have limitations in updating small newly built buildings with low-resolution images.
2021	Zheng et al. [2]	ChangeOS framework	• Precise building object generation. • End-to-end building damage assessment.	• Framework-specific and may require additional labeled data. • Effectiveness may vary with disaster types.
2023	Ding et al. [42]	Semi-LCD method	• Enhances Binary Change Detection (BCD) performance with limited labeled samples. • Addresses model complexity.	• Effectiveness may depend on the availability of labeled data. • Complexity tradeoffs.
2021	Wang et al. [43]	CNNs for corner and line segment detection, collaborative branch for semantic annotation	• Detects structured building rooflines. • Promotes 3D reconstruction and other applications.	• Specific to structured building rooflines. • Evaluation may vary with different datasets.
2023	Mohammadian et al. [44]	SiamixFormer siamese model	• Uses pre- and post-disaster images for building and change detection. • Utilizes hierarchical transformer architecture.	• May require large datasets for optimal performance. • Performance depends on the quality of input images.

C. Morphological Operations for Binary Image Processing: Closing Operation with Structuring Elements

A crucial part of image processing is morphological operations, which are commonly used to work with binary images, where the pixels have binary values of 0 or 1. Because these procedures can change the shape and structure of binary images, they have a wide range of applications, such as object detection, smoothing, and noise removal [48]. These techniques offer ways to enhance image quality, extract significant information, and get images ready for further processing or analysis. The morphological operation carried out in Eq. (3) is closing, which entails applying erosion and dilation procedures one after the other. In order to improve object detection accuracy in later processing stages, the closing procedure is used to fill in tiny gaps in foreground objects [23].

$$M_q(r,c) = (T(r,c) \oplus K) \ominus K \tag{3}$$

The following is the mathematical expression (3) for the closing operation carried out in this investigation. Let K be the structuring element, let $T(r,c)$ be the input binary image, and let $\oplus$ and $\ominus$ stand for dilation and erosion operations, respectively. Image $T(r,c)$ is first dilated using the structuring element K, and then it is eroded using the same structuring element K. Following the operation, the final image is saved as $M_q(r,c)$.

D. Contour Detection for Object Recognition and Segmentation

Applications for contour detection include object recognition, tracking, and segmentation. It is an essential procedure for determining the borders that divide multiple objects or areas inside an image. In order to highlight picture features and make the $M_q(r,c)$ binary image from Eq. (3) suitable for contour detection, it is subjected to morphological processes such as erosion or dilation. As a result, this method may be applied to detect the borders between highways, buildings, and other objects in a picture [49]. In this study, by using Eq. (4), all the contours are retrieved and used to construct a full hierarchy of nested contours. The contour approximation method employed compresses horizontal, vertical, and diagonal segments, leaving only their endpoints. Mathematically, contour detection can be represented as follows:

$$C = \text{findContours}(M_q(r,c), \text{Mode}, \text{Method}) \tag{4}$$

In the mathematical Eq. (4) of contour detection, the binary image $M_q(r,c)$ is subjected to contour detection with the use of two parameters: Mode, which specifies the contour retrieval mode, and Method, which specifies the contour approximation method. The resulting output C is a list of detected contours.

E. Building Contour Filtering Based on Area and Aspect Ratio

As mentioned previously, Google's machine learning algorithms analyze satellite and aerial imagery to identify and map the shapes of buildings. However, these building outlines may not always be accurate, as shadows, vegetation, or other features can sometimes be misinterpreted as building outlines. Commonly used geometric metrics, such as area or length-width ratio, can help remove small, noisy items or elongated objects such as roads [6].

To eliminate object contours in an image that are not classified as buildings, two filtering conditions are applied based on their area and aspect ratio. In Eq. (5), first, contours with an area less than 500 pixels are considered too small to be a building and are discarded. Second, contours with an aspect ratio of the bounding rectangle less than 0.5 are considered too narrow to be a building and are also discarded. The values of 500 for the area and 0.5 for the aspect ratio were chosen empirically based on the image resolution and the desired level of accuracy for detecting building outlines. These filtering conditions exclude contours that are unlikely to represent buildings, thus improving the accuracy of subsequent processing steps.

$$B = \begin{cases} \text{building} & \text{if area} > 500 \wedge \text{aspect\_ratio} > 0.5 \\ \neg\text{building} & \text{otherwise} \end{cases} \tag{5}$$

Where,

$$\text{area} = 0.5 \times |(x_1y_2 - x_2y_1) + \cdots + (x_ny_1 - x_1y_n)| \tag{6}$$

and,

$$\text{aspect\_ratio} = \frac{w}{h} \tag{7}$$

The filtered list of building contours is represented by B, which is obtained by applying two conditions based on the area and aspect ratio of the contours. Here, the symbol $\neg$ represents the logical NOT operator, and the caret symbol $\wedge$ represents the logical AND operator. The resulting list B contains only the contours that satisfy both conditions and are identified as buildings. Eq. (6) calculates the area of a contour, where n is the number of points in the contour and (x_i, y_i) are the coordinates of the ith point in the contour. The vertical bars $|\ldots|$ indicate the absolute value of the sum of the terms inside. The aspect ratio of the contour is then calculated in Eq. (7) as the ratio of the width (w) to the height (h), normalized by converting the w value to a floating-point number and dividing it by h.

F. Buildings Detection and Visualization of Identified Buildings on Satellite Images

Finally, the filtered contour list is superimposed on the satellite image of the target location, providing a visual representation of the identified buildings within the image. Building outlines from Google Maps are used as a baseline by the Roadmap-to-Satellite Building Detector (RSBD), which offers an effective method of detecting buildings from satellite photos. This approach may find use in construction monitoring, disaster response, and urban planning.

IV. Test Cases Analysis

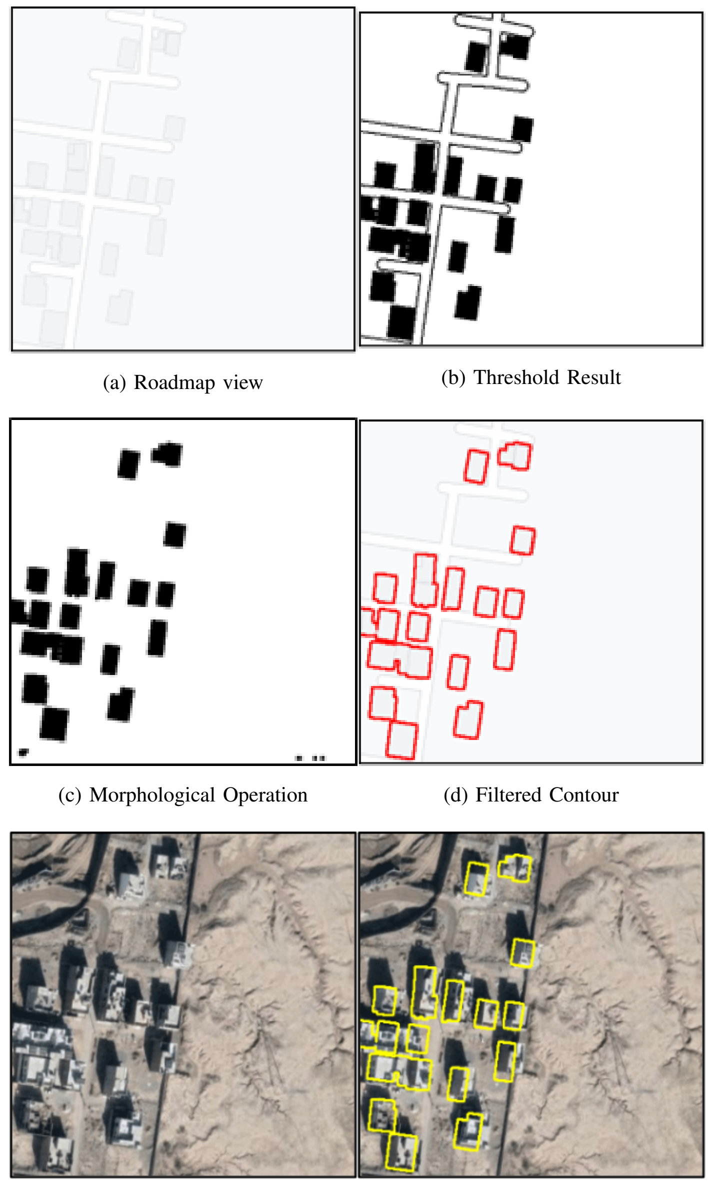
The trials carried out to assess the effectiveness of the Roadmap-to-Satellite Building Detector (RSBD) methodology are detailed in this section. In order to evaluate RSBD's robustness and generalizability in identifying distinct building kinds in difficult situations, the study tests it on a varied collection of Google Maps photos from different parts of the world in Section VI(A). Furthermore, a quantitative comparison of the detection findings with ground truth data is provided in Section IV(B). Metrics like True Positives had to be calculated for this analysis. False Negatives, False Positives, Completeness, Correctness, and Quality to measure the accuracy and effectiveness of Roadmap-to-Satellite Building Detector (RSBD). Furthermore, Section VII explains our rationale for using a specific threshold value of 243 for thresholding grayscale images consistently throughout our experiments.

