A Comprehensive Survey on Framework for Satellite Image Processing

Yogesh S. Sirsath[1], Dr. Ashwini S. Gaikwad[2], Prachi D. Waghmare[3], Shubhangi B. Gaikwad[4]

[1]*M. tech Student, DIEMS, Chh. Sambhaji Nagar*

[2]*Associate Head CSE, DIEMS Chh. Sambhaji Nagar*

[3]*Assistant Professor, DEIMS, Chh. Sambhaji Nagar*

[4]*Assistant Professor, Mangaldeep College of Engineering, Chh. Sambhaji Nagar*

***Abstract*—As water and land boundaries are always changing, it's more important than ever to be able to correctly classify field as well as territorial limits. Changes in administrative borders, plant life, and water systems are common on historical maps, so it's important to use reliable tools to find these changes. Satellite imagery has become a principal resource for observing these changes, highlighting the necessity for an in-depth comprehension of satellite processing images methodologies when handling historical cartographic data. This study provides a comprehensive assessment of the advantages and drawbacks of various image processing methodologies employed in this field. There are many different computational methods, but their effectiveness depends a lot on the type of images and the needs of each application. Choosing the wrong method can lead to less-than-ideal results, which shows how important it is to make sure that your methodological choices match the goals of the analysis. This paper describes the processing procedures and satellite communication imaging methods that are appropriate for different situations. Also, comparative evaluations are done to show how different methods work in different situations. This synthesis aims to facilitate the creation of informed and creative approaches to the prevalent challenges faced in satellite-based applications for image processing.**

***Index Terms*—remote sensing; change detection; fusion; feature extraction; segmentation; classification**

I. INTRODUCTION

The combination of satellite-based field boundary detection is a strong way to keep an eye on the changing borders between land and water features. By looking at a series of satellite images taken over time, you can tell if certain areas have grown, shrunk, or changed shape. These kinds of time-based studies help make accurate maps that can be used for many different purposes.

Because of this, satellite image processing has become an important computer tool in many fields, such as defence, agriculture, disaster relief, and resource assessment. But the huge amount and complexity of satellite data make it very hard to process it quickly and correctly. Remote sensing images usually have a lot of information, but they aren't very useful if the images are of poor quality or if the wrong feature sets are chosen during analysis. Standard visual interpretation depends on things like shape, color, tone, and texture. But it's often hard for people to interpret more than one image at a time.

Consequently, subjective interpretation and image quality predominantly influence the duration and precision of manual classification. These limitations have sped up the move toward computational methods, which can quickly analyse huge datasets and handle multi-band spectral data that would be too much for human analysts to handle. So, image processing is now a must-have for modern remote sensing uses, where the accuracy of the processing method directly affects how reliable the information is that is extracted. So, you need to know a lot about different image processing methods to choose the best one for a specific job. Improvements in satellite technology have made the need for quick, high-resolution images even greater, especially for emergency response and public safety. New Earth observation systems are getting better at providing continuous monitoring. This has led to the need for new ways to make sure that the data that is available is used well. The main goal is to give decision makers timely and accurate information, especially during important events like natural disasters.

Even though there is a lot of satellite and aerial imagery available, one of the biggest problems is turning raw data into useful information. It is still hard to get relevant patterns, features, as well as structures with high accuracy. There are many ways to process data, but traditional methods often need to be carefully tested to see if they are right for a certain use case. The rise of AI and machine learning has made it easier to extract features, especially from high-resolution images. This has led to the creation of advanced multi-layered processing frameworks. Even with these improvements, there is still a lot of room for existing systems to work better and be more flexible. To make new automated workflows that can handle the many different needs of satellite image analysis, you need to know a lot about traditional methods.

This work gives a thorough look at important image processing methods and how they can be used, pointing out their pros and cons. This synthesis of past and present methodologies seeks to facilitate the development of more efficient and imaginative solutions to persistent difficulties associated with satellite image processing.

A. Image Processing in Remote Sensing

The satellite image processing techniques addressed include enhancement, feature extraction, segmentation, fusion, change detection, compression, classification, and feature detection, as illustrated in Figure 1.

