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Building change detection via classification in high-resolution aerial imagery

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ABSTRACT

This research investigates the detection of changes in building structures within high-resolution aerial images of Baghdad, Iraq, over two years, 2007 and 2024. Employing advanced remote sensing techniques and sophisticated image processing algorithms, this study aims to identify and quantify alterations in the urban landscape accurately by addressing the key challenges inherent in the image registration process, as well as the availability associated with change detection (CD) techniques. We examined the data collection strategies, evaluated matching methods, and compared CD approaches. Aerial images were accurately analyzed to detect changes in building footprints, construction activities, and destruction. We developed a comprehensive annotation methodology tailored to the complex urban environment of Baghdad. These findings emphasize the rapidly evolving nature of Baghdad's urban fabric and the critical need for ongoing monitoring to inform urban planning and management strategies. The results demonstrate the efficacy of utilizing high-resolution aerial imagery with object-based CD techniques for detailed urban analysis. This research advances the existing knowledge by providing a robust framework for urban CD, with implications for enhancing urban planning and policy-making processes. Future research will focus on refining the annotation processes and incorporating additional data sources to enhance the accuracy and comprehensiveness of urban CD methodologies.

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1. INTRODUCTION

Change detection (CD) in aerial images plays a pivotal role in analyzing and monitoring dynamic environments. Aerial images captured from various platforms, such as satellites, drones, or aircraft, provide a valuable source of information for detecting and understanding changes occurring on the Earth's surface. CD involves the identification and characterization of alterations between two or more images acquired at different periods. These changes can encompass a wide range of phenomena, including land cover transformations, urban growth, natural disasters, vegetation dynamics, and infrastructure development. The ability to detect and quantify changes in aerial images has significant implications in multiple fields, including environmental monitoring, spatial planning, emergency response management, agriculture, and resource management. It enables decision-makers, researchers, and policymakers to gain insights into temporal and spatial patterns of change, assess the impacts of human activities, and make informed decisions for sustainable development.

- When geographic metadata is unavailable or unreliable, what are the inherent challenges and performance limitations of conventional registration techniques (such as scale invariant feature transform (SIFT) combined with Brute Force Matcher)?
- In scenarios lacking spatial referencing information, what strategies can be employed to improve the robustness and accuracy of key points detection and matching?
- How do various CD methodologies, such as algebraic, classification-based, and transformation-based approaches, compare in terms of their accuracy, reliability, and computational efficiency?
- When applied to real-world aerial datasets (e.g., imagery of Baghdad), which of these CD techniques demonstrates the highest level of performance and practical applicability?

CD techniques provide researchers and analysts with essential insights into the dynamic characteristics of the earth's surface. In the field of CD, numerous techniques are available; however, identifying an optimal and definitive method remains a challenge. Due to the complexity of CD, data analysts employ a variety of methods, utilizing their expertise to effectively detect changes. Nonetheless, the processing of heterogeneous data is widely recognized as one of the most significant challenges in CD. Detection of changes in real-time applications poses significant challenges due to the need for multiple processing steps. These steps include identifying issues related to CD, preprocessing the images, and assessing the performance of the application-specific algorithm. The challenge is further compounded by the need to develop an appropriate methodology for detecting changes in very high-resolution imagery.

Advancements in remote sensing imaging technologies and the growing availability of high-resolution satellite data have greatly facilitated image analysis techniques tailored for remote sensing-based applications, which were previously reliant on laborious field surveys. Conducting an individual area survey was time-consuming and arduous, but today, the utilization derived from satellite observations collected in real time has simplified this process. Real-time satellite data plays a crucial role in various applications, with remote sensing being a primary beneficiary. It enables accurate detection of environmental changes, contributing to a better understanding of human-nature interactions. This understanding, in turn, aids decision-making, particularly in the context of urban development.

2. RELATED WORKS

In the field of agricultural studies, CD techniques are employed for monitoring deforestation, evaluating the impacts of natural disasters, and analyzing patterns of shifting cultivation. In the military domain, these methods play a critical role in intelligence gathering. This includes the identification of newly established military installations, the monitoring of enemy troop movements, battlefield assessment, and damage evaluation [1].

In the civil context, it functions as a regulatory mechanism for managing urban development and guiding the spatial expansion of cities [2]. Although CD algorithms provide substantial benefits across a wide range of applications, they are also associated with notable challenges. For example, vegetation growth and changes in surface reflectance characteristics, such as those caused by soil conditions before and after rainfall, can significantly impact the reliability and validity of the detected changes [3]. Accurate image registration is crucial for reliable CD, particularly when analyzing multitemporal or multi-source imagery. The process involves extracting key features and estimating a spatial transformation to align the moving image with the fixed image, enabling consistent comparison across time and space [4].

Feature-based image registration matches distinct features, while hybrid methods combine region-based and attribute-oriented methods. Traditional techniques operate in the spatial domain and are classified as manual, semi-automatic, or automatic [5]. Advancements in remote sensing technologies, such as higher spatial and spectral levels of detail, improved image acquisition techniques, and advanced data processing algorithms, have revolutionized the field of CD in aerial imagery. These advancements have enhanced our ability to extract valuable information from images and detect subtle or complex changes that may have been challenging to identify using traditional survey methods alone. In this context, this article aims to explore the fundamental concept, methodologies, and applications of CD in aerial images.