A. Qualitative Analysis

33 Google Map [20] photos taken from various parts of the world, including Pakistan, Canada, the United Arab Emirates, India, Yemen, and Thailand, were used to test the Roadmap-to-Satellite Building Detector (RSBD). These regions presented significant challenges due to variations in building types, number of buildings, materials, and occlusions by objects such as trees and shadows. Out of these 33 images, six were acquired from different sites in Pakistan, six from Canada, five from UAE, six from India, five from Yemen, and five from Thailand. The objective of testing the methodology on different regions of the world was to evaluate its robustness and generalizability to various urban areas with varying characteristics. Some building detection results can be found in the following paragraphs.

B. RSBD Performance in Identifying Small Buildings in Sub-Urban Areas: Test Case in Quetta, Pakistan

In this study, we took a series of actions through the roadmap-to-Satellite Building Detector (RSBD) process and reported the detailed results in Fig. 3 based on the test case concerning satellite low-rise building extraction in residential areas. The selected image, shown in the Fig. 3, is a view of an area, which is a suburb of Quetta, Pakistan, was taken using Google maps, [50](let:30.2668639, and long: 66.9495658). The RSBD was tested at identifying small buildings, typically residential buildings that tend to be low and have small footprints with this case. The RSBD procedure consists of processes such as contour detection, filtering, and classification. First, detected contours on the roadmap view are filtered with two conditions, namely area and aspect ratio. This is done by establishing criteria to determine if the contour smatch what is regarded as a typical building in terms of shape and size. Contours that are too small or have aspect ratios that do not correspond to regular building sizes, for example, are eliminated. This step is important as it helps to reduce the occurrence of false positives wherein some other features which are not buildings, or other such life is wrongly detected as buildings. This filtering is shown on the output of Fig. 3(d) where some contours are filtered out based on less than meets the conditions set. By aggregating data from various sources through a rigorous selection process, the accuracy of the building detection mechanism drastically improves, as only authentic buildings get recognized. Also, the result presented in Fig. 3(f) confirms the RSBD's ability to correctly pinpoint and delineate small structures. This ensures accuracy for urban planning and development in suburban areas where identification of the spatial distribution of residential structures is critically important. Of specific interest for application development, building detection can be highly beneficial for housing development, infrastructure deployment, resource allocation and disaster management strategies. The RSBD process plays an important role in enabling evidence-based urban & suburban development decisions by effectively mapping and monitoring these structures.



(a) Roadmap view (b) Threshold Result

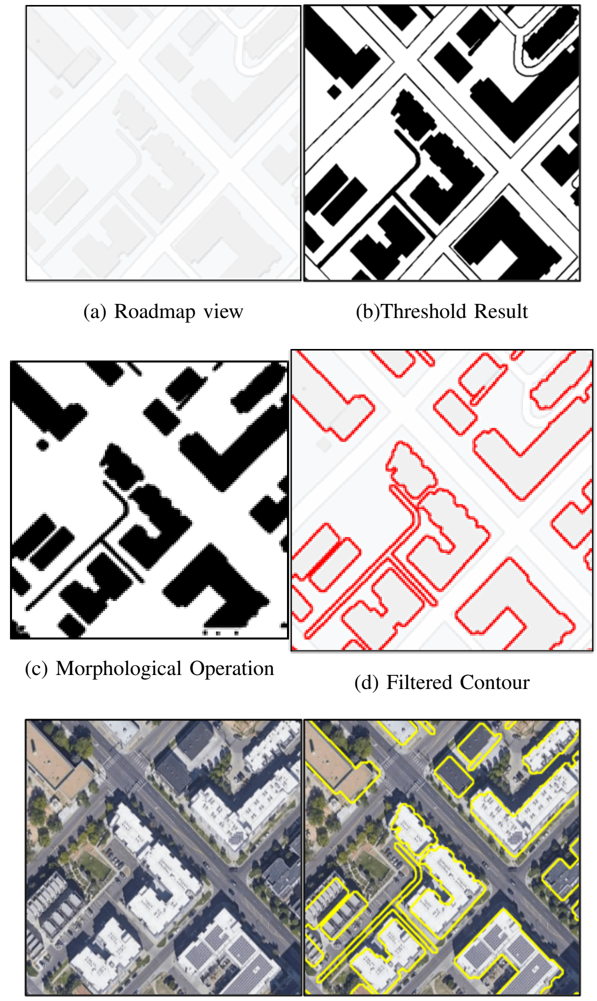
(c) Morphological Operation (d) Filtered Contour

(e) Satellite view (f) Detected Buildings

Figure 3. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies small residential buildings in sub-urban areas: A test case in Quetta, Pakistan.

C. RSBD Performance in Identifying High-Rise Buildings: Test Case in Denver, Canada

Fig. 4 [51] is an example of a test scenario with satellite image of urban region with tall buildings. A satellite imagevfrom Google Maps [44] of the commercial buildings in Denver Canada along the heights at latitude 39.7491684 and longitude -104.980819 The specific test case was devised to test the strength of the roadmap-to-Satellite Building Detector (RSBD) to detect several enormous high-rise buildings (tall commercial structures with large footprints) in the scene [5]. These structures are typically located in business districts or as part of a downtown area, making building detection particularly challenging due to their scale and architectural complexity. Therefore, the manual collection of such data is both rich in time and labor cost, which comprise limitations to collection of data and task automation, allowing the RSBDs ability for such high-rise buildings detect, classification as prerequisite for requirement on order chronicles such, namely, environmental, disaster, urban planning applications. With the rapid growth of urbanization, the accurate recognition and monitoring of high-rise buildings became crucial for sustainable city management. They hold significance as social and economic constructs in cities across the world. Their existence impacts the skyline and cityscape, infrastructure demands, emergency services and more. As shown in Fig. 4(f), the RSBD can accurately identify and delineate these structures, indicating its potential to advance in these areas. The successful outcome demonstrates the ability of the RSBD to accurately delineate large high-rise buildings with meaningful implications for urban development and management. Such literacy contributes to the sustainable development of cities by promoting more efficient infrastructure investment, urban planning and emergency responses. The RSBD provides valuable information about the stuff of high-rise buildings, records data on their location and dimensions, and allows urban planning decision-making to be better informed, leading to more efficient resource allocation and improved resilience to natural or human-made disasters.