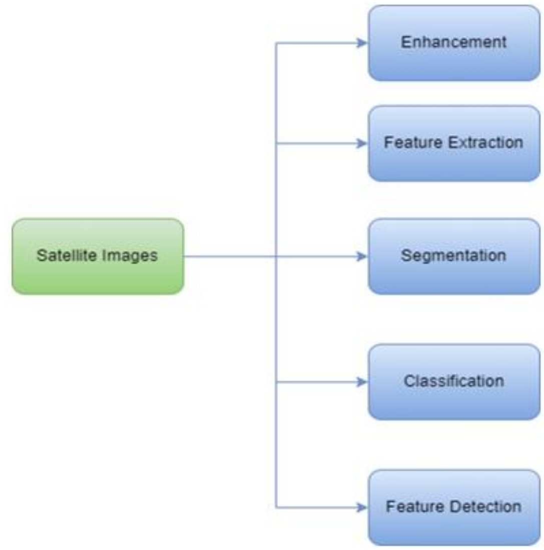

Figure 1 Image Processing Methodology

B. Image Enhancement

Satellite images often exhibit low brightness levels, which makes enhancement a critical step in ensuring that essential details are preserved while improving overall visual quality. Among the perceptual factors that influence subjective evaluation of an image, contrast plays a central role, as it enables clear differentiation between objects and their surrounding background. In practical terms, variations in brightness and color between scene elements determine how effectively features can be interpreted. To address limitations related to insufficient illumination and poor contrast, a wide range of enhancement algorithms has been introduced in the literature. Enhancement is typically performed prior to advanced processing tasks such as segmentation and object recognition, given that downstream analysis heavily depends on the clarity and quality of the input imagery. Image enhancement methods are broadly categorized into spatial-domain and frequency-domain approaches [1].

Among these, histogram equalization remains one of the most widely applied techniques, capable of adjusting intensity distributions across either the entire image or selected regions. Although traditional histogram equalization can significantly improve global contrast, it often struggles to preserve the average luminance of the original image. Consequently, several refined variants such as Bi-Histogram Equalization (BHE), Recursive Mean

Separate Histogram Equalization (RMSHE), and related methods have been developed to overcome these limitations and produce more natural enhancement results.

The enhancement methods and their evaluation metrics are shown in Table 1.

Table 1. Image Enhancement methods and their performance metrics.

Method	Test Images	Performance Metrics
Histogram Planting [2]	Phobos Images from Satellites	Mean, Average Information
Modified differential evolution [3]	Images from NASA, Satpalda Geospatial Services and Satellite Imaging Corp.	Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Universal Quality Index (UQI), Normalized Absolute Error (NAE), Structural Contrast-Quality Index (SC-QI):
Fractional Differential (FD) unsharp masking [4]	Infrared Images	Average brightness (B), Average contrast (V), Average discrete information content (or entropy, E), Sharpness (S), Colourfulness (C), Correlation (R), Energy (E) and Homogeneity (M)

Despite the effectiveness of RMSHE, certain visual inconsistencies and artifacts were observed in the enhanced images. Many of these issues can be mitigated by employing Histogram Planting (HP) [2], a distribution-based enhancement method that has shown considerable potential in producing more balanced contrast adjustments. HP operates through two principal distribution strategies: equality-spaced distribution (HP-ESD) and proportionality-spaced distribution (HP-PSD). Although these approaches generally yield satisfactory improvements, they may still introduce minor distortions in some cases. To address such limitations, researchers have proposed an advanced enhancement technique that integrates a modified differential evolution process with the Cuckoo Search (CS) optimization algorithm [3].

This hybrid approach effectively reduces unwanted artifacts while preserving fine image details and maintaining average luminance. The underlying objective is to design a transformation capable of remapping pixel intensities into a more informative range. In this framework, local feature extraction is undertaken through a sliding window, though this step is computationally intensive. To balance accuracy and efficiency, the Modified Differential Evolution (MDE) algorithm strategically combines global and local extraction processes.

Further improvements are achieved by incorporating multi-resolution satellite imagery from different sensors, enabling enhanced accuracy without heavily relying on Ground Control Points (GCPs) [5]. In this method, only a subset of rational polynomial coefficients is utilized, while tie points are identified manually to compute root mean square error values across multi-resolution datasets. Future advancements may automate this tie-point selection process, reduce manual intervention and increase consistency across large image collections.

To evaluate the effectiveness of enhancement methods, several quantitative measures are commonly used. Peak Signal-to-Noise Ratio (PSNR) assesses the fidelity of the reconstructed image, while Absolute Mean Brightness Error (AMBE) measures deviations in average brightness between the original and enhanced versions. Entropy serves as an indicator of the information richness within the image, reflecting improvements in detail visibility. Additionally, Mean Square Error (MSE) quantifies the squared differences between the input and processed images, providing insight into the magnitude of structural changes introduced during enhancement.

C. Feature Extraction

Feature extraction involves generating measurable attributes that can be used for selecting and categorizing image components, forming the basis for subsequent classification tasks. These features play a decisive role in determining how effectively an image classification system performs, as the quality of extracted descriptors directly influences the accuracy and robustness of the final output [6]. Broadly, features may be grouped into two categories: general features and domain-specific features. General features include common visual properties such as color, shape, and texture, while domain-specific features capture specialized characteristics tailored to a particular application or context.

Among the approaches explored for feature correspondence, a graph-theoretic matching method has been proposed in Reference [7]. Although this technique can handle nonlinear intensity variations, it relies on Mutual Information (MI) as the similarity measure, which, while effective, is computationally demanding. To overcome such limitations, alternative descriptors such as Local Self-Similarity (LSS) have been developed, offering reduced complexity and improved resilience to illumination changes. Additionally, Uniform Robust (UR) variants of the Scale-Invariant Feature Transform (SIFT) have been introduced to enhance the consistency of feature distribution, improving the stability of matches under scale and orientation changes. In assessing these methods, recall defined as the proportion of correctly matched features relative to all true matches and precision representing the proportion of correct matches among all detected matches serve as key performance indicators. Table 2 provides a comparative overview of these feature extraction techniques along with their corresponding evaluation metrics.