Machine learning algorithms are commonly classified into supervised, unsupervised, and reinforcement learning. Supervised classifiers perform best with wide labeled data and can be further categorized as parametric or nonparametric based on data distribution assumptions [6]. Execution time is a key factor in implementing and operationalizing machine learning models, referring to the duration needed for a single inference. Optimization techniques aim to reduce this time while preserving accuracy, enhancing the model's practical utility. In this context, random forest (RF) is widely used both for building accurate predictive models and for evaluating the relative importance of input variables [7]. CD in earth surface imagery has long been recognized as a fundamental challenge in the field of remote sensing [8]. Effective CD in remote sensing requires clearly defined research objectives and a well-specified study area.

CD entails the identification of alterations in surface features over time using multi-temporal imagery, offering valuable insights into the temporal dynamics of natural and anthropogenic processes [9]. Reliable CD requires image pairs to be spectrally, spatially, and temporally aligned. This is achieved through preprocessing steps such as co-registration of multi-temporal images over the same location [10]. Karker [11] describes image alignment as a process that uses image tie points (ITPs) to compute geometric transformations, enabling one image to be spatially aligned with another. By understanding and harnessing the power of CD in aerial images, we can gain deeper insights into the evolving earth's surface and contribute to more informed decision-making and sustainable development practices.

Chen *et al.* [12] introduces an synthetic aperture radar (SAR) remote sensing algorithm for detecting changes in imagery that uses adaptive techniques for real-time parameter estimation and a sparse automatic encoder to detect significant regions and reduce speckle noise. Principal component analysis and K-means clustering enhance CD by minimizing isolated pixel impact. Experimental results show high detection accuracy, effectively handling environmental interferences like seawater fluctuations and ship presence. According to Bao *et al.* [13], patch and pixel change network (PPCNET) for detecting in bitemporal high-resolution images. This deep learning approach integrates patch and pixel-level CD to achieve precise boundaries of change areas while also surpassing the speed of pixel-level-based deep learning methods. Extensive experiments comparing PPCNET, traditional methods, and other deep networks using satellites and aerial images demonstrated the effectiveness and feasibility of detecting changes in high-resolution remote sensing images.

Peng *et al.* [14] claimed a newly proposed end-to-end framework for CD method using the UNet++ architecture, which learns change maps directly from annotated datasets. This approach addresses limitations of existing CD methods by reducing error accumulation and intermediate processing steps. It outperforms other methods in visual and quantitative evaluations but relies on a substantial number of true change maps, potentially limiting its broader application. Huang *et al.* [15] developed an automatic CD method using planar-vertical features, object-based temporal correction, and a multi-temporal CD model to identify non-covered building areas (NCBAs). Testing in Beijing and Shanghai showed satisfactory results, but limitations included errors in detecting rebuilt areas and constraints from the ZY-3 satellite, which limited time-series image availability.

Viana *et al.* [16] examined land use and land cover (LULC) changes in a rural region over 21 years (1995-2015) using Landsat imagery. They used open-source LULC data and K-means clustering to refine spectral signatures for each class. By integrating data from the official Portuguese LULC map, Carta de Uso e Ocupação do solo (COS), for 1995, 2007, 2010, and 2015, they generated representative training samples. The method achieved an overall accuracy of 76%, demonstrating its effectiveness and providing valuable insights into significant LULC changes during the period. Vivekananda *et al.* [17] focused on classifying LULC changes between the years 1999 and 2019. Researchers employed a combination of India's topographic map survey and temporal satellite imagery to gather data.

Remote sensing and geographic information system (GIS) techniques were integrated to quantify and comprehend the LULC changes in Anantharaman spanning a period of 40 years, from 1978 to 2018. The confusion matrix was employed to assess the classification accuracy, which was satisfactory. Tewabe and Fentahun [18] analyzed LULC changes in the Tana basin using Landsat thematic mapper (TM) images from 1986, 2002, and 2018. They classified six land cover types and assessed accuracy using the Kappa coefficient. The findings revealed overall accuracies of 84.21%, 83.32%, and 91.40% for the years 1986, 2002, and 2018, respectively, within the basin. The corresponding kappa coefficients were determined as 79.02%, 83.32%, and 89.66%.

3. MATERIALS AND METHOD

The research employed a quantitative approach known as CD. This method involved classifying each satellite image and comparing it based on a pixel-by-pixel method with the resulting LULC maps in 2024 that were provided by the remote sensing department of the University of Baghdad. Our first methodology in employed in the study consisted of the steps as illustrated in Figure 1: i) collecting the data, ii) image pre-processing, iii) image registration (IR), iv) data classification, v) outlier removing model, vi) time performance model as in our cited [19], and finally, the vii) CD step will be presented in this study. The second methodology is presented in section 4.1.