(a) Roadmap view (b)Threshold Result

(c) Morphological Operation (d) Filtered Contour

(e) Satellite view (f) Detected Buildings

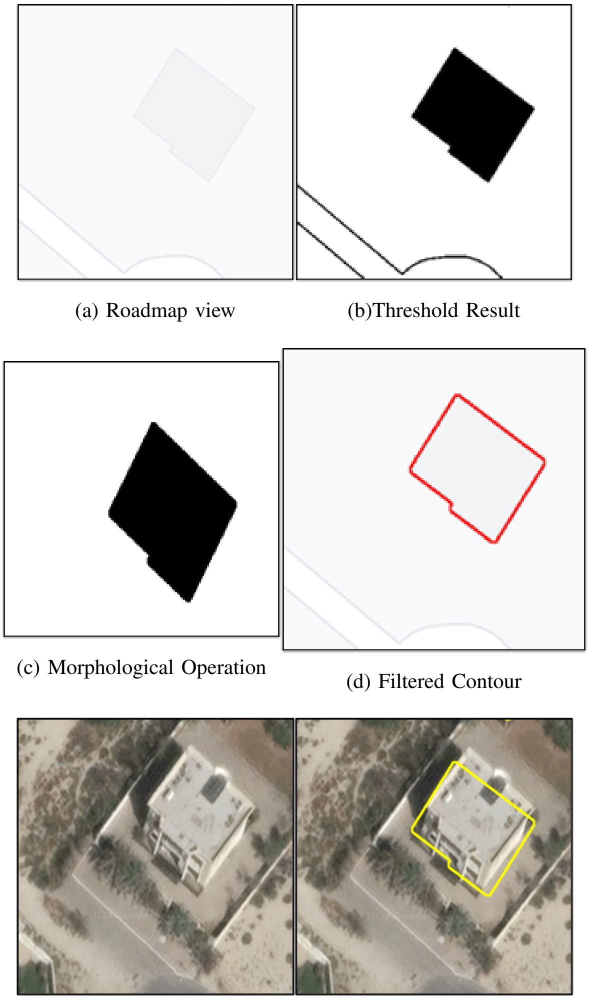
Figure 4. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies high-rise commercial buildings: A test case in Denver, Canada.

D. RSBD Performance in Identifying Individual Structures: Test Case in Dubai, UAE

The performance of the roadmap-to-Satellite Building Detector (RSBD) in identifying a single structure was evaluated using a test image urban areas with a single structure (see Fig. 5). Moving to the next step, we extracted the geographical coordinates of the building: a building in Dubai, United Arab Emirates with latitude (25.0980968) and longitude (55.2373434) [52]. This case was used to test the RSBDs ability to highlight on only one building from an image in an urban filled setting. The results show that RSBD was able to locate and delineate the only building in the image, suggesting it is effective on such images. This is useful in numerous use cases like disaster response, infrastructure assessment, urban planning, etc. In crowded urban centers such as Dubai, it is important to properly identify and track individual buildings. The RSBD supports these efforts through mapping and monitoring isolated buildings with a high degree of precision. Accurate identification is vital for work that includes the assessment of the state of individual buildings, urban planning optimization and effective emergency response in big cities. Focusing on individual buildings can improve the accuracy and effectiveness of urban management strategies, from assessing structural integrity after a natural disaster to planning new infrastructure projects. This ability of the RSBD to compute such analyses positions it as a crucial tool for urban planners, emergency responders, and infrastructure modelers alike, providing them with valuable insights upon which they can rely confidently.

E. RSBD Performance in Detecting Multiple Buildings: Test Case in Mumbai, India

Satellite view from Google Maps [53] in Fig. 6 showing an urban area in Mumbai, India, latitude:19.088443, longitude: 72.9033463. This test case tested the capability of our Roadmap-to-Satellite Building Detector (RSBD) to identify multiple buildings that are closely clustered in a single image. Development of the test area covered urban and suburban buildings of varying height, shape, and type representative of the Mumbai skyline The outcomes illustrated in Fig. 6(f) confirm the RSBD's ability to correctly label and segment multiple structural elements of the image. This capability is

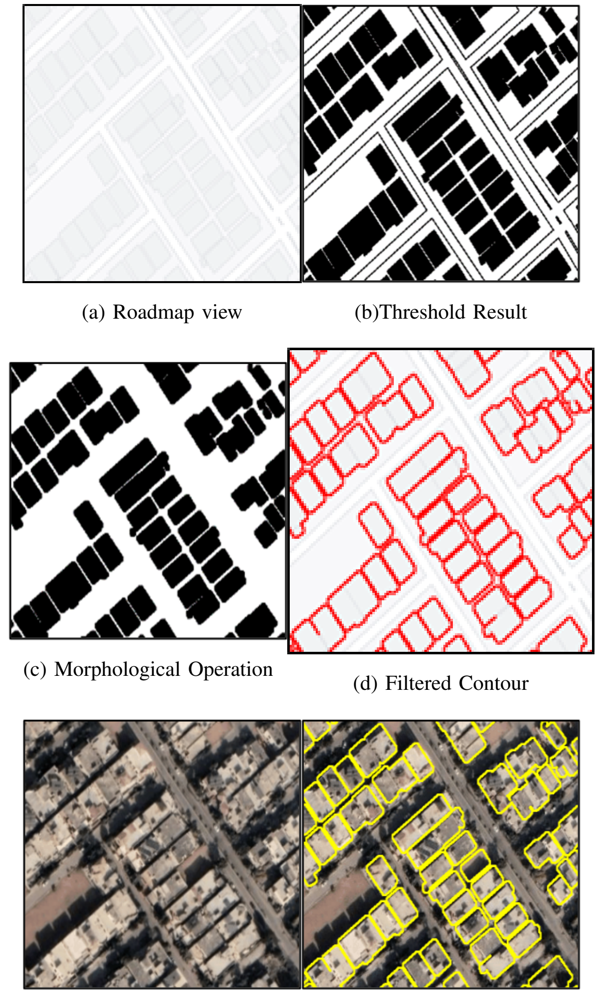


(a) Roadmap view (b)Threshold Result

(c) Morphological Operation (d) Filtered Contour

(e) Satellite view (f) Detected Buildings

Figure 5. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies high-rise commercial buildings: A test case in Dubai, UAE.



(a) Roadmap view (b)Threshold Result

(c) Morphological Operation (d) Filtered Contour

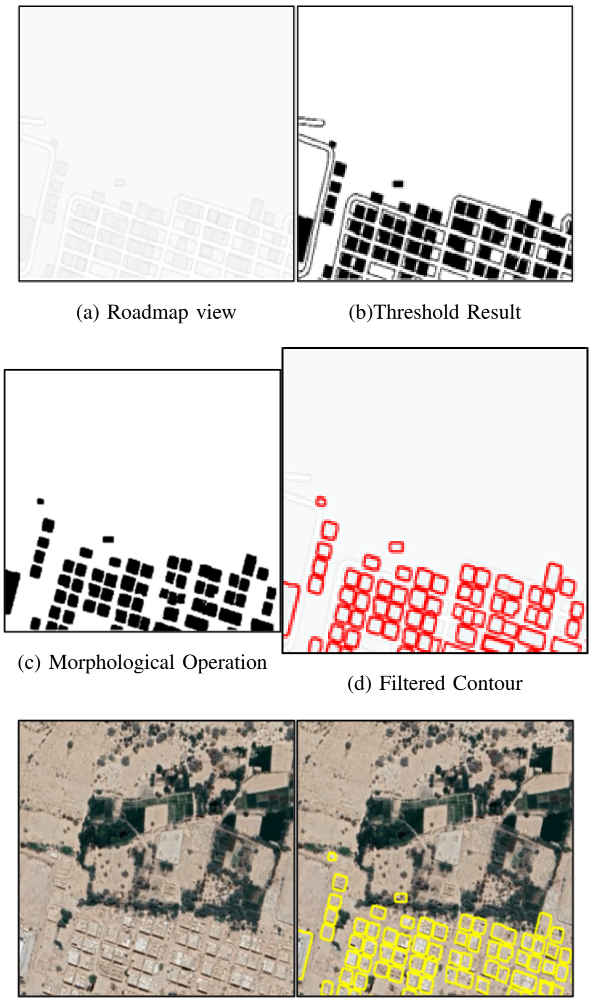
(e) Satellite view (f) Detected Buildings

Figure 6. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies high-rise commercial buildings: A test case in Mumbai, India.

especially vital in crowded areas such as Mumbai, where up-to-the-minute information about buildings is critical for all manner of urban management tasks. Precise building detection aids infrastructure development, land-use planning, and disaster management, critical elements for sustainable urban development and resilience. The success of the RSBD at detecting buildings of various sizes and types highlights its versatility and adaptability across urban environments. This functionality is a boon for urban analysts and urban planners worldwide, as it improves the eviction mapping with better accuracy and aids in decision making at various levels. Regardless of the definition, the RSBD's reliability at identifying numerous structures mean that it will be an important tool for urban planners, whether it be for efficiently formulating infrastructure needs in high-density urban areas or keeping track of the suburbs.