Table 2 Feature extraction approaches

Method	Test Images	Feature Extracted	Performance Metrics
Uniform Competency Feature Extraction [8]	Synthetic Images: ETM+, World View 2, Real Images: SPOT4, SPOT6, Quick Bird, GeoEye1, ASTER	Rotation and scale invariant Local features	Recall, Precision, Root Mean Square Error
RepTree, Machine Learning and Euclidean distance [9]	Envisat images	Continues features such as roads, rivers	Efficiency and processing time
Multi image saliency analysis [10]	SPOT 5 images	ROI extraction such as clouds	Recall, precision, F-measure.
Digital Surface Models	ZY-3 satellite images	Pixel and feature level extraction of urban scenes	Overall accuracy kappa coefficient
Reversible jump Markov chain Monte Carlo sampler [12]	Synthetic image	Extraction of rivers, channels and roads	Completeness, correctness

Early feature extraction methods often relied on specially designed filters to isolate local structures such as roads. Over time, however, these techniques were increasingly replaced by boundary-based detection approaches, which demonstrated better reliability in handling complex spatial patterns. In recent years, machine learning has become the dominant paradigm for feature extraction. A representative example is the framework combining machine learning techniques with Euclidean distance measures as described in [9]. In this approach, satellite imagery serves as the primary input, and algorithms are trained to identify specific feature blocks, including linear bodies such as rivers. The REPTree classifier is particularly effective in this context, constructing decision trees iteratively to extract and refine relevant features.

Saliency-based analysis has also emerged as a powerful method for separating prominent structures from background noise. By using k-means clustering on multispectral images, saliency maps can be produced that highlight regions of interest. A similar strategy is applied to panchromatic imagery, where co-occurrence histograms help emphasize the salient characteristics of selected regions. Once individual saliency maps are generated, a fusion mechanism is employed to merge them, effectively suppressing irrelevant background information while enhancing the clarity of meaningful features. This integrated approach significantly improves overall image interpretability.

In the context of high-resolution urban imagery, angular feature-based classification methods provide another promising direction [11]. These techniques utilize three distinct Angular Difference Features (ADFs) to analyze variations at both pixel and feature levels. The core idea is that anthropogenic structures such as rooftops and building edges exhibit characteristic geometric signatures that differ from natural landscapes. Despite their advantages, angular-based methods may underestimate the height or prominence of elevated structures due to visual distortions inherent in high-resolution imagery. As a consequence, some features may appear ambiguous, particularly within shadowed regions, leading to occasional mismatches or misinterpretations in the classification process.

D. Image Segmentation

Image segmentation refers to the process of partitioning an image into meaningful regions so that distinct objects and their boundaries can be accurately identified [13]. Among the various optimization-driven segmentation techniques, the Cuckoo Search (CS) algorithm has been applied effectively to color image segmentation. An enhancement to the traditional CS approach was introduced in Reference [14], incorporating McCulloch's method, which relies on Lévy flight distributions to improve the exploration behaviour of the algorithm. Although heuristic optimization methods such as Particle Swarm Optimization (PSO), Artificial Bee Colony Optimization (ABC), and CS have been widely adopted, their computational demands tend to rise sharply with an increasing number of segmentation thresholds, limiting their efficiency for complex tasks.

A key difference in the modified CS framework lies in its use of McCulloch's strategy to generate more stable random numbers, which contributes to improved convergence characteristics. The method can be further extended by integrating multilevel thresholding to refine segmentation outcomes in more heterogeneous imagery. In remote sensing applications, especially those involving uniformly illuminated scenes, pixel-based clustering is often employed to manage ambiguous or visually similar regions. The Hopfield Neural Network clustering method is one such approach, offering improved performance when a relatively large number of clusters are required. Table 3 summarizes several segmentation algorithms and compares their performance using standard evaluation metrics.

Table 3. Image segmentation methods and their performance metrics.

Method	Test Images	Performance Metrics
Cuckoo Search, McCulloch's method [14]	Pleiades satellite images	Recall, Precision, Root Mean Square Error
Markov Random Filed method [15]	Quick Bird bands with four spectral bands	Recall, Precision
Deep convolutional Neural Network [16]	IR images	Recall, precision, F-measure.
Levy flight firefly algorithm [17]	Multiband satellite images from NASA	Overall accuracy, kappa coefficient
Graph based segmentation, Gabor filter [18]	Quick bird satellite images	Completeness, correctness

Histogram-based thresholding remains one of the most widely used techniques for image segmentation. In its simplest form, bi-level thresholding assigns pixels to two classes using a single threshold, while multilevel thresholding employs multiple thresholds to partition the image into several distinct regions [19]. Threshold determination is typically driven by optimization criteria such as maximizing inter-class variance or minimizing classification error [20]. Comparative analyses consistently show that multilevel thresholding delivers better segmentation performance than its bi-level counterpart, particularly in images with complex intensity distributions. Further improvements can be achieved through the incorporation of Markov Random Field (MRF) models, as outlined in Reference [15]. By utilizing smaller pixel clusters to estimate likelihoods and neighbourhood interactions, MRF-based segmentation enhances classification stability and supports minimum-distance classification schemes. Once segmentation is performed, a supervised Random Forest classifier can be applied to each extracted segment, demonstrating that effective classification is achievable even when limited feature sets are available.

