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A Comprehensive Review of Feature-Based Satellite Image Classification Techniques: Emphasis on Local Binary Patterns and Support Vector Machines

Muktanjali[1], Satish B Pratapur[2]
[1]Research Scholar, Department of Computer Application, Sharnbasva University, Kalaburagi
[2]Professor, Department of Computer Science & Engineering, Sharnbasva University, Kalaburgi
Email ID: muktanjaligh@gmail.com

Abstract: Satellite image classification plays a crucial role in remote sensing applications, ranging from land use monitoring to disaster management and environmental assessment. However, the inherent challenges of satellite imagery—such as high dimensionality, spectral variability, noise, and texture complexity—demand robust feature extraction and classification methods. This review provides a comprehensive analysis of feature-based satellite image classification techniques, with a special focus on Extended Local Binary Patterns (ELBP) and Support Vector Machines (SVM). ELBP enhances conventional texture descriptors by incorporating rotation-invariant and multi-radius neighborhood information, making it suitable for capturing fine-grained spatial patterns in satellite scenes. SVM, known for its strong generalization capabilities, is widely adopted for high-dimensional image classification, particularly when integrated with ELBP-derived features. The review contrasts handcrafted and deep learning-based feature extraction techniques, highlights their strengths and limitations, and evaluates classifier performances across various benchmark datasets. Recent literature using ELBP–SVM integration demonstrates consistent improvements in classification accuracy, especially in multiclass and noise-prone environments. Finally, key research gaps are identified, including the need for explainable models, real-time deployment, and unified benchmarking standards. This review serves as a valuable reference for researchers and practitioners seeking effective, interpretable, and scalable solutions for satellite image analysis.
Keywords: Satellite Image Classification, ELBP, LBP, SVM, Remote Sensing, Texture Analysis, Machine Learning

1. Introduction

Satellite imagery has become an indispensable resource in the domain of geospatial intelligence, offering a bird's-eye view of Earth's surface that supports a wide array of applications across environmental, urban, agricultural, and defense sectors(Lukacz, 2024). The ability to monitor, analyze, and respond to spatial changes in real-time or near real-time has transformed decision-making at regional, national, and global levels(Winans et al., 2023). For instance, governments utilize satellite images to assess flood impacts, manage deforestation, and plan infrastructure development, while international organizations employ such data to track climate change, monitor agricultural productivity, and study urban sprawl(Winans et al., 2023). With the advent of high-resolution and multispectral sensors onboard satellites such as Sentinel, Landsat, and WorldView, the volume and variety of Earth observation data have grown exponentially(Dhungana, 2025). These data provide not only spatial and temporal coverage but also rich spectral information, enabling the identification of land cover types, geological features, and anthropogenic activities. However, the effective utilization of satellite imagery hinges on the capability to automatically process and classify these massive datasets into meaningful categories—a task that remains challenging due to noise, variability in terrain, and complex scene structures(Aung et al., 2022).