3.1. Change detection methods

Based on the CD processing as can be seen in Figure 2, there are a multi various approaches that have been developed to be used for, and each tailored to its specific application. In cases where the CD images are acquired through various sensor modalities, it becomes crucial to perform image registration before applying the algorithm designed for CD. Image registration ensures proper alignment and synchronization of the images, enabling accurate and meaningful change analysis [20]. By employing CD techniques, researchers and analysts can gain valuable insights into the dynamic nature of the Earth's surface.

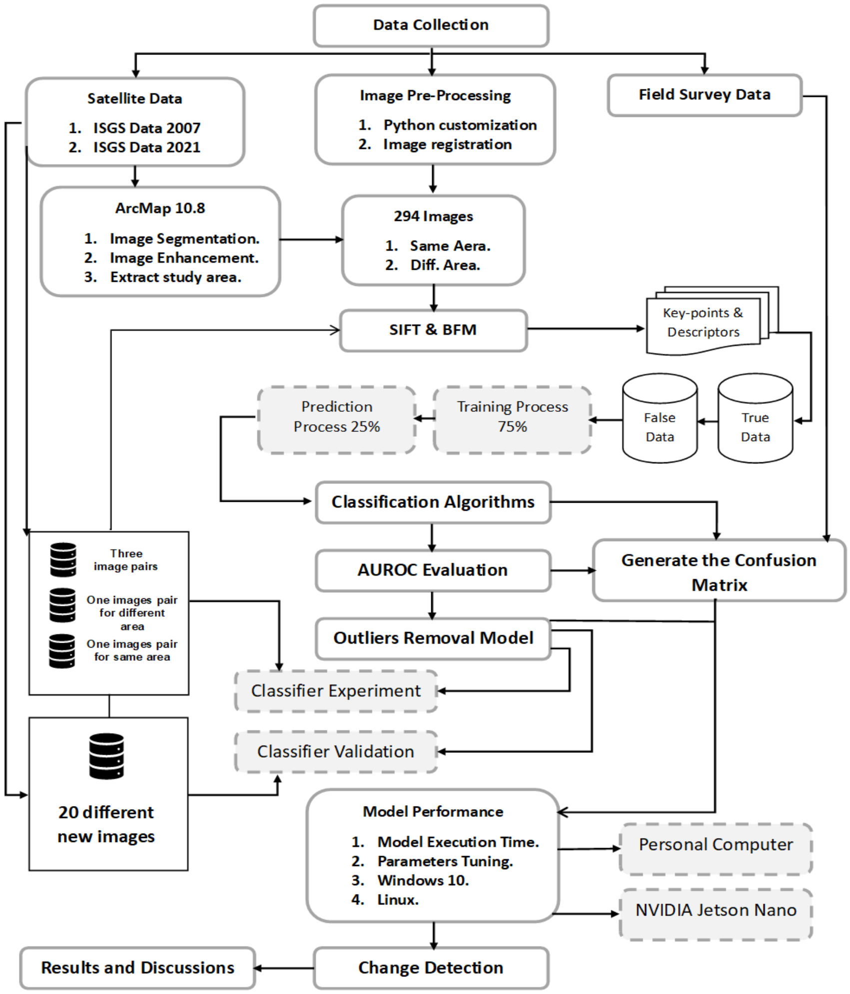

Figure 1. Phase one of the proposal methodology

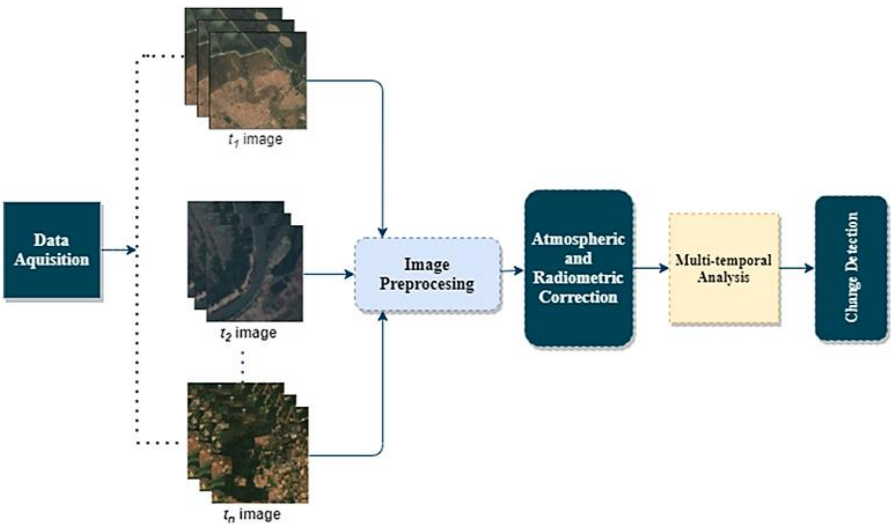

Figure 2. CD process

3.1.1. Change detection-based algebra

Algebra-based is one of the CD approaches, which involves employing mathematical operations on individual image pixels to generate a different image. This method calculates the discrepancies between corresponding pixels in two or more images, highlighting areas where significant changes have occurred. One widely used algebra-based CD technique is image differencing [21]. Typically, this approach includes several methods like image ratioing, image differencing, and change vector analysis (CVA), which involves a mathematical technique for change identification. This type of CD has a disadvantage, specifically with nosing, which occurred during preprocessing.