Reference [16] introduces a Deep Convolutional Neural Network (DCNN) architecture specifically designed for segmenting high-resolution satellite imagery. This approach integrates edge detection with the SEGNET architecture, which operates through an encoder–decoder design to assign pixel-level labels across multiple classes. While the method is capable of producing detailed and accurate segmentations, it is computationally intensive due to the substantial size of the decoder component. This complexity poses practical challenges for researchers and practitioners working with resource-constrained environments or large-scale remote sensing datasets [21].

A notable limitation of many segmentation techniques is that the extracted boundaries often appear fuzzy or poorly defined. To address this, a firefly optimization approach incorporating a fuzzy entropy function has been proposed [17]. In this method, fuzzy entropy is used to evaluate the contrast between neighbouring regions, and threshold values are selected through minimization of a fitness function so that the resulting segments maintain consistent entropy levels. The firefly algorithm itself is inspired by the luminescent communication behaviour of fireflies, where each individual is attracted to others based on perceived brightness. This mechanism enables an efficient global search, making it suitable for identifying optimal threshold sets in challenging segmentation tasks.

Extracting road networks in dense urban environments presents additional difficulties due to the complex arrangement of buildings and their textured surroundings. To improve the separability of such structural patterns, Gabor filters are applied to amplify textural cues prior to segmentation. The refined scene is subsequently processed through a graph-based segmentation framework [18]. This approach includes two major steps: constructing a graph representation of the segmented image and then performing region division and merging based on similarities in color and shape. Further advancements are demonstrated in Reference [22], where a Cuckoo Search (CS)-based algorithm incorporating Tsallis entropy is used for multilevel color image thresholding. Tsallis entropy, which depends on the global characteristics of the image histogram, offers flexibility by introducing an adjustable parameter for threshold determination. However, the approach is computationally demanding because of the algorithm’s complexity.

Object-based image analysis aims to identify segmentation methods that maximize overall classification performance. This typically involves two stages: segmenting the image into homogeneous regions and then categorizing those segments. Supervised approaches are generally preferred for quantitative evaluation, while qualitative assessments remain subjective but easier to perform. Segmentation quality is often measured using Under-Segmentation Error (USE) and Over-Segmentation Error (OSE), where each reference segment is evaluated independently before summing the errors to produce an overall performance indicator. Additional evaluation metrics include pixel accuracy, which reflects the proportion of correctly classified pixels, precision, which measures the correctness of positive classifications, and recall, which gauges the completeness of detected objects relative to the ground truth.

E. Change Detection

Change detection plays a critical role in monitoring variations within a geographic region, particularly because satellite observations for most locations are readily accessible [46]. Broadly, change detection techniques can be categorized into four groups: algebraic, transformative, Geographic Information System (GIS)-based, and advanced model-based approaches. Algebraic techniques rely on mathematical operations to quantify visual differences, with commonly used methods including image differencing, Change Vector Analysis (CVA), and Principal Component Analysis (PCA). Image differencing is particularly effective for assessing vegetation growth, while PCA is often employed to analyse changes in water quality and vegetation composition. Transform-based methods use mathematical transformations to highlight temporal differences, and the Tasseled Cap Transformation (TCT) remains a well-established technique for this purpose. TCT is especially useful for assessing the impacts of deforestation, whereas image differencing performs well in tropical regions, and TCT offers reliable change monitoring in urban environments. Reference [47] provides a comprehensive overview of such change detection strategies.

GIS-based techniques offer an integrated environment for managing, comparing, and interpreting multi-temporal images. These methods align historical and current maps to identify and classify changes more effectively. For instance, vegetation cover changes have been analyzed through GIS-supported strategies as detailed in Reference [48], while Reference [49] proposes a GIS-based framework for land cover change detection. Beyond these conventional approaches, more advanced techniques make use of spectral unmixing and reflectance models, where reflectance values from satellite images are converted into physical parameters to better understand underlying surface properties. Reference [50] introduces temporal unmixing using spectral mixture models for vegetation change analysis. Additionally, Digital Surface Models (DSMs), which represent surface elevation characteristics, are valuable for urban development monitoring and vegetation mapping. Reference [51] demonstrates how DSMs can be employed to detect structural changes in urban areas.