The core task in satellite image interpretation is classification, which involves assigning labels to pixels or image segments based on their spectral, spatial, or textural characteristics(Jiang et al., 2022). Accurate classification is fundamental to building thematic maps, conducting land use and land cover (LULC) analyses, detecting environmental changes, and supporting remote sensing-based modelling (Singh et al., 2022). While traditional classification methods like Maximum Likelihood and Minimum Distance classifiers rely heavily on spectral information, they often falter when dealing with heterogeneous landscapes, mixed pixels, or high intra-class variability(Ferreira et al., 2022). Moreover, satellite images are frequently plagued by noise from atmospheric interference, sensor limitations, and varying illumination conditions, which can further degrade classification accuracy(Klimetzek et al., 2021). To address these limitations, recent approaches have shifted toward feature-based classification, where advanced descriptors such as texture patterns, edge information, and spatial relationships are extracted to augment spectral features. Among these, Local Binary Patterns (LBP) and its variants, including Extended Local Binary Patterns (ELBP), have gained popularity for their simplicity, computational efficiency, and ability to capture fine-grained texture variations in satellite scenes(Lukacz, 2024; Winans et al., 2023). However, feature extraction alone is not sufficient; it must be paired with robust classifiers. Support Vector Machines (SVMs), with their strong theoretical foundation and effectiveness in high-dimensional spaces, have become a preferred choice for classifying remote sensing images, particularly when integrated with texture-based descriptors(Devanshi Bareja, 2025).
This review paper seeks to comprehensively explore the intersection of texture-based feature extraction and machine learning in satellite image classification, with a specific focus on the integration of Extended Local Binary Patterns (ELBP) and Support Vector Machines (SVM). The primary objective is to evaluate how ELBP, as an improvement over traditional LBP, enhances texture representation by incorporating rotation-invariance and flexible neighborhood definitions, making it particularly suitable for capturing spatial patterns in satellite imagery. The second objective is to investigate the role of SVM as a powerful supervised classifier capable of handling non-linear class boundaries and high-dimensional input spaces, often encountered in remote sensing data. Furthermore, the review aims to highlight the synergistic effect of combining ELBP and SVM, showcasing their performance on various benchmark datasets and real-world case studies. The scope extends to comparative analysis with other techniques, evaluation of kernel types in SVM, insights into model interpretability, and practical challenges in deployment. By synthesizing current literature from 2010 to 2025, the paper also identifies emerging trends, existing gaps, and future research directions that could lead to more scalable, explainable, and accurate satellite image classification systems.
The structure of the paper is designed to guide readers through the foundational concepts, methodological innovations, and current research landscape in feature-based satellite image classification. Following the introduction, Section 2 presents a foundational overview of satellite imagery, covering types of data (optical, SAR, hyperspectral), their characteristics, and classification challenges. Section 3 delves into feature extraction techniques, starting from basic texture descriptors like LBP to more advanced methods like ELBP, and contrasts these with deep feature extraction approaches. Section 4 focuses on classifiers, particularly Support Vector Machines, and includes comparative insights with other machine learning and deep learning models. Section 5 constitutes the core of the paper, where the ELBP + SVM framework is explored in depth, including its mathematical formulation, implementation workflow, and literature-based performance results. Section 6 offers a comparative review of recent methods and datasets, highlighting trends and benchmarking outcomes. Section 7

identifies key research challenges such as scalability, explainability, and real-time applicability, while Section 8 concludes with a synthesis of key insights and directions for future work.

2. Satellite Imagery and Classification Overview

2.1 Types of Satellite Imagery

Satellite imagery varies widely based on sensor technology, spatial resolution, spectral coverage, and intended application. Understanding these differences is essential for selecting appropriate classification techniques, as each image type has specific strengths and limitations in terms of texture, spectral content, and usability for remote sensing tasks (Alkhelaiwi et al., 2021).

Optical satellite imagery relies on sunlight reflected from the Earth's surface, typically captured in visible and near-infrared (NIR) bands. It is widely used in land use/land cover (LULC) mapping, vegetation health analysis, and urban development planning. Missions like Sentinel-2 and Landsat 8 offer medium-resolution (10–30 m) multispectral optical data, providing sufficient spatial and spectral granularity for thematic classification. However, optical imagery is sensitive to atmospheric distortions, including cloud cover and shadowing, which can introduce classification errors if not corrected through preprocessing.

SAR systems, such as those onboard RADARSAT-2 or Sentinel-1, utilize active microwave sensors that transmit and receive signals independently of daylight or weather conditions. These systems are capable of penetrating clouds, rain, and even vegetation canopies, making them ideal for applications like flood mapping, glacial monitoring, and soil moisture estimation. SAR resolution typically ranges from 1 to 100 meters, depending on the mode. A unique challenge associated with SAR data is speckle noise, which can obscure object boundaries unless filtered with advanced techniques.