F. RSBD Performance in Detecting Earthen Buildings: Test Case in Shibam, Yemen

Houses are built from mud in many other parts of the world which we call earthen houses. This construction material is common in many areas since it is easily available and is comparatively cheap. However, many of these structures have spectral characteristics comparable to their environment, making them difficult to detect using conventional methods. The result of a case of satellite image of Shibam, Yemen with coordinates (15.9223003, 48.6393691) [54] is represented in Fig. 7. Shibam is famous for its mud-brick structures dating back centuries and representing the traditional building style of the area. This test aimed to evaluate the performance of RSBD in the detection and segmentation of buildings in cases where the spectral differences between the buildings and the surrounding terrain are weak. As shown in Fig. 7, it is apparent that the RSBD was able to accurately separate the mud houses from their surroundings, whilst also suppressing the background landscape in the process due to spectral similarity. This finding highlights the strength and versatility of the RSBD to identify buildings built with natural materials, which are prevalent in rural, and some urban, areas across the globe. Capability of classifying such buildings is important for urban planning, heritage conservation, and disaster management, especially in areas of the world where earthen houses predominate. It aids efforts to keep current records of building inventories and to ensure appropriate measures are taken to decorate architectural heritage and for disaster preparedness. The success of the RSBD in these challenging detection scenarios validates its potential as a versatile tool that can be utilized in several distinct geographical and cultural settings.



(a) Roadmap view (b)Threshold Result

(c) Morphological Operation (d) Filtered Contour

(e) Satellite view (f) Detected Buildings

Figure 7. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies high-rise commercial buildings: A test case in Shibam, Yemen.

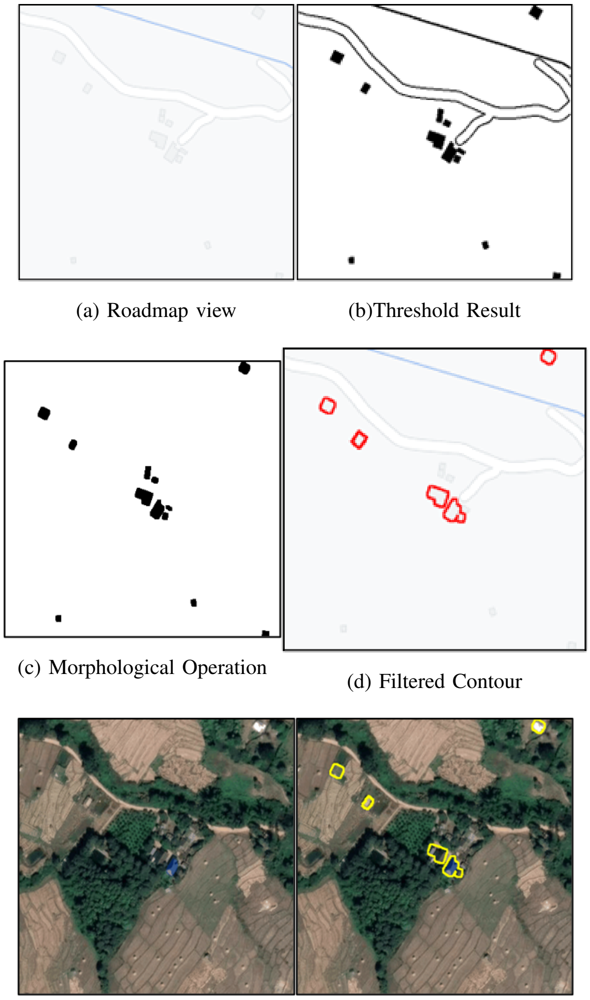
G. RSBD Performance in Detecting Buildings Obstructed by Objects: Test Case in Thailand

The last test scenario was used to assess the ability of the roadmap-to-Satellite Building Detector (RSBD) S2 to detect buildings that are difficult to identify given the surrounding features of the environment, which may include various obstructions (trees and shadows). For many of these real-world scenario's buildings can be fully or partially hidden from sight, leading to misclassification when detecting buildings in satellite data because of the Spectro-physical overlap between the elements hiding buildings. Fig. 8 shows the satellite image from Google Maps, is a suburb region in Thailand latitude 19.3287643, longitude 98.3887638 [47] [55]. House have forest,3D Rendering The difficulty of RSBD monitoring with the vegetative coverage of buildings, which may impede image processing conventional methods. Fig. 8(f) shows the overall effectiveness of the RSBD in accurately segmenting anatomy across all patients, even in such challenging scenarios. And even though some buildings were covered by trees, the RSBD has been able to tell the difference and remains an advanced detection tool in cases where natural elements hinder visibility. This feature is vital for applications like urban forestry management, land-use planning, and disaster response, where accurate recognition of concealed buildings is crucial for sound decision-making and resource allocation.

The RSBD has demonstrated strong performance in both obscured and unobscured conditions (79.9% and 73.1%, respectively), reinforcing the ability to reliably detect person-borne threats in different environmental contexts. Such robustness allows for its utilization for many remote sensing applications and urban studies and helps maintain accurate inventories of buildings and preparedness against natural or human-made disasters. Overall, this successful detection of hidden structures is a powerful enhancement of the utility of the RSBD in a wide range of settings, further validating its utility as a general-purpose solution to complex urban detection problems.

H. Quantitative Analysis

A quantitative comparison of the detection results with the ground truth was used to validate the Roadmap-to-Satellite Building Detector (RSBD). The evaluation results of the RSBD approach applied to a set of 33 test photos sourced from Google Map satellite imagery are displayed in Table II. We gathered satellite imagery for every nation, concentrating on certain categories like “Earthen Buildings,” “Multiple Buildings,” “Individual Building,” “High-rising Buildings,” “Small Buildings,” and “Buildings Obstructed”. True Positives (TP), False Negatives (FN), and False Positives (FP) are evaluation metrics that are derived from ground truth data and are essential parts of detection accuracy measurements. After a thorough, careful, and time-consuming process of photo interpretation, an expert manually constructed and annotated the ground truth, which includes the precise locations of the buildings. Furthermore, three quality metrics are presented and computed using the previously specified detection metrics: Completeness, Correctness, and Quality [56]. Specifically, FP stands for the number of buildings that were not found in the image, FN for the structures that were not found, and TP for the number of buildings that were correctly identified. According to Eq. (8), completeness is the number of real structures found in the picture. According to Eq. (9), correctness is a metric that quantifies the proportion of detected buildings that were, in fact, buildings. Completeness and Correctness are combined to create Quality, which is a measure of the algorithm's overall performance as given by Eq. (10). Therefore, one can assess an algorithm's efficacy and accuracy in identifying buildings



(a) Roadmap view (b)Threshold Result

(c) Morphological Operation (d) Filtered Contour

(e) Satellite view (f) Detected Buildings

Figure 8. Roadmap-to-Satellite Building Detector (RSBD) successfully identifies high-rise commercial buildings: A test case in Thailand.

in an image by computing these three measures.

$$\text{Completeness} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{8}$$

$$\text{Correctness} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{9}$$

$$\text{Quality} = \frac{2 \times \text{Completeness} \times \text{Correctness}}{\text{Completeness} + \text{Correctness}} \times 100\% \tag{10}$$

With an average Completeness score of 79%, the Roadmap-to-Satellite Building Detector (RSBD) does a respectable job of identifying buildings in the test photos, according to the data shown in Table II. This suggests that over 80% of the real structures in the pictures can be identified by the RSBD. Furthermore, the majority of the recognized buildings appear to be real buildings, as indicated by the average Correctness score of 9%. The RSBD achieves a reasonable balance between correctness and completeness, as seen by its average Quality score of 85%.