The maximum likelihood classifier is frequently used as an initial step to categorize land cover classes in remote sensing imagery [52]. After validating the classified groups, image differencing or statistical change detection using probability matrices is applied to distinguish changes across different time periods. The success of maximum likelihood classification depends heavily on accurate training data, as misclassification of pixels can reduce overall efficiency. To improve detection in rapidly evolving environments, Multi-Step Image Matching (MSIM) has been proposed, integrating fast clustering, feature detection, and boundary matching to identify changes in disaster-prone regions [55]. Likewise, graph-based approaches can be used to trace spatial and temporal variations through object-level analysis, as illustrated in Reference [56]. These approaches complement classifier-based techniques, which often fall short in capturing complex temporal dynamics. In graph-based analysis, correlation coefficients are commonly computed to support quantitative evaluation.

Performance assessment of change detection methods typically relies on several key metrics. Overall Accuracy (OA) measures the proportion of correctly identified changed and unchanged pixels. False Alarm (FA) indicates the percentage of unchanged pixels mistakenly labeled as changed, while Missed Alarm (MA) represents the proportion of actual changes that remain undetected. Together, these metrics provide a comprehensive evaluation of how effectively a change detection method responds to both subtle and pronounced variations in satellite imagery.

F. Image Classification

Effective image classification techniques are essential for organizing and interpreting satellite imagery, particularly given the increasing availability and complexity of Earth observation data [66,67]. Image classification functions as a pattern recognition process in which pixels or image segments are assigned to predefined classes based on similarity measures. Broadly, classification approaches fall into three groups: supervised, unsupervised, and post-classification methods. Supervised classification relies on training data to guide the algorithm in identifying relevant patterns. These techniques may be parametric where class assignments follow algebraic assumptions, as seen in Bayesian classifiers and decision trees or non-parametric, which do not require explicit probability density functions. The latter includes methods such as k-Nearest Neighbour (k-NN) and logistic regression [68]. Unsupervised classification, by contrast, groups pixels into clusters without prior knowledge of class labels and may employ hierarchical clustering or partition-based techniques.

Satellite image classification is challenged by two persistent issues: the presence of mixed pixels, where a single pixel represents multiple land cover types, and the difficulty of processing large, high-dimensional datasets. Among the widely adopted solutions, the Random Forest classifier has gained prominence for land use and land cover mapping. As an ensemble method, it aggregates predictions from multiple decision trees to determine the final class assignment. For example, Reference [69] demonstrates a Random Forest-based wetland classification using optimized geometric and spectral features extracted from multi-sensor imagery. Reference [67] further refines this approach through the use of a genetic algorithm to optimize feature selection and tree parameters for improved land cover classification.

The mixed pixel problem is frequently addressed through spectral unmixing, often referred to as soft classification. In this method, each pixel's spectral signature is decomposed to estimate its fractional composition across different land cover types.

Reference [70] applies spectral unmixing to compute fractional abundances for more accurate class representation. A hybrid strategy combining supervised and unsupervised unmixing is presented in Reference [71] for multispectral image classification, while Reference [72] introduces a Multiple Endmember Spectral Mixture Analysis (MESMA) approach for urban land cover mapping, enabling a single class to be represented through multiple endmembers that capture intra-class variability.

Neural network-based classifiers also contribute significantly to remote sensing applications. Radial Basis Function Neural Networks (RBFNNs) offer advantages such as robustness to noise and flexibility through numerous tenable parameters [73]. To correct misclassifications that persist after initial analysis, a post-classification refinement technique Classification Errors Correction (CEC) has been developed using Discrete Wavelet Transform (DWT) to merge highly correlated spectral bands for improved accuracy [74]. Deep learning approaches have further advanced the field; Reference [75] proposes a deep feature learning pipeline in which images are decomposed into multiple scales, each scale serving as a training input for a Deep Convolutional Neural Network (DCNN). Spatial Pyramid Pooling (SPP) is used to accelerate training by accommodating varying input sizes while preserving shared network parameters.

Cloud detection, another important task in satellite image analysis, has been addressed using Bayesian network classifiers [76]. In this approach, attributes related to cloud structure and appearance are analyzed, and classification performance is evaluated through k-fold cross-validation to ensure robust generalization. To further strengthen classification reliability, an integrated framework combining fuzzy evaluation with Dempster–Shafer theory (FSE-DST) has been proposed in Reference [77]. This strategy begins with object-based classification and then applies evidence fusion to enhance decision confidence, contributing to more precise and interpretable classification outcomes. Such hybrid methods continue to play a vital role in advancing the accuracy and reliability of satellite image classification.

G. Image Feature Detection

There has been an increase in the satellite images which helps to understand and analyze various applications. Feature recognition is gaining importance with the advancement in deep learning. Table 6 represents the different feature detection methods and performance metrics.

Table 6. Feature Detection methods and their performance metrics.