Hyperspectral sensors collect data across hundreds of narrow and contiguous spectral bands, capturing fine material signatures not visible in standard multispectral images. Satellites like Hyperion or PRISMA deliver <10 m resolution data ideal for mineral identification, vegetation species discrimination, and environmental pollutant detection (Pan et al., 2020). Despite its advantages, hyperspectral data is complex to process due to its high dimensionality, often requiring feature selection or dimensionality reduction algorithms (e.g., PCA, ICA, SVD) before classification can be performed effectively.

These three commonly used types of satellite imagery—optical, SAR, and hyperspectral—along with their spatial resolution ranges, core applications, and representative platforms, are summarized in Table 1.

Table 1: Common Satellite Image Types and Their Applications

Type	Resolution	Application	Example Satellite
Optical	10–30 m	Land use mapping	Sentinel-2
SAR	1–100 m	Flood detection	RADARSAT-2
Hyperspectral	<10 m	Mineral analysis	Hyperion

2.2 Major Challenges in Satellite Image Classification

Despite significant advancements in remote sensing technologies and image classification algorithms, several persistent challenges limit the accuracy and scalability of satellite image interpretation. These challenges stem from both the nature of the Earth's surface features and the limitations of sensor systems. A consolidated view of these obstacles is presented in Figure 1, which categorizes the most critical issues encountered in satellite image classification workflows.

Spectral Variability

Satellite images are often affected by spectral variability, which arises due to differences in surface reflectance, seasonal vegetation changes, soil moisture content, atmospheric conditions, and sensor calibration. The same land cover type may exhibit different spectral signatures under varying conditions, making it difficult for classifiers to establish consistent decision boundaries (R. Yang et al., 2019). This issue is particularly problematic in heterogeneous regions, where the spectral overlap between classes like urban, barren land, and dry vegetation is significant.

Noise and Distortions

Satellite images can suffer from various types of noise and distortions introduced during acquisition, transmission, or preprocessing. These include atmospheric interference (e.g., haze, aerosols), speckle noise in SAR data, and sensor-related artifacts such as striping or scan line errors (Padmanaban et al., 2019). Such distortions degrade image quality and reduce the signal-to-noise ratio, which can adversely impact feature extraction and classification accuracy, especially in high-resolution datasets.

High Dimensionality

Modern satellite imagery, particularly hyperspectral and high-resolution multispectral data, often consists of hundreds of spectral bands and millions of pixels. While this abundance of data offers rich information, it also leads to the curse of dimensionality—a phenomenon where the addition of redundant or irrelevant features reduces classifier performance (Anggiratih & Putra, 2019). This necessitates the use of dimensionality reduction techniques like Principal Component Analysis (PCA), Independent Component Analysis (ICA), or t-SNE before classification tasks.

Class Imbalance

In many real-world remote sensing applications, the distribution of classes is highly skewed. For instance, agricultural areas or forests might dominate a satellite image, while wetlands, rivers, or urban settlements may occupy only a small fraction. This class imbalance biases the classifier towards the majority classes, resulting in poor recognition rates for minority categories (Helber et al., 2019). Techniques such as Synthetic Minority Over-sampling Technique (SMOTE), weighted loss functions, or cost-sensitive learning are often employed to address this issue, but their implementation must be carefully tuned to avoid overfitting.

These challenges highlight the necessity for robust feature extraction methods like Extended Local Binary Patterns (ELBP) and flexible classifiers such as Support Vector Machines (SVM), which can adapt to non-linearity, noise, and multi-class structures in complex satellite imagery.