TABLE II. Evaluation of the Detection Results in the Test Image Set

Country	Satellite Image	TP	FN	FP	Complete	Correct	Quality
Pakistan*	Small Buildings (1)	17	4	1	81%	94%	87%
	Small Buildings (2)	23	3	4	88%	85%	87%
	High-rising Buildings	6	1	0	86%	100%	92%
	Single Building	1	0	0	100%	100%	100%
	Multiple Buildings	22	4	2	85%	92%	88%
	Earthen Buildings	20	2	0	91%	100%	95%
Canada*	Small Buildings	16	3	0	84%	100%	91%
	High-rising Buildings	6	1	1	86%	86%	86%
	Single Building	1	1	0	50%	100%	67%
	Multiple Buildings (1)	19	5	2	79%	90%	84%
	Multiple Buildings (2)	21	5	0	81%	100%	89%
	Buildings Obstructed	8	2	0	80%	100%	89%
UAE*	Small Buildings	17	9	0	65%	100%	79%
	High-rising Buildings	8	1	0	89%	100%	94%
	Multiple Buildings (1)	20	6	1	77%	95%	85%
	Multiple Buildings (2)	23	3	3	88%	88%	88%
	Earthen Buildings	22	4	0	85%	100%	92%
India*	Small Buildings (1)	18	8	2	69%	90%	78%
	Small Buildings (2)	16	10	1	62%	94%	74%
	High-rising Buildings	4	0	1	100%	80%	89%
	Multiple Buildings (1)	19	7	1	73%	95%	83%
	Multiple Buildings (2)	21	5	1	81%	95%	87%
	Buildings Obstructed	6	3	1	67%	86%	75%
Yemen*	Small Buildings	23	3	2	88%	92%	90%
	Single Building	1	0	0	100%	100%	100%
	Multiple Buildings (1)	22	4	1	85%	96%	90%
	Multiple Buildings (2)	17	9	2	65%	89%	75%
	Earthen Buildings	20	6	4	77%	83%	80%
Thailand*	Small Buildings	18	8	1	69%	95%	80%
	High-rising Buildings	9	2	0	82%	100%	90%
	Multiple Buildings (1)	19	7	3	73%	86%	79%
	Multiple Buildings (2)	21	5	2	81%	91%	86%
	Buildings Obstructed	4	1	1	80%	80%	80%

It is important to note, too, that the RSBD performs differently in various geographical areas. In particular, the RSBD outperforms Yemen and India in terms of construction detection in Pakistan, Canada, the United Arab Emirates, and Thailand. This regional variation in performance suggests that variables like geographic features and differences in building kinds and densities may have an impact on the RSBD accuracy.

V. Results

The performance of the Roadmap-to-Satellite Building Detector (RSBD) is demonstrated in Fig. 9 utilizing six distinct satellite pictures from Pakistan, with an emphasis on the identification of various building types. In terms of quality evaluation and detection accuracy, the data shows encouraging outcomes. Notably, RSBD received a 95% overall quality score for "Earthen Buildings," with 91% completeness and 100% accuracy. Likewise, for "Multiple Buildings," the RSBD revealed an overall quality score of 88%, a completeness of 85%, and an accuracy of 92%. RSBD obtained a perfect completeness and correctness rate of 100% for "Individual Building" detection. Furthermore, RSBD demonstrated excellent completeness scores of 86% and 81% for "High-rising Buildings" and "Small Buildings," respectively, in addition to high accuracy rates, yielding overall quality ratings of 9% and 87%, respectively. These results highlight how well the Roadmap-to-Satellite Building Detector (RSBD) can recognize a variety of building types across Pakistan's regions.

Figure 9. Roadmap-to-Satellite Building Detector (RSBD) Performance Across Different Satellite Images in Pakistan.

The performance of the Roadmap-to-Satellite Building Detector (RSBD) across six distinct satellite pictures in Canada is shown in Fig. 10. Among the many image categories, RSBD demonstrated a remarkable degree of accuracy, with correctness ranging from 86% to 100%. The RSBD technique is strong, as seen by its completeness, which ranges from 50% to 86% and assesses the capacity to discover true positives. The total RSBD quality ranges from 67% to 91%, demonstrating how well RSBD can recognize buildings in satellite imagery from a variety of Canadian locales.

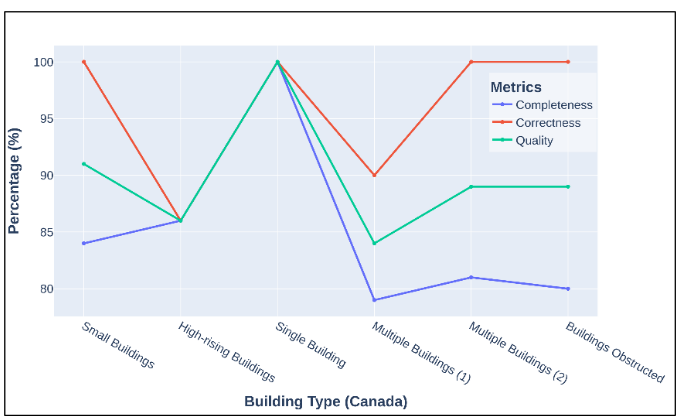


Figure 10. Roadmap-to-Satellite Building Detector (RSBD) Performance across different satellite images in Canada.

Findings from an examination of satellite imagery from different parts of the United Arab Emirates (UAE) are shown in Fig. 11, with an emphasis on the identification of distinct building types. The Roadmap-to-Satellite Building Detector (RSBD) performance in these categories is shown in the graph, which shows encouraging outcomes. Notably, RSBD received an overall quality score of 85% for the "Multiple Buildings" category, with 77% completeness and 95% accuracy. Likewise, with "Earthen Buildings," RSBD achieved a remarkable 85% completeness and 100% accuracy, yielding a 92% quality score. For "Small Buildings" and "High-rising Buildings," respectively, RSBD demonstrated high accuracy rates of 100% and outstanding quality scores of 79% and 94%. These findings underscore the potential of Roadmap-to-Satellite Building Detector (RSBD) in accurately identifying diverse building types in UAE satellite imagery, contributing to advancements in remote sensing applications.

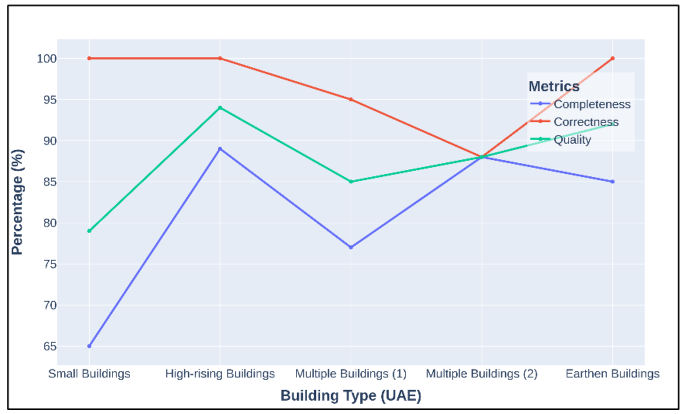


Figure 11. Roadmap-to-Satellite Building Detector (RSBD) Performance across different satellite images in UAE.