Method	Test Images	Application	Performance Metrics
Fuzzy logic-based detection	Hyperspectral image	Edge detection	PSNR, MSE
Deep Convolutional Neural Network	Quick Bird VHR image	Informal settlement detection	Overall accuracy
Invariant pixel detection, PCA	Landsat 7 ETM+ images	Cloud detection	Accuracy and F-measure
Active contour model	Google Earth images	Shadow detection and height estimation	Precision and recall

The ability to distinguish between features such as buildings, roads, vegetation, and other landscape elements is fundamental to applications in environmental monitoring, urban analysis, and disaster assessment. When attempting to establish correspondences across multiple images, it is essential to identify distinctive and repeatable salient points within each image. During classification, these feature descriptors are compared against those extracted from training samples, and the class yielding the highest correspondence is selected as the best match. Global and texture-based descriptors are often effective for retrieving visually similar images from large databases, while structure-oriented local features are typically better suited for detailed classification tasks. However, the detection of nonlinear features such as informal urban settlements, oil spills, or irregular natural formations remains challenging, making the identification of salient points in these complex structures crucial for reliable classification outcomes. Consequently, robust feature detection is foundational to accurate image classification.

Edge detection, a key component of feature extraction, is widely used to delineate object boundaries within satellite imagery. Conventional edge detectors such as Prewitt, Laplacian, and Laplacian of Gaussian filters are frequently employed, but they suffer from limitations such as fixed edge thickness and sensitivity to threshold settings. To address these constraints, linear time-invariant filters treat edges as abrupt changes in grayscale intensity and offer improvements in computational efficiency. A fuzzy logic-based edge detection technique has also been proposed to enhance boundary identification in complex scenes [78]. In cloud detection tasks, a Digital Surface Model (DSM) can be derived through stereo image matching and subsequently compared with a Digital Elevation Model (DEM) to identify cloud seed points based on elevation differences [82]. Cloudy regions are then classified by integrating height information with spectral cues.

Image quality can also be degraded by jitter introduced during satellite motion or sensor instability. Detecting and correcting such distortions is therefore essential for ensuring accurate analysis. A displacement-based model has been introduced to identify high-altitude jitter in satellite imagery [83], where bidirectional Kalman filtering and smoothing operations help reduce jitter effects, followed by a re-imaging model to reconstruct corrected outputs. Fully Convolutional Networks (FCNs) have additionally demonstrated strong capability in learning pixel-level dependencies [79], enabling the differentiation of formal and informal settlements based on morphological characteristics. Wavelet transforms are frequently used to extract spatial information necessary for identifying such patterns.

Oil spill detection is another application of feature-based image analysis, particularly important for maritime navigation and environmental protection. Machine learning-driven feature selection methods have been developed to enhance oil spill identification using wide-coverage SAR imagery [84]. In the domain of aerial vehicle detection, Reference [85] introduces a transfer learning approach built upon a super-resolution framework, where sparse coefficients learned from high- and low-resolution image patches guide the detection process. Although initial implementations rely on a linear SVM search technique, their effectiveness is limited by challenges in matching similar image fragments. This limitation is alleviated through dictionary learning and sparse coding, enabling the creation of low-resolution representations using shared coefficients derived from their high-resolution counterparts.

A comparison of various image processing methods reveals that their performance is strongly dependent on the application context, noise characteristics, and the type of imagery being analyzed. The accuracy of feature extraction, detection, fusion, and change detection ultimately influences segmentation quality and, consequently, the overall analytical outcome. Different enhancement techniques may be required depending on the nature of image noise, while structural complexity in terms of edges, contours, and textures highlights the need for robust and adaptable feature extraction methods. Selecting techniques tailored to the problem at hand ensures that the final image processing results align with the intended objectives.

II. LITERATURE OVERVIEW

The reviewed literature spans a comprehensive range of satellite image processing techniques, covering enhancement, feature extraction, segmentation, fusion, classification, change detection, and evaluation methodologies. Each reference contributes a distinct perspective on how remotely sensed data can be analysed, interpreted, or optimized for various real-world applications. To provide a clear and structured overview of these works, the following table consolidates all 92 cited studies and summarizes their core concepts, techniques, and areas of application. This organized representation helps in understanding the evolution of methods across different domains, identifying thematic connections, and highlighting the foundational studies that inform the subsequent sections of this research.