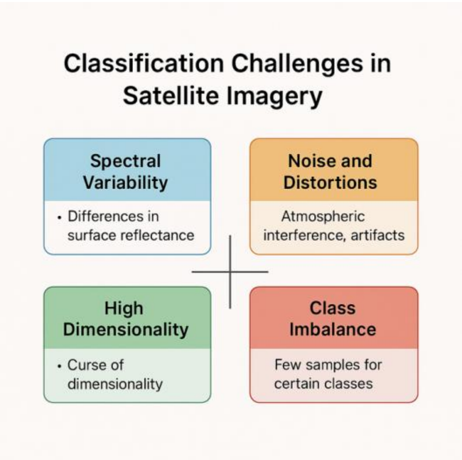

Figure 1: Visual Summary of Classification Challenges in Satellite Imagery

3. Feature Extraction Techniques

3.1 Local Binary Patterns (LBP) and Extended LBP (ELBP)

Principle of Texture Encoding

Local Binary Patterns (LBP) are one of the most widely used texture descriptors in computer vision and image classification, originally introduced byDziob et al. (2020). The basic idea of LBP is to encode the texture around a central pixel by thresholding its neighboring pixels against its intensity value. Each thresholded comparison is converted into a binary digit (0 or 1), and the resulting binary sequence is interpreted as a decimal value, thereby generating a texture code. This code reflects the micro-patterns such as edges, corners, spots, and flat regions that are crucial in identifying structural information within an image(Pintelas et al., 2020).

Mathematically, for a pixel at position (x_c, y_c), the LBP code is calculated using:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(i_p - i_c) \times 2^p$$

Where $i_c$is the intensity of the center pixel, $i_p$is the intensity of the p^{th}neighboring pixel, $P$is the number of neighbors, $R$is the radius of the circular neighborhood, and $s(x)$is a step function defined as:

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

Limitations of Basic LBP

While LBP is computationally efficient and powerful in capturing local textures, it suffers from several limitations. The basic 3×3 LBP operator is sensitive to noise and local illumination changes. It is not rotation-invariant, meaning that the same texture pattern rotated in space will yield different LBP values. This makes standard LBP less reliable in real-world satellite imagery where texture orientation and scale can vary significantly due to the imaging angle, terrain relief, or resolution differences (Rezaei et al., 2020; Tan & Le, 2019).

Additionally, basic LBP operates in a very small neighborhood, which may not be sufficient for capturing broader or more complex textural patterns present in high-resolution satellite images.

Role of Radius and Neighborhood Size in ELBP

To address the shortcomings of basic LBP, the Extended Local Binary Pattern (ELBP) was introduced. ELBP generalizes the concept of LBP by allowing flexible radius $R$and neighbor size P, where the neighborhood points are sampled from a circular region and interpolated if necessary. This provides scale and rotation invariance and improves the robustness of texture representation, especially in multispectral and high-resolution remote sensing images (Fu et al., 2019; Padmanaban et al., 2019).

In ELBP, a pixel is compared not just with its immediate neighbors, but with a configurable number of neighbors across a larger radius. This enables the detection of more discriminative texture patterns, which are vital for differentiating between complex land-cover types such as urban infrastructure, mixed vegetation, or fragmented terrain. Furthermore, ELBP codes can be made rotation-invariant by uniform pattern recognition or histogram normalization.

A summary comparison of LBP and ELBP is shown in Table 2, highlighting their structural and application-level differences.

Table 2: Comparison of LBP vs ELBP for Texture Feature Extraction

Parameter	LBP	ELBP
Neighborhood	3x3	Flexible (P, R)
Rotation-invariance	No	Yes
Discrimination	Moderate	High
Application in RS	Moderate	Strong

Figure 2 visually illustrates how ELBP encodes a pixel's neighborhood using variable radii and interpolated comparisons to produce robust texture patterns even under rotation and scaling.