The performance of the Roadmap-to-Satellite Building Detector (RSBD) on six distinct satellite photos of India is shown in Fig. 12. According to the graph, when recognizing several buildings, the Roadmap-to-Satellite Building Detector (RSBD) obtained an exceptional average completeness rate of 77% and an accuracy rate of 95%, yielding a quality score of 83%. RSBD obtained a 78% overall quality score, a 66% completeness rate, and a 92% accuracy rate for small buildings. Furthermore, with 100% completeness and 80% correctness rate, RSBD demonstrated exceptional performance in identifying high-rise buildings, earning an 89% quality score. RSBD obtained a quality score of 75%, a correctness rate of 86%, and a completeness rate of 67% when working with obstructed buildings. These results highlight how well Roadmap-to-Satellite Building Detector (RSBD) can recognize and classify buildings in satellite photos, especially when it comes to seeing several, tall buildings. A thorough examination of satellite image data from multiple Yemeni regions is shown in Fig. 13, with an emphasis on the identification of distinct building types. With completeness ranging from 65% to 100% and correctness ranging from 83% to 100%, the graph shows encouraging results in terms of detection accuracy. With an average score of 87%, the overall quality of the buildings that were detected likewise shows excellent performance. With the best performance seen in the recognition of individual buildings, these results demonstrate the promise of the Roadmap-to-Satellite Building Detector (RSBD) for precise building detection in Yemen.

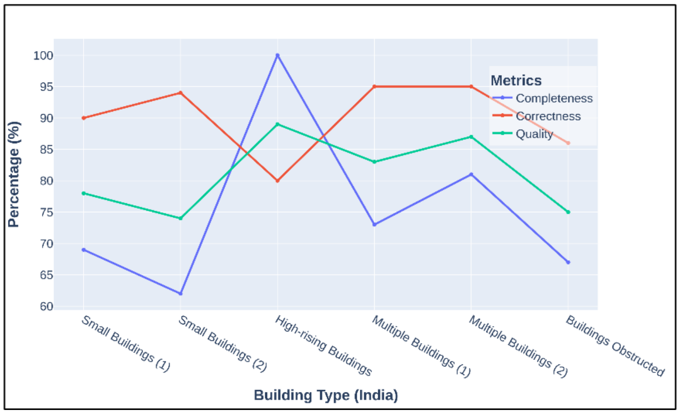


Figure 12. Roadmap-to-Satellite Building Detector (RSBD) Performance across different satellite images in India.

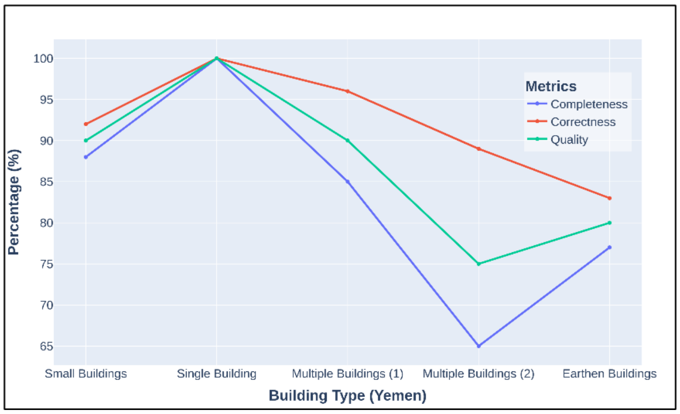


Figure 13. Roadmap-to-Satellite Building Detector (RSBD) Performance across different satellite images in Yemen.

Findings from satellite photos of different parts of Thailand are shown in Fig. 14, with an emphasis on identifying structures and classifying them according to their kind. Significant differences in the performance metrics between the various building categories are shown in the graph. For example, Roadmap-to-Satellite Building Detector (RSBD) received a 79% overall quality score in the "Multiple Buildings" category, with 73% completeness and 86% accuracy. Conversely, the "Small Buildings" category had an overall quality score of 80% due to its higher accuracy of 95% and lower completeness of 69%. These results highlight how crucial it is to modify detection tactics according to particular building types when using satellite data for urban study in Thailand. Moreover, the "High-rising Buildings" category demonstrated exceptional performance with an 82% completeness, 100% correctness, and a remarkable overall quality score of 90%. This suggests that RSBD excels in detecting taller structures in these satellite images.

VI. Discussion

This section presents and analyzes the findings from the Roadmap-to-Satellite Building Detector (RSBD) approach. In addition to exploring the findings' wider ramifications, the discussion will offer an interpretation of these results in light of earlier research and working ideas.

Figure 14. Roadmap-to-Satellite Building Detector (RSBD) Performance across different satellite images in Thailand.

A. *Robustness and Generalizability*

The robustness and generalizability of RSBD were demonstrated by the qualitative study conducted in several geographical areas. Despite differences in building kinds, sizes, materials, and occlusions, RSBD was able to detect buildings in a variety of scenarios. The methodology's flexibility to diverse urban settings is demonstrated by its high performance in several regions. These results are consistent with earlier research that emphasized the significance of creating reliable building detection techniques for satellite photography, considering the variety of urban settings found throughout the world.

B. *Detection Accuracy*

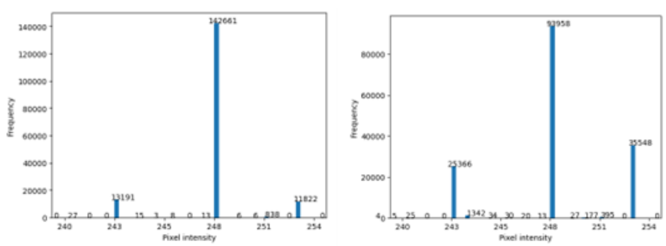
The quantitative analysis offered a thorough evaluation of the detection accuracy of RSBD. The performance was assessed using the True Positives (TP), False Negatives (FN), and False Positives (FP) measures. With an average completeness score of 79%, the approach was able to identify roughly 79% of the real structures in the test photos. The bulk of the structures that were spotted were, according to the average accuracy score of 93%, genuine positives. A good balance between completeness and correctness was indicated by the quality score, which averaged 85%. One significant finding is the regional variance in performance, with RSBD doing better in certain areas than others. Variations in image quality, building density, and geographic elements could all be responsible for this discrepancy. It highlights that in order to achieve the best results, the methodology must be modified to account for certain area features. Additionally, it is in line with earlier studies that have emphasized the difficulties in detecting buildings in various geographical locations.

C. *Machine Learning vs. Image Processing*

The fact that RSBD relies on image processing methods rather than machine learning or deep learning algorithms is one of its noteworthy features. Benefits of this option include lower data needs, resilience to changes in weather and lighting, and efficiency when dealing with partially blocked structures. These benefits are consistent with the drawbacks of machine learning models that were covered in the introduction, where issues with data quality, generalization, and environmental sensitivity were noted. Because machine learning and deep learning techniques work well on particular datasets, they have frequently been preferred in earlier research for constructing detection. Nevertheless, RSBD's findings imply that image processing methods can outperform machine learning models in certain areas while still producing competitive outcomes. This discovery adds to the continuing debate on whether methods are best suited for building detecting jobs.

VII. Threshold Value Analysis

As mentioned earlier, thresholding is a commonly used technique to convert grayscale images into binary images by classifying each pixel as foreground or background. This approach is particularly useful in separating the object of interest, which in this study pertains to building outlines, from the background and streamlining subsequent image analysis. In this study, a threshold value of 243 was consistently employed throughout all experiments. This choice was made after a thorough examination of the features of the building outlines in the grayscale pictures. Fig. 15 shows the histogram of pixel intensity values for two grayscale images acquired using Eq. (1) in various test scenarios to further clarify our choice. These graphs demonstrate that 243, 249, and 253 were the intensity values that appeared most frequently in the grayscale photographs. These specific intensity values were found to correlate with ground, roads, and building outlines, respectively, after empirical investigation.