Table 1 – Consolidated Reference Summary

Ref. No.	Topic / Category	Core Technique / Concept	Summary of Contribution	Application Area
[1]	Image Enhancement	Digital Image Processing Fundamentals	Establishes foundational concepts for contrast improvement, filtering, and spatial/frequency transformations.	General remote sensing & image preprocessing
[2]	Image Enhancement	Histogram Planting (Brightness Preservation)	Proposes a modified histogram-based method that enhances contrast without distorting average brightness.	Low-light satellite imagery
[3]	Image Enhancement	Modified Differential Evolution	Optimizes enhancement functions using evolutionary computation for better contrast while preventing artifacts.	High-resolution multispectral images
[4]	Image Enhancement	Fractional Differential Unsharp Masking	Applies fractional calculus to improve edges while maintaining natural image appearance.	Infrared and thermal images
[5]	Image Fusion	Rational Polynomial Coefficient Fusion	Combines multi-resolution images without requiring dense ground control points.	Multi-sensor fusion
[6]	Feature Extraction	SIFT (Scale-Invariant Features)	Identifies stable feature points under scale, orientation, and illumination variations.	Object recognition & remote sensing
[7]	Feature Extraction	Mutual Information-Based Matching	Uses statistical dependence between images to enhance multimodal feature matching accuracy.	Multisensor image registration
[8]	Feature Extraction	Scale-Invariant Keypoints	Identifies rotation/scale-stable keypoints for robust image comparison.	Pattern matching
[9]	Feature Extraction / ML	Machine Learning with REPTree	Uses decision-tree learning to extract meaningful spatial features from satellite images.	Landform mapping
[10]	Feature Extraction	Spectral Residual Saliency	Extracts visually prominent regions by analyzing spectral frequency behavior.	Cloud/ROI extraction
[11]	Feature Extraction	Angular Difference Features (ADF)	Uses angular responses to distinguish man-made structures from natural terrain.	Urban scene interpretation
[12]	Feature Extraction	RJ-MCMC Sampling	Searches parameter space for line-like features such as roads or rivers.	Large-area feature extraction
[13]	Image Segmentation	Seeded Region Growing	Separates regions through similarity-driven growth from seed points.	Land cover segmentation
[14]	Image Segmentation	Cuckoo Search Optimization	Uses Levy flights to optimize multilevel thresholds for complex segmentation.	Color satellite image segmentation
[15]	Segmentation & Classification	Markov Random Fields	Models' pixel interactions to obtain smoother and more consistent segmentation.	Land-use mapping
[16]	Deep Learning Segmentation	SegNet	Encoder-decoder network performing pixel-level classification in high-resolution imagery.	Multi-class object segmentation
[17]	Segmentation	Firefly Optimization	Balances threshold selection using light-attraction behaviour in swarm algorithms.	Multi-band satellite data
[18]	Segmentation	Graph Model + Gabor Filters	Uses texture features and graph partitioning for more accurate object delineation.	Urban scene segmentation
[19]	Segmentation	Otsu Thresholding	Automatic thresholding maximizing between-class variability.	Gray-scale satellite segmentation
[20]	Segmentation	Minimum Error Thresholding	Selects thresholds that minimize probability of misclassification.	Multilevel classification
[21]	Semantic Segmentation	Fully Convolutional Networks	Converts classification CNNs into fully convolutional models for dense prediction.	Remote sensing semantic labelling
[22]	Segmentation	Tsallis Entropy	Uses generalized entropy for multilevel thresholding in complex imagery.	Color image segmentation
[46]	Change Detection	General Remote-Sensing Techniques	Establishes early framework for detecting temporal variations in multispectral images.	Vegetation/land change mapping
[47]	Change Detection	Comparative CD Strategies	Provides systematic review of change detection categories and methods.	Forest ecology

[48]	Change Detection	GIS-Driven Mapping	Integrates remote sensing with GIS layers for multi-temporal vegetation analysis.	Ecosystem monitoring
[49]	Change Detection	GIS Land Cover Update	Uses spatial overlays to determine urban and agricultural land cover change.	Urban planning
[50]	Change Detection	Spectral Mixture Modeling	Uses temporal unmixing to analyze fractional vegetation changes.	Forest and rangeland assessment
[51]	Change Detection	Digital Surface Models	Derives elevation-based indicators to detect newly built structures.	Urban expansion
[52]	Classification	Maximum Likelihood Method	Probabilistic classifier assigning pixels based on statistical class distributions.	Land cover classification
[53]	Time Series CD	Seasonal Trend Detection	Introduces multi-temporal analysis to detect gradual and abrupt forest disturbances.	Environmental monitoring
[54]	Time Series CD	BFAST Algorithm	Identifies multiple structural breaks in satellite-image time series.	Deforestation analysis
[55]	Change Detection	Multi-Step Image Matching	Combines clustering, boundary detection, and matching for rapid disaster change mapping.	Disaster response
[56]	Change Detection	Graph-Based Temporal Modeling	Tracks changes by comparing object graphs across time steps.	Object-based change detection
[66]	Classification	Remote Sensing Fundamentals	Describes foundations for interpretation, classification, and sampling of RS images.	Land cover mapping
[67]	Classification	Random Forest Optimization	Enhances land cover models by fine-tuning tree and feature selection parameters.	Multisensory classification
[68]	Classification	k-NN Classifier	Introduces instance-based learning for non-parametric classification.	Class label prediction
[69]	Classification	Random Forest for Wetlands	Uses geometric/spectral features for wetland differentiation.	Hydrological mapping
[70]	Classification	Spectral Unmixing	Breaks down mixed pixels into constituent component fractions.	Mixed land cover analysis
[71]	Classification	Hybrid Unmixing	Combines supervised & unsupervised unmixing to handle complex pixel mixtures.	Multispectral classification
[72]	Classification	MESMA	Adapts endmembers per pixel to improve urban material identification.	Urban land cover
[73]	Classification	RBF Neural Networks	Applies radial basis functions for robust classification even in noisy data.	Nonlinear classification
[74]	Classification	Error Correction via DWT	Removes misclassified pixels by analysing wavelet-merged spectral bands.	Post-classification refinement
[75]	Classification	Deep Feature Learning	Utilizes pyramid pooling and deep CNNs for multiscale image recognition.	High-resolution classification
[76]	Classification	Bayesian Cloud Detection	Classifies cloud types using probabilistic graphical models.	Cloud masking
[77]	Classification	Fuzzy + Dempster-Shafer	Combines fuzzy evaluation with evidence theory for reliable classification validation.	Decision support
[78]	Feature Detection	Fuzzy Edge Detection	Uses fuzzy rules to detect uncertain or weak edges in grayscale imagery.	Edge detection
[79]	Feature Detection	Fully Convolutional Networks	Learns pixel dependencies for outlining complex structures like settlements.	Informal settlement mapping
[82]	Feature Detection	DSM via Image Matching	Generates dense surface models by matching stereo satellite imagery.	Elevation modelling
[83]	Feature Detection	Jitter Detection using Kalman Filtering	Compensates for platform-induced jitter to stabilize satellite images.	Satellite motion correction
[84]	Feature Detection	ML-Based Oil Spill Detection	Identifies slick regions using machine learning on SAR imagery.	Maritime surveillance
[85]	Feature Detection	Transfer Learning for Vehicles	Detects small vehicles using sparse coding and super-resolution learning.	UAV / aerial detection
[86]	Metrics	Confusion Matrix Framework	Establishes rules for evaluating classification accuracy using confusion tables.	Accuracy assessment