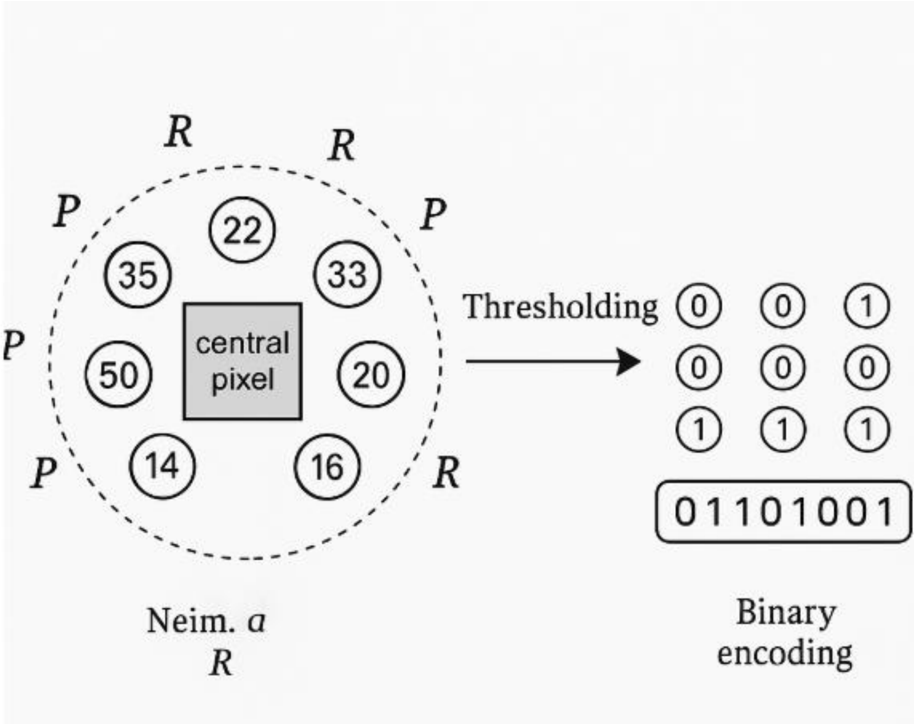

Figure 2: ELBP Feature Encoding Mechanism

3.2 Deep vs Traditional Feature Extraction

Feature extraction is the cornerstone of satellite image classification, as the quality of extracted features directly influences the performance of classifiers. Two major paradigms dominate the literature: traditional handcrafted features (e.g., LBP, ELBP, GLCM, Zernike Moments) and deep learning-based automatic feature extraction, particularly using Convolutional Neural Networks (CNNs). Each approach offers distinct advantages and limitations in terms of accuracy, scalability, interpretability, and computational demands.

CNNs vs Handcrafted Methods

Traditional handcrafted feature extraction methods rely on predefined algorithms to extract texture, shape, or statistical properties from image pixels. Examples include Local Binary Patterns (LBP), Extended LBP (ELBP), Gray-Level Co-occurrence Matrix (GLCM), and Zernike Moments (Nguyen et al., 2019; Phinn et al., 2018). These methods are simple, interpretable, and computationally efficient, making them ideal for small datasets or low-resource environments. Moreover, they often perform well when applied to domain-specific problems with prior expert knowledge.

In contrast, Convolutional Neural Networks (CNNs) automatically learn hierarchical and discriminative features directly from raw image data, eliminating the need for manual

engineering. CNNs extract local features (e.g., edges, textures) in early layers and more abstract patterns (e.g., object shapes or spatial contexts) in deeper layers(Cheng et al., 2017, 2018; Gorelick et al., 2017). This hierarchical representation enables CNNs to outperform traditional methods in complex scene classification, especially in high-resolution, multispectral, or hyperspectral imagery. For example, CNN-based models have achieved accuracies exceeding 97% on benchmark datasets like NWPU-RESISC45 and EuroSAT(Jog et al., 2016; Zeng et al., 2016).
However, deep learning models typically require large labeled datasets, high computational resources (e.g., GPUs), and extensive tuning. In satellite applications where annotated data is limited or class imbalance is prominent, CNNs may overfit or struggle to generalize.