(a) Test Image 1 (b) Test Image 2

Figure 15. Threshold selection for building outlines in grayscale images: Using pixel intensity histogram analysis.

This study led to the selection of 243 as the threshold value for all studies. This choice was made since it was discovered that this specific intensity value worked best for recognizing building outlines in the grayscale pictures. Additionally, the Roadmap-to-Satellite Building Detector (RSBD) produced great results, showing that this method of detecting buildings from satellite photos has several uses, such as urban planning and catastrophe management. This method allows us to precisely recognize and examine building outlines from satellite photos, yielding insightful information for a range of uses.

VIII. Conclusion

The experimental findings show that the Roadmap-to-Satellite Building Detector (RSBD) has the ability to automatically identify and categorize buildings in satellite imagery from Google Maps. The approach successfully recognized and categorized buildings in six global locations, including low-rise and high-rise, urban and rural, and successfully handled single and multiple structures in an image. To improve the precision and resilience of the detection process, this methodology makes use of sophisticated capabilities, such the Google Maps Roadmap view, and uses contour filtering and morphological procedures. Furthermore, it is well-suited for universal applications due to its adaptability to different building kinds, sizes, and shapes throughout worldwide areas. Nevertheless, this suggested approach has a drawback. The RSBD method uses Google Maps Road Map view's footprints to identify structures in satellite photos. As a result, RSBD won't recognize buildings whose outlines Google has supplied are out-of-date or missed by Google's algorithm. The significance of regional adaptation is highlighted by the regional differences in RSBD's performance. Future studies might concentrate on adjusting the methodology to particular geographical areas while accounting for elements like construction types, regional materials, and environmental circumstances. This modification may result in improved precision and dependability in many settings. Even though RSBD mostly uses image processing, future studies might look into using machine learning or deep learning methods to improve its functionality even more. To increase detection accuracy, machine learning models could be trained to adjust to local variables. Even greater outcomes could be achieved by combining the advantages of machine learning with image processing. To sum up, the Roadmap-to-Satellite Building Detector (RSBD) presents a viable way to address the difficulties associated with automatically identifying and categorizing buildings in satellite imagery. The methodology's potential for worldwide applications is demonstrated by its resilience and flexibility in a variety of urban settings. Future research and development in the area of automatic building detection and classification from high-resolution satellite data can benefit greatly from the conclusions of this work.

Authors' Contribution

Mr. Arbab Sufyan Wadood: Conceptualization, Methodology, Data Collection, Writing – Original Draft, Dr. Ahthasham Sajid: Data Analysis, Software Development, Validation, Dr. Muhammad Mansoor Alam: Literature Review, Formal Analysis, Writing – Review & Editing, Dr. Mazliham MohD Su'ud: Supervision, Project Administration, Funding Acquisition, Mr. Arshad Mehmood: Formatting and camera ready preparation Dr. Inam Ullah Khan: reviews handling.

Data Availability Statement

Data Available Upon Request: "The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.".

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

- **RSBD** - Roadmap-to-Satellite Building Detector
- **GIS** - Geographic Information System
- **HRS** - High-Resolution Satellite
- **OBIA** - Object-Based Image Analysis

- **NDVI** - Normalized Difference Vegetation Index
- **DEM** - Digital Elevation Model
- **CNN** - Convolutional Neural Network

REFERENCES

[1] B. Sirmacek and C. Unsalan, "Urban-area and building detection using sift keypoints and graph theory," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 4, pp. 1156–1167, 2009.

[2] Z. Zheng, Y. Zhong, J. Wang *et al.*, "Building damage assessment for rapid disaster response with a deep object-based semantic change detection framework: From natural disasters to man-made disasters," *Remote Sensing of Environment*, vol. 265, p. 112636, 2021.

[3] X. Zhang, P. Xiao, X. Feng *et al.*, "Separate segmentation of multi-temporal high-resolution remote sensing images for object-based change detection in urban area," *Remote Sensing of Environment*, vol. 201, pp. 243–255, 2017.

[4] P. Saeedi and H. Zwick, "Automatic building detection in aerial and satellite images," in *2008 10th International Conference on Control, Automation, Robotics and Vision*. IEEE, 2008, pp. 623–629.

[5] M. Wahbi, I. El Bakali, B. Ez-zahouani *et al.*, "A deep learning classification approach using high spatial satellite images for detection of built-up areas in rural zones: Case study of soussmassa region-morocco," *Remote Sensing Applications: Society and Environment*, vol. 29, p. 100898, 2023.

[6] X. Huang and L. Zhang, "A multidirectional and multiscale morphological index for automatic building extraction from multispectral geoeye-1 imagery," 2011.

[7] W. Liu and V. Prinet, "Building detection from high-resolution satellite image using probability model," in *Proceedings. 2005 IEEE International Geoscience and Remote Sensing Symposium, 2005. IGARSS'05.*, vol. 6. Citeseer, 2005, pp. 3888–3891.

[8] M. Awrangjeb, M. Ravanbakhsh, and C. S. Fraser, "Automatic detection of residential buildings using lidar data and multispectral imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 65, no. 5, pp. 457–467, 2010.

[9] B. Sirmacek and C. Unsalan, "Building detection from aerial images using invariant color features and shadow information," in *2008 23rd International Symposium on Computer and Information Sciences*. IEEE, 2008, pp. 1–5.

[10] A. Schneider, K. C. Seto, and D. R. Webster, "Urban growth in chengdu, western china: application of remote sensing to assess planning and policy outcomes," *Environment and Planning B: Planning and Design*, vol. 32, no. 3, pp. 323–345, 2005.

[11] A. Asokan, J. Anitha, M. Ciobanu, A. Gabor, A. Naaji, and D. J. Hemanth, "Image processing techniques for analysis of satellite images for historical maps classification—an overview," *Applied Sciences*, vol. 10, no. 12, 2020. [Online]. Available: https://www.mdpi.com/2076-3417/10/12/4207

[12] Y. Cao, X. Huang, and Q. Weng, "A multi-scale weakly supervised learning method with adaptive online noise correction for high-resolution change detection of built-up areas," *Remote Sensing of Environment*, vol. 297, p. 113779, 2023.

[13] A. Fallatah, S. Jones, and D. Mitchell, "Object-based random forest classification for informal settlements identification in the middle east: Jeddah a case study," *International Journal of Remote Sensing*, vol. 41, no. 11, pp. 4421–4445, 2020.

[14] H. Guo, Q. Shi, A. Marinoni *et al.*, "Deep building footprint update network: A semisupervised method for updating existing building footprint from bi-temporal remote sensing images," *Remote Sensing of Environment*, vol. 264, p. 112589, 2021.

[15] H. Farhadi, H. Ebadi, and A. Kiani, "F2bfe: Development of feature-based building footprint extraction by remote sensing data and gee," *International Journal of Remote Sensing*, vol. 44, no. 19, pp. 5845–5875, 2023.

[16] R. Qin, J. Tian, and P. Reinartz, "Spatiotemporal inferences for use in building detection using series of very-high-resolution space-borne stereo images," *International Journal of Remote Sensing*, vol. 37, no. 15, pp. 3455–3476, 2016.

[17] Z. Zhang, W. Guo, M. Li *et al.*, "Gis-supervised building extraction with label noise-adaptive fully convolutional neural network," *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 12, pp. 2135–2139, 2020.

[18] B. Sirmacek and C. Unsalan, "A probabilistic framework to detect buildings in aerial and satellite images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 1, pp. 211–221, 2010.