3.1.2. Change detection-based transform

This category involves using the transformation-based pixel. The primary advantage of this type is its ability to minimize redundant information across the bands. The illustration in Figure 3 presents the structure of CD based on transformation. Many studies have investigated multi-temporal CD by using satellite image fusion techniques like discrete wavelet transform (DWT) and homogeneous pixel transformation (HPT) in [22], [23], respectively. However, transform-based methods struggle to precisely label change areas in the transformed image [20].

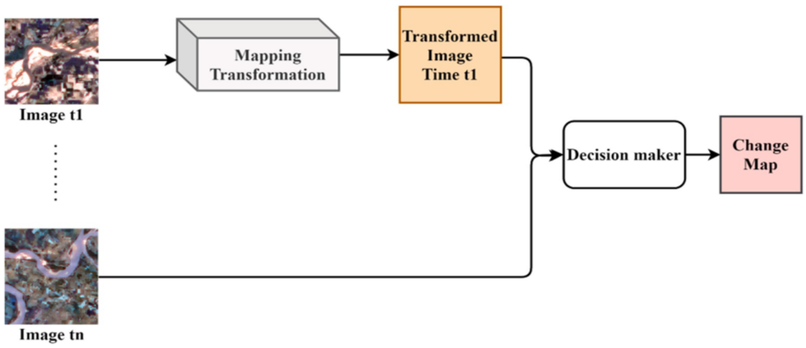

Figure 3. CD-based transformation

3.1.3. Change detection-based classification

The primary benefit of this approach, as in Figure 4, lies in its ability to offer precise alteration details that remain largely uninfluenced by external elements such as atmospheric disturbances. Input images from different time points undergo feature extraction, and the resulting feature maps are filtered and concatenated. These are then processed by a CD network, trained on simulated samples to generate the final change map. It encompasses post-classification compression, CD conducted through unsupervised methodologies and techniques, and approaches based on artificial neural networks. The effectiveness of this category is contingent upon the careful choice of training data. Table 1 provides an extensive overview of CD techniques centered around classification.

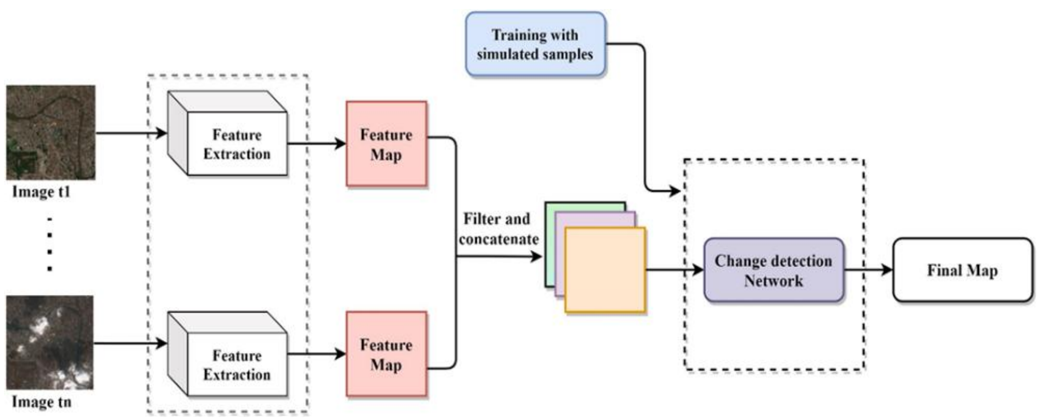

Figure 4. CD-based classification

Table 1. Comprehensive analysis of CD strategies employing a classification framework

Author	Feature used	Classification algorithm
Rahbani and Pakhirehzan [24]	Position of the closest centroid	Shepard classification
Liu *et al.* [23]	Image deep features by predefined scale	DCNN
Singh and Singh [25]	Cluster centers finding	Radial basis training by genetic algorithm
Azzouzi *et al.* [26]	Texture attributes, spatial, and spectral	Function of Gaussian radial
Gong *et al*. [27]	Intra-cluster similarity	CNN
Montesinos *et al.* [28]	Attributes of data collection	Classifiers of Bayesian networks

3.1.4. Change detection based advanced model

The advanced methodology for detecting changes encompasses various reflection and spectral mixing models. These approaches involve transforming image values into significant variables by employing the principles of linear pattern analysis [29]. The authors are presented with the Hopfield neural network (HNN) [30]. An alternative CD approach, known as the temporal un-mixing method, has been introduced by [31]. The analyses of landscape images aim to identify changes in the coverage area over time. A novel approach for CD is investigated, utilizing a hybrid spectral change-based methodology by [32]. This approach delineates differences in spectral values and shape, relying solely on spectral features to identify modifications that are not easily detectable.