[87]	Metrics	Classification Accuracy Standards	Provides accepted guidelines for validating thematic maps.	Land cover validation
[88]	Metrics	Precision–Recall Framework	Explains statistical interpretation of precision, recall, and F-measure.	Classifier evaluation
[89]	Metrics	Land Cover Change Case Study	Demonstrates multi-year change assessment using confusion matrices.	Watershed monitoring
[90]	Metrics	Multinomial Distribution	Describes statistical testing for multi-class classification outcomes.	Accuracy significance testing
[91]	Metrics	Quality Control Column Set	Introduces per-class quality thresholds during map validation.	Reference-based evaluation
[92]	Metrics	Information Retrieval Metrics	Defines F-measure and related evaluation metrics for classification.	Pattern recognition

The consolidated reference summary highlights the depth and diversity of research that has shaped modern satellite image processing. By examining contributions across enhancement, segmentation, feature extraction, classification, and change detection, the table reflects how each method addresses specific challenges arising from sensor variability, environmental complexity, and computational limitations. The collective insights from these studies not only clarify the progression of techniques but also reveal consistent gaps where current approaches struggle such as mixed pixel handling, multi-sensor fusion reliability, and fine-grained feature discrimination. These observations reinforce the importance of adopting a holistic, methodically integrated framework when designing new solutions. The following section builds upon this foundation by detailing the steps, architectural decisions, and experimental strategies adopted in the present research.

Overall, the findings affirm that no single technique is universally optimal; instead, the selection of an appropriate processing method must be guided by the nature of the imagery, the presence of noise, and the objectives of the analysis. Continued advancements in sensor technology, coupled with the evolution of artificial intelligence and image processing strategies, will further enhance the capacity to extract meaningful information from satellite data. Future research should focus on developing hybrid and adaptive frameworks that integrate the strengths of traditional and modern approaches, enabling more accurate, scalable, and application-specific solutions for remote sensing challenges.

III. CONCLUSION

This paper presented a comprehensive examination of satellite image processing techniques, emphasizing their role in feature extraction, segmentation, classification, enhancement, and change detection across a wide range of remote sensing applications. The review demonstrated that the performance of these techniques is highly dependent on image characteristics, computational complexity, and the specific requirements of the application domain. Traditional methods such as histogram-based enhancement, clustering, and algebraic change detection remain relevant, yet they often face limitations in handling mixed pixels, noisy inputs, or large-scale datasets. Advanced approaches ranging from swarm intelligence, fuzzy logic, and spectral unmixing to deep learning architectures have significantly improved the ability to analyze complex spatial patterns, recognize nonlinear features, and provide higher levels of automation and accuracy.

The study also highlighted the challenges associated with segmentation quality, boundary ambiguity, and classifier performance, all of which influence the reliability of satellite-derived information. Evaluation techniques including confusion matrices, accuracy metrics, and probabilistic quality control frameworks provide valuable insights into classification effectiveness but also underscore the need for robust and balanced datasets. Moreover, the integration of machine learning and optimization algorithms has emerged as a powerful direction for addressing issues related to feature variability, data imbalance, and multi-sensor information fusion.

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