[19] N. O'Mahony, S. Campbell, A. Carvalho *et al.*, "Deep learning vs. traditional computer vision," in *Advances in Computer Vision: Proceedings of the 2019 Computer Vision Conference (CVC)*, vol. 1. Springer, 2020, pp. 128–144.

[20] T. Partovi, F. Fraundorfer, R. Bahmanyar, H. Huang, and P. Reinartz, "Automatic 3-d building model reconstruction from very high resolution stereo satellite imagery," *Remote Sensing*, vol. 11, no. 14, 2019. [Online]. Available: https://www.mdpi.com/2072-4292/11/14/1660

[21] Google, "Google maps," 2023, https://www.google.com/maps.

[22] G. Svennerberg, *Beginning Google Maps API 3*. Apress, 2010.

[23] A. Benchabana, M.-K. Kholladi, R. Bensaci *et al.*, "Building detection in high-resolution remote sensing images by enhancing superpixel segmentation and classification using deep learning approaches," *Buildings*, vol. 13, no. 7, p. 1649, 2023.

[24] "From google maps to a fine-grained catalog of street trees," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 135, pp. 13–30, 2018.

[25] C. Zhang, Y. Cui, Z. Zhu, S. Jiang, and W. Jiang, "Building height extraction from gf-7 satellite images based on roof contour constrained stereo matching," 2022. [Online]. Available: https://www.mdpi.com/2072-4292/14/7/1566

[26] A. Lorette, X. Descombes, and J. Zerubia, "Texture analysis through a markovian modelling and fuzzy classification: Application to urban area extraction from satellite images," *International Journal of Computer Vision*, vol. 36, no. 3, pp. 221–236, 2000.

[27] J. A. Benediktsson, M. Pesaresi, and K. Amason, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 9, pp. 1940–1949, 2003.

[28] M. Aamir, Y.-F. Pu, Z. Rahman *et al.*, "A framework for automatic building detection from low-contrast satellite images," *Symmetry*, vol. 11, no. 1, p. 3, 2018.

[29] R. Avudaiammal, P. Elaveni, S. Selvan *et al.*, "Extraction of buildings in urban area for surface area assessment from satellite imagery based on morphological building index using svm classifier," *Journal of the Indian Society of Remote Sensing*, vol. 48, pp. 1325–1344, 2020.

[30] D. Kohli, R. Sliuzas, and A. Stein, "Urban slum detection using texture and spatial metrics derived from satellite imagery," *Journal of Spatial Science*, vol. 61, no. 2, pp. 405–426, 2016.

[31] N. L. Gavankar and S. K. Ghosh, "Object-based building footprint detection from high-resolution multispectral satellite image using k-means clustering algorithm and shape parameters," *Geocarto International*, vol. 34, no. 6, pp. 626–643, 2019.

[32] V. Dey, Y. Zhang, and M. Zhong, "Building detection from pan-sharpened geoeye-1 satellite imagery using context-based multi-level image segmentation," in *2011 International Symposium on Image and Data Fusion*. IEEE, 2011, pp. 1–4.

[33] K. Karantzalos and D. Argialas, "A region-based level set segmentation for automatic detection of man-made objects from aerial and satellite images," *Photogrammetric Engineering & Remote Sensing*, vol. 75, no. 6, pp. 667–677, 2009.

[34] S. Cao, Q. Weng, M. Du *et al.*, "Multi-scale three-dimensional detection of urban buildings using aerial lidar data," *GIScience & Remote Sensing*, vol. 57, no. 8, pp. 1125–1143, 2020.

[35] M. Thaiki, L. Bounoua, and H. Cherkaoui Dekkaki, "Using satellite data to characterize land surface processes in morocco," *Remote Sensing*, vol. 15, no. 22, 2023. [Online]. Available: https://www.mdpi.com/2072-4292/15/22/5389

[36] M. Turker and D. Koc-San, "Building extraction from high-resolution optical spaceborne images using the integration of support vector machine (svm) classification, hough transformation, and perceptual grouping," *International Journal of Applied Earth Observation and Geoinformation*, vol. 34, pp. 58–69, 2015.

[37] A. S. Buriboev, K. Rakhmanov, T. Soqiyev, and A. J. Choi, "Improving fire detection accuracy through enhanced convolutional neural networks and contour techniques," *Sensors*, vol. 24, no. 16, 2024. [Online]. Available: https://www.mdpi.com/1424-8220/24/16/5184

[38] I. Idris, A. Mustapha, O. Caleb *et al.*, "Application of artificial neural network for building feature extraction in abuja," *International Journal of Multidisciplinary Education Research (IJMCER)*, vol. 3, no. 4, pp. 09–15, 2021.

[39] B. B. Ekici, "Detecting damaged buildings from satellite imagery," *Journal of Applied Remote Sensing*, vol. 15, no. 3, pp. 032 004–032 004, 2021.

[40] K. Rastogi, P. Bodani, and S. A. Sharma, "Automatic building footprint extraction from very high-resolution imagery using deep learning techniques," *Geocarto International*, vol. 37, no. 5, pp. 1501–1513, 2022.

[41] M. Pepe, D. Costantino, V. S. Alfio, G. Vozza, and E. Cartellino, "A novel method based on deep learning, gis and geomatics software for building a 3d city model from vhr satellite stereo imagery," *ISPRS International Journal of Geo-Information*, vol. 10, no. 10, 2021. [Online]. Available: https://www.mdpi.com/2220-9964/10/10/697

[42] Q. Ding, Z. Shao, X. Huang *et al.*, "Consistency-guided lightweight network for semi-supervised binary change detection of buildings in remote sensing images," *GIScience & Remote Sensing*, vol. 60, no. 1, p. 2257980, 2023.

[43] J. Wang, H. Xiong, J. Gong *et al.*, "Structured building extraction from high-resolution satellite images with a hybrid convolutional neural network," in *2021 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 2021, pp. 2417–2420.

[44] A. Mohammadian and F. Ghaderi, "Siamixformer: A fully-transformer siamese network with temporal fusion for accurate building detection and change detection in bi-temporal remote sensing images," *International Journal of Remote Sensing*, vol. 44, no. 12, pp. 3660–3678, 2023.

[45] H. Fan, A. Zipf, Q. Fu *et al.*, "Quality assessment for building footprints data on openstreetmap," *International Journal of Geographical Information Science*, vol. 28, no. 4, pp. 700–719, 2014.

[46] H. M. Bui, M. Lech, E. Cheng *et al.*, "Using grayscale images for object recognition with convolutional-recursive neural network," in *2016 IEEE Sixth International Conference on Communications and Electronics (ICCE)*. IEEE, 2016, pp. 321–325.

[47] J. COBB, "Some reflections on color," *Optics and Photonics News*, vol. 6, pp. 51–51, 1995.

[48] D. Chaudhuri, N. K. Kushwaha, A. Samal *et al.*, "Automatic building detection from high-resolution satellite images based on morphology and internal gray variance," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 9, no. 5, pp. 1767–1779, 2015.

[49] G. Liasis and S. Stavrou, "Building extraction in satellite images using active contours and colour features," *International Journal of Remote Sensing*, vol. 37, no. 5, pp. 1127–1153, 2016.

[50] Google, "Quetta, sub-urban area," https://www.google.com/maps, 2023.

[51] ——, "Canada, urban area," https://www.google.com/maps, 2023.

[52] ——, "Dubai, urban area," https://www.google.com/maps, 2023.

[53] ——, "Mumbai, urban area," https://www.google.com/maps, 2023.

[54] ——, "Shibam, urban area," https://www.google.com/maps, 2023.

[55] ——, "Thailand, sub-urban area," https://www.google.com/maps, 2023.

[56] M. Vakalopoulou, K. Karantzalos, N. Komodakis *et al.*, "Building detection in very high resolution multispectral data with deep learning features," in *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 2015, pp. 1873–1876.