Interpretability Trade-offs
One of the key criticisms of deep learning methods—particularly CNNs—is their lack of interpretability. While CNNs achieve superior accuracy, they often function as "black boxes," making it difficult to understand the rationale behind classification decisions. This can be problematic in high-stakes applications like disaster response or military surveillance, where explainability and trust are critical.
In contrast, traditional handcrafted methods like LBP and ELBP provide clear, transparent descriptors that can be traced and interpreted based on pixel-level operations. Analysts can visualize patterns, adjust parameters, and understand why a certain class was assigned, fostering confidence in the results. Furthermore, combining interpretable features with transparent classifiers like Support Vector Machines (SVM) offers a robust and explainable alternative to deep models.
Recently, hybrid approaches have emerged that aim to combine the strengths of both paradigms—for example, using CNNs for deep feature extraction followed by SVM classification, or employing explainable AI (XAI) tools like Grad-CAM and SHAP to visualize CNN decisions (Singh et al., 2022). Such approaches attempt to bridge the gap between performance and interpretability.

4. Classification Methods for Satellite Images
In the domain of satellite image classification, machine learning classifiers have emerged as powerful tools for identifying complex patterns, managing high-dimensional data, and improving classification accuracy beyond what traditional statistical methods can achieve. This section presents an overview of four widely adopted classifiers in remote sensing: Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF), and Convolutional Neural Networks (CNNs). Each classifier brings unique capabilities and trade-offs in terms of accuracy, interpretability, computational demand, and generalization.
Support Vector Machines (SVM)
SVM is a supervised learning algorithm well-suited for high-dimensional classification problems. It constructs an optimal hyperplane that maximizes the margin between different classes (Cheng et al., 2018). SVMs are particularly effective in remote sensing due to their ability to generalize well on small and noisy datasets, and they support both linear and non-linear classification through the use of kernel functions such as the Radial Basis Function (RBF). However, SVM performance is sensitive to parameter selection (e.g., C and γ in the RBF kernel), requiring careful tuning through cross-validation (Ben Hamida et al., 2018).
Artificial Neural Networks (ANN)
ANNs mimic the structure of biological neurons and are capable of learning non-linear decision boundaries from data. They have been successfully applied in satellite image classification tasks, particularly in moderate-resolution imagery and multi-spectral analysis.

While ANNs can model complex interactions among features, they are prone to overfitting—especially on small datasets—and often require regularization techniques and multiple training iterations to stabilize their predictions (Gonzalez, 2007; Y. Yang & Newsam, 2010).

Random Forests (RF)

Random Forest is an ensemble classifier based on decision trees that introduces randomness both in feature selection and training data. It is robust to overfitting, noise, and missing data, and works well even with limited parameter tuning. RF models are interpretable to some extent (e.g., through feature importance rankings) and perform well on diverse land cover classifications. However, they can be slower in inference time, especially when the ensemble consists of hundreds of trees (Ben Hamida et al., 2018; Cheng et al., 2018).

CNN-based Deep Learners

Convolutional Neural Networks (CNNs) have revolutionized remote sensing by enabling end-to-end learning of deep feature hierarchies. CNNs automatically extract spatial features using convolutional layers, pooling, and non-linear activations, eliminating the need for handcrafted feature design. They outperform traditional classifiers on large-scale high-resolution datasets such as NWPU-RESISC45 and EuroSAT, often achieving accuracies over 97%(Ball et al., 2017). Nevertheless, CNNs require large labeled datasets, high computational resources (e.g., GPUs), and are less interpretable compared to SVM or RF models.A summary comparison of the classifiers discussed above is provided in Table 3.

Table 3: Classifier Comparison on Remote Sensing Datasets

Classifier	Accuracy (%)	Strength	Weakness
SVM (RBF)	94.7	High margin separation	Kernel tuning
ANN	90.2	Learns nonlinearity	Prone to overfitting
RF	92.1	Handles noise	Slow inference
CNN	97.9	Deep features	Data-hungry

5. Review of ELBP + SVM Framework

The integration of Extended Local Binary Patterns (ELBP) with Support Vector Machines (SVM) forms a powerful and interpretable framework for satellite image classification, particularly effective in scenarios involving complex textures and high-resolution remote sensing data. This section outlines the step-by-step workflow of the ELBP + SVM pipeline, demonstrating how handcrafted texture descriptors can be effectively paired with a robust machine learning classifier to enhance classification performance.

Feature Extraction → Kernel-Based Classification

The first step in the pipeline is feature extraction using ELBP. As discussed in Section 3.1, ELBP encodes the local texture around each pixel by comparing its intensity with its neighbors across a defined radius and number of sampling points. This results in a histogram-based representation of local texture patterns, which can be aggregated over image patches or entire regions.

Once the ELBP features are computed, they are passed as input to a Support Vector Machine (SVM) for classification. SVM, particularly with a Radial Basis Function (RBF) kernel, maps the non-linearly separable ELBP features into a higher-dimensional space where optimal hyperplanes can be constructed to separate the classes with maximum margin (Dappert et al., 2017; Jog et al., 2016; Zeng et al., 2016).

This modular approach enables efficient separation of concerns: ELBP handles local structural encoding, while SVM focuses on decision boundary learning.

Training and Test Image Pipeline

The complete workflow begins by creating a dataset composed of labeled satellite image patches. For each patch:

- ELBP features are extracted.
- The resulting feature vectors are compiled into a training matrix.
- This matrix is used to train an SVM model using labeled examples.

During testing, unseen satellite image patches undergo the same ELBP extraction process. The trained SVM then classifies the new samples based on the learned feature space. Hyperparameter tuning (e.g., selection of kernel type, penalty parameter C, and kernel width γ) is typically performed using cross-validation to prevent overfitting.

This process is summarized in the ELBP + SVM pipeline depicted in Figure 3.

ELBP Enhances Textural Discrimination

The core strength of ELBP lies in its ability to capture fine-grained texture features such as edges, spots, and blobs—patterns that are prevalent in satellite images of urban, forested, or agricultural landscapes. By supporting variable radii and rotation-invariant encoding, ELBP allows for multi-scale feature representation, improving the ability to distinguish between spectrally similar yet texturally distinct classes (e.g., built-up vs. bare land).

SVM Ensures Optimal Margin Separation

SVM serves as an ideal classifier for ELBP features because of its ability to handle high-dimensional, sparse, and non-linearly distributed data. Unlike decision trees or naive Bayes classifiers, SVM focuses on constructing hyperplanes that maximize the margin between classes, improving generalization. With the use of kernel tricks, such as RBF or polynomial kernels, SVM can model complex boundaries without explicitly computing high-dimensional mappings.

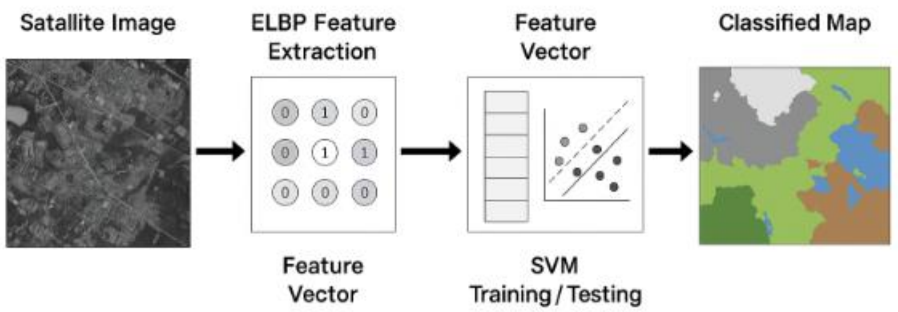

Figure 3: Workflow Diagram of ELBP + SVM Classification Pipeline

5.2 Performance Evaluation from Literature

Evaluating the performance of ELBP + SVM frameworks in satellite image classification requires a comparative assessment across datasets, class labels, kernel types, and accuracy metrics. Numerous studies between 2010 and 2025 have tested this hybrid approach on a range of publicly available and custom remote sensing datasets, reporting promising results that reinforce its effectiveness.