3.2. Comparison of image matching algorithms

Comparative studies have evaluated the performance of image matching algorithms, focusing on the challenge of achieving invariant feature detection across diverse transformations. The choice of algorithm depends on the image type and variations like scale and orientation [33]. The criteria for achieving true invariant feature detection under transformations are as follows,

- Consistency: the detected position must remain invariant to variations in scale and orientation.
- Accuracy: features must be identified as accurately as possible about their true locations.
- Speed: the algorithm must possess sufficient efficiency to process the image swiftly.

3.2.1. Scale invariant feature transform

The method was originally proposed by Lowe in 2004, the SIFT algorithm has become a standard in computer vision and photogrammetry. This algorithm extracts distinctive features from images, enabling robust matching across diverse landscape scenes. Additionally, it computes descriptors for these features, facilitating more accurate and efficient image analysis [34].

3.2.2. Speeded up robust feature

The speeded up robust feature (SURF) is an accelerated version of the SIFT algorithm. It is both a local key-point detector and descriptor. It generates descriptors with either 64 or 128 dimensions. In the phase of feature detection, SURF utilizes the Laplacian of Gaussian (LoG). Additionally, for feature description, SURF applies wavelet responses in both vertical and horizontal. While SURF offers improved speed over SIFT, it is still not ideal for real-time applications. The SURF was introduced in 2006 [35].

3.2.3. Acceleration of KAZE algorithm

Acceleration of KAZE algorithm (AKAZE), introduced by Sharma and Jain [36], is an improved version of the KAZE algorithm. AKAZE detects features by finding extrema of second-order derivatives within a nonlinear multi-scale pyramid based on image diffusion. AKAZE utilizes fast explicit diffusion (FED) within a pyramidal framework, optimizing the speed of feature detection in a nonlinear scale space. This algorithm significantly enhances the efficiency and performance of the feature detection process.

3.2.4. Oriented FAST and rotated BRIEF

The oriented FAST and rotated BRIEF (ORB) feature extraction method was chosen for feature extraction in aerial images, which was introduced in 2011 [37]. It is a computationally efficient alternative to SIFT and SURF, combining FAST key-point detection with the BRIEF descriptors. Despite FAST's lack of orientation calculation and BRIEF's limitations with rotation, modifications have enhanced ORB's performance. ORB exhibited an issue with uneven and sparse distribution of feature points. Despite this limitation, ORB demonstrates significant advantages in terms of computational efficiency. We chose the SIFT algorithm for our study based on its superior performance in our comparison, as shown in Figures 5 and 6, and Table 2. Each pair in Figure 5 shows the original and processed satellite images, with red lines indicating corresponding keypoints detected and matched by the algorithms. This comparison highlights the performance and robustness of SIFT and SURF in identifying spatially consistent features. The bar chart in

Figure 6 shows that SIFT achieved the highest number of matches (51), followed by SURF (30), while AKAZE and ORB produced fewer matches. The dashed line indicates the minimum match count threshold required for acceptable performance.

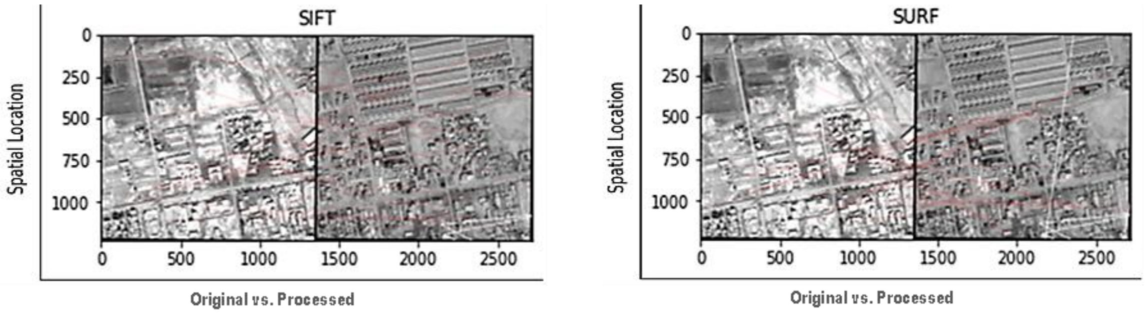

Figure 5. Visual comparison of feature matching using SIFT and SURF algorithms

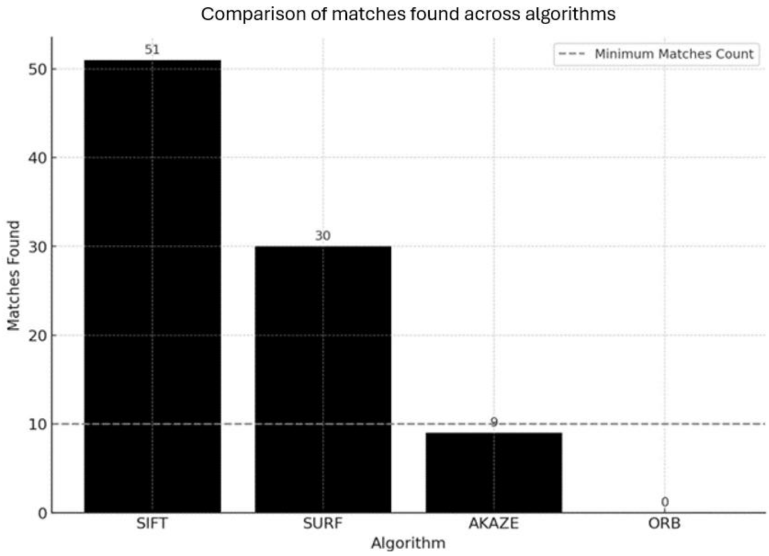

Figure 6. Comparison of the number of feature matches detected by four algorithms

Table 2. Results of four matching algorithms

Algorithm	Minimum matches count	Result	Notes
SIFT	10	SIFT matches are found - 51/10	Better matches
SURF	10	SURF matches are found - 30/10	Good matches
AKAZE	10	AKAZE matches are found - 9/10	Not enough matches are found
ORB	10	ORB matches are found - 0/10	Not enough matches are found

4. RESULTS AND DISCUSSION

Firstly, we conduct a comprehensive analysis and comparison of results. We validate our proposed method through experiments through employed five evaluation metrics: precision, recall, F1-score, and accuracy, see (1) to (4), instead of the area under the receiver operating characteristics curve (AUROC) which is serves as a quantitative measure employed to assess the effectiveness the efficacy of classification models. F1-score serves as a measure of the binary classification model's accuracy. The five metrics are employed over five classification algorithms: naïve Bayes (NB), decision tree (DT), gradient boosting (GB), RF, and logistic regression (LR), as shown in Tables 3 and 4, and Figure 7.

$$Precision = \frac{TP}{(TP+FP)} \tag{1}$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$F1 - score = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)} \quad (3)$$

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ number\ of\ Predictions} \quad (4)$$

Table 3. Classification metrics based on five algorithms

Classification algorithm	Dataset True (1)	Dataset False (0)	Precision True (1)	Precision False (0)	Recall True (1)	Recall False (0)	F1-score True (1)	F1-score False (0)
NB	86573K	86573K	0.52	0.51	0.48	0.55	0.50	0.53
DT	86573K	86573K	0.52	0.51	0.48	0.54	0.50	0.53
GB	86573K	86573K	0.52	0.52	0.47	0.58	0.49	0.55
RF	86573K	86573K	0.57	0.56	0.53	0.61	0.55	0.58
LR	86573K	86573K	0.52	0.52	0.48	0.55	0.50	0.53

Table 4. Accuracy and AUROC based on five algorithms

Classification algorithm	Dataset records True (1)	Dataset records False (0)	Support True (1)	Support False (0)	Accuracy	AUROC
NB	86573K	86573K	43316	43256	0.52	0.519799
DT	86573K	86573K	43447	43125	0.51	0.517717
GB	86573K	86573K	43253	43319	0.52	0.530965
RF	86573K	86573K	21671	21615	0.57	0.552928
LR	86573K	86573K	43316	43256	0.52	0.524968

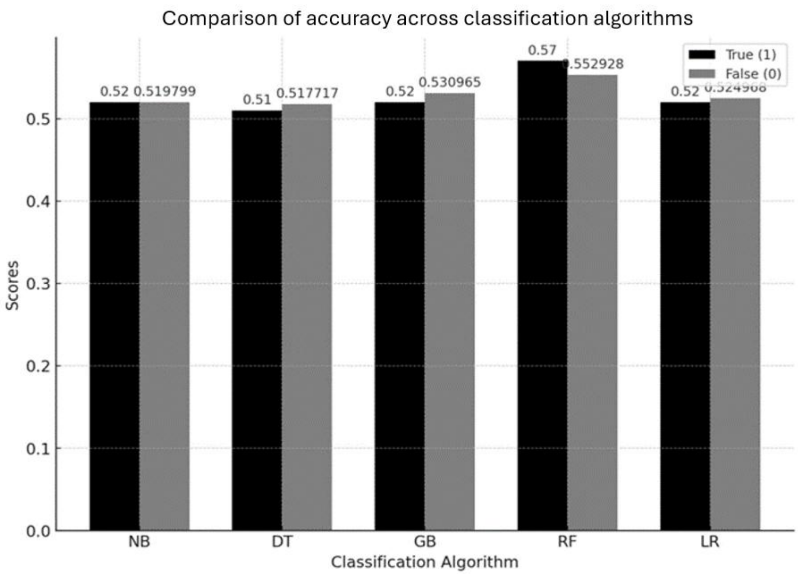

Figure 7. Results of metrics for five classification algorithms

4.1. Change detection process

For the second part of our CD methodology, as illustrated in Figure 8, a key challenge in our study is the uncertainty of the image's exact location within the global coordinate system, so extracting building footprints from aerial images is a vital preprocessing step in image analysis, enhancing accuracy in CD tasks. This preprocessing step enhances image matching by preparing datasets to identify altered features in very high-resolution images, such as buildings, roads, or vehicles [38]. Upon identifying the corresponding masks, the SIFT matching algorithm demonstrates high efficacy in feature detection within the new dataset.