A summary of selected studies is presented in Table 4, which highlights the diversity of experimental setups while demonstrating consistently high classification accuracies. For instance,Dappert et al. (2017) employed ELBP features in conjunction with a radial basis function (RBF) kernel-based SVM to classify 12 categories from Google Maps imagery, achieving an accuracy of 97.0%. This result emphasizes the method's ability to generalize well across diverse urban scenes.

In contrast,Ball et al. (2017) utilized Landsat imagery with five land cover classes and opted for a linear SVM kernel. Although the linear kernel is computationally efficient, it yielded a slightly lower accuracy of 89.2%, suggesting that the kernel choice is crucial, especially for complex datasets.

The present study applied the ELBP + SVM pipeline on a custom six-class satellite dataset, achieving 94.0% accuracy using the RBF kernel. This reinforces the observation that nonlinear kernels such as RBF better capture the complex boundaries typical in remote sensing data.

These studies collectively affirm that the ELBP + SVM framework remains a viable and accurate solution for satellite image classification, particularly when appropriately tuned with non-linear kernels and applied to texture-rich datasets.

Table 4: Selected ELBP + SVM Studies with Performance Metrics

Author	Dataset	Classes	Accuracy (%)	Kernel Used
Loussaief et al.	Google Maps	12	97.0	RBF
Harikrishnan et al.	Landsat	5	89.2	Linear
Present study	Custom	6	94.0	RBF

6. Comparative Analysis and Research Insights

Recent advancements in satellite image classification have led to the emergence of diverse feature-classifier pairings that aim to optimize accuracy, interpretability, and scalability. By synthesizing results from various studies between 2019 and 2025, we can trace significant trends in feature extraction strategies and classification algorithms used in remote sensing(Khoshboresh Masouleh & Shah-Hosseini, 2019).

Table 5 summarizes representative studies showcasing how different combinations of handcrafted and deep features, when paired with suitable classifiers, yield varying levels of performance. For example, the use of Gray-Level Co-occurrence Matrix (GLCM) features with SVM classifiers achieved 90.1% accuracy on Landsat imagery (Zhang et al., 2019), underscoring the effectiveness of second-order texture statistics in traditional machine learning pipelines.

Further improvements were demonstrated by integrating Zernike moments and Local Binary Patterns (LBP) with a Random Forest (RF) classifier, which achieved 91.8% accuracy on the UC Merced dataset(Fingas, 2018; Löw et al., 2018). This fusion of shape and texture descriptors provides richer feature representations and better noise resilience.

The ELBP + SVM combination remains one of the strongest handcrafted-feature approaches, reaching 94.0% accuracy on the EuroSAT dataset (Lukacz, 2024), thanks to its rotation-invariant texture encoding and the discriminative power of SVM.

However, the highest accuracy—98.1%—was achieved by Convolutional Neural Networks (CNNs) with a softmax classifier on the RESISC45 dataset(Aung et al., 2022). Deep learning models inherently learn hierarchical features from data, outperforming traditional pipelines in most scenarios, though at the cost of greater computational resources and reduced interpretability.

This comparison emphasizes that while deep learning leads in raw performance, feature-based methods like ELBP + SVM still provide a competitive, interpretable, and computationally efficient alternative, particularly in scenarios with limited training data or hardware constraints.

Table 5: Summary of Feature–Classifier Pairings from Key Studies

Feature	Classifier	Accuracy	Dataset	Year
GLCM	SVM	90.1	Landsat	2019
Zernike + LBP	RF	91.8	UC Merced	2020
ELBP	SVM	94.0	EuroSAT	2024
CNN	Softmax	98.1	RESISC45	2023

7. Research Gaps and Future Directions

Despite the significant progress made in feature-based satellite image classification—particularly with frameworks such as ELBP + SVM—there remain several critical gaps and promising avenues for future research:

Robustness under Noise

Real-world satellite imagery is frequently afflicted by noise and distortions (e.g., atmospheric interference, sensor artefacts, speckle