Our contribution includes the preparation of very high-resolution aerial imagery at a consistent resolution of 6 cm. Each image pair is associated with a corresponding mask, thereby minimizing noise and ensuring clarity. For the masking process, we utilized a single mask for the image pair of Baghdad 2007 and

2024, with a total of 25 image pairs in TIF format, which generated (86,573 K) records, consisting of both true and false labeled data. Although there are benchmark datasets available for CD, assessment of changes in the LULC was conducted by utilizing our newly collected dataset.

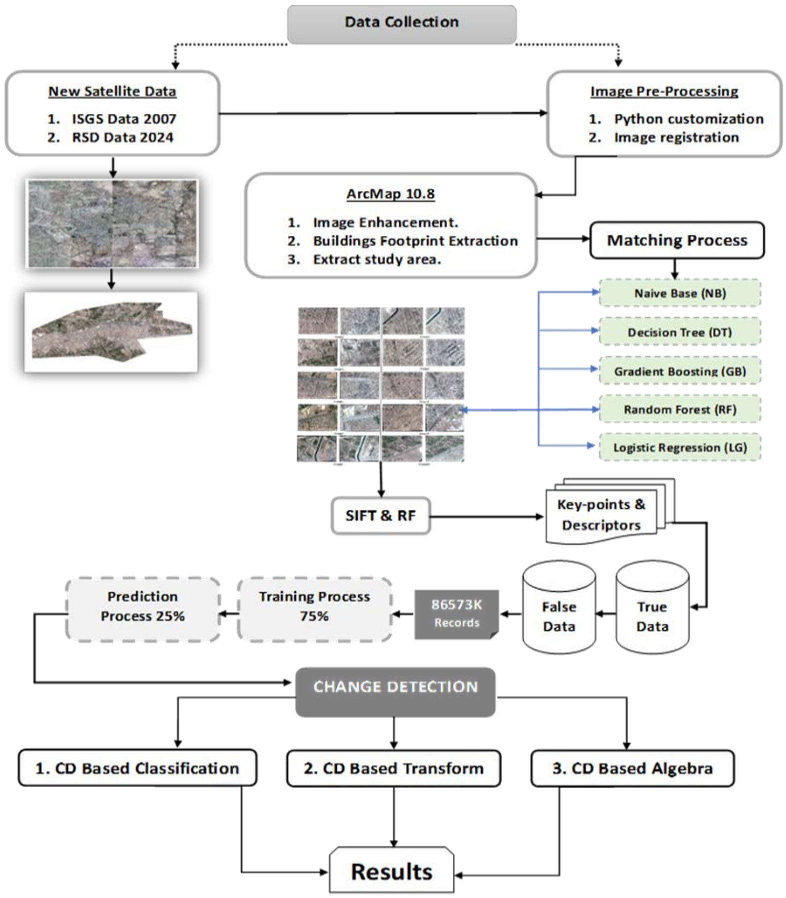

Figure 8. Phase two of the proposal methodology

4.2. Change detection based on three approaches

For the problem of CD, we used two pairs of images as a sample, drawn from our datasets of 2007 and 2024. Our proposed method was implemented by using Python and the Jupyter platform in a 64-bit Windows system, equipped with an Intel Iris CPU and 8 GB of RAM. Here, the CD is trained and tested by using three CD methods as shown in Figure 9, Figure 9(a) shows the CD-based classification, Figure 9(b) shows the CD-based transformation, and Figure 9(c) shows the CD-based algebra.

The first method produced more accurate results than other methods, and the areas of change demonstrate a high degree of consistency with the ground truth data. As can be seen clearly that the changing area highlighted in yellow color was perfect. Despite our building's concern, we computed multiple classes (urban, water, vegetation, non-vegetation, and bar) in pairs of images as shown in Table 5. The results of detecting changes in the second a CD approach grounded in our dataset, were the worst, since in this method, redundant spectral bands are minimized by decomposing the objects, so it couldn't cover both small and large areas. Regarding to the third CD method, the blue lines indicated to the features detection that differing between two images, and the green lines represent the boundaries of changes areas in pairs of images. The CD results was good, but as a crucial aspect of traditional algebra method is to determine threshold value, as it directly influences the ability to identify specific areas of an image for evaluating the extent of change. Although this technique is relatively simple to implement, selecting an appropriate threshold is often difficult. A poorly chosen threshold can result in inaccurate estimations of the degree of change. Finally, regarding the multi-class of LULC, we also computed the changes over the period in 2007-2024 as shown in Table 6, in addition to computing the percentage of built-up and non-built-up through using the normalized difference built-up index (NDBI) as represented in Table 7.

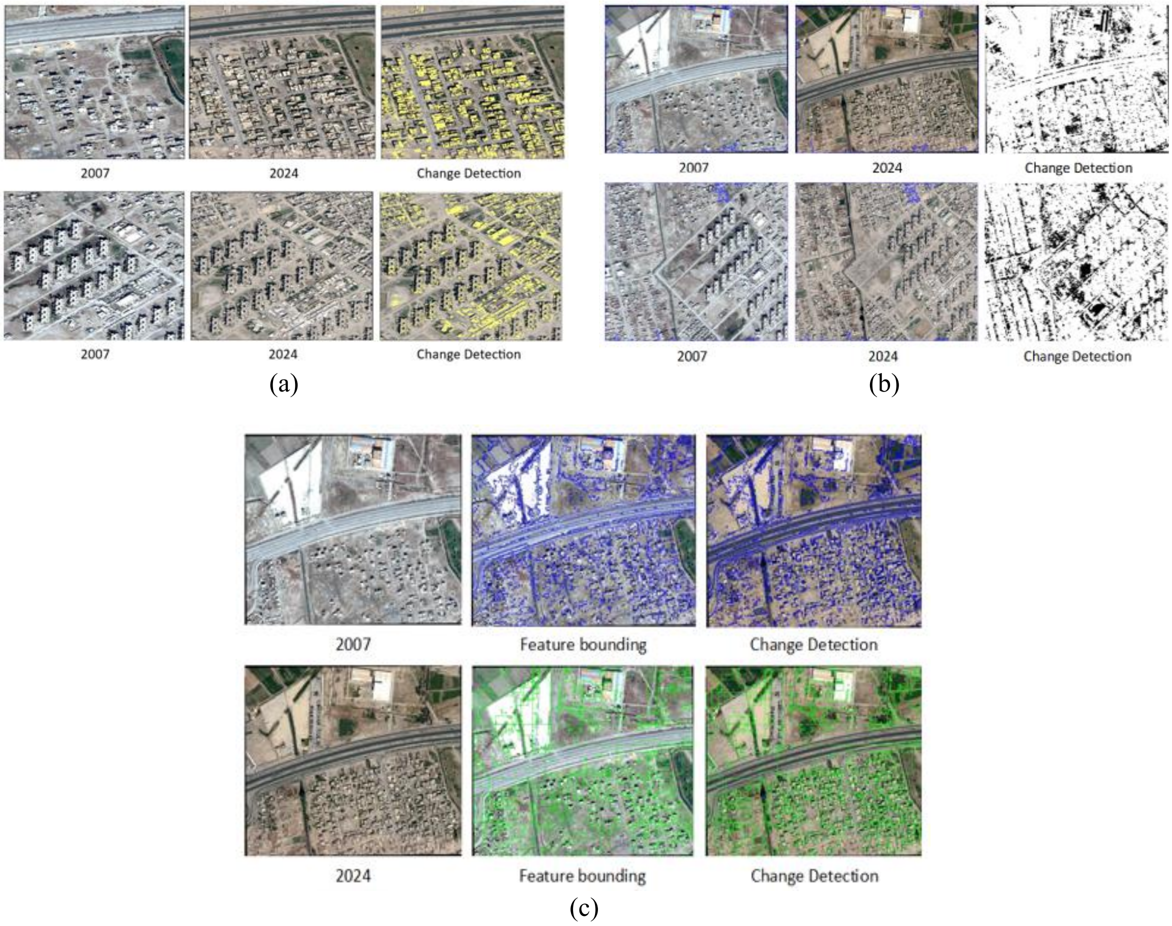

Figure 9. Methods of CD based on (a) classification, (b) transformation, and (c) algebra

Table 5. Areas CD in 2007-2024

Type	2007	Area (%)	2024	Area (%)
Urban	1107.4981	21.73	1243.8451	24.41
Water	184.7537	3.62	170.2132	3.35
Vegetation	899.1296	17.64	1033.665	20.28
Non-vegetation	878.0772	17.24	801.5152	15.72
Bare	2026.9354	39.77	1847.1547	36.24

Table 6. Changes of classes in 2007-2024

Type	2007	2024	Change 2007-2024
Urban	1107.4981	1243.8451	136.347
Water	184.7537	170.2132	-14.5405
Vegetation	899.1296	1033.665	134.536
Non-vegetation	878.0772	801.5152	-76.562
Bare	2026.9354	1847.1547	-179.7807

Table 7. Built-up and non-built-up in 2007-2024

Type	2007	Area (%)	2024	Area (%)
Built-up	998.127	19.58	1181.584	23.18
Non-built-up	4098.267	80.42	3914.81	76.82

5. CONCLUSION

This paper presented the CD approach in multi-high-resolution aerial images in 2007 and 2024 at the study area in the capital of Iraq (Baghdad). To highlight significant change features and suppress irrelevant features across the spatial ground truth, an adaptive classification approach among multiple types of CD is used for feature identification and detection. Moreover, for improving the performance of CD, we proposed pixel-by-pixel change methods by involving other CD types for generating a change map with more accurate. The effectiveness of our proposed method is tested by the evaluation using two distinct datasets. The indication of classification results can accurately indicate the change in complexity areas. Additionally, the evaluation of detectors and matching algorithms is provided. For future work, we will focus on using another CD type, such as the advanced, which is used for multiple kinds of CDs in one step, and try to use aerial images with different scales and orientations. Future research should refine the experimental design, building on initial promising results to develop a fully automated system. The scope of CD could also be extended to include roads, vegetation, and other objects in aerial imagery.

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Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [HMM], upon reasonable request. The data are not publicly available due to privacy considerations and restrictions related to participant confidentiality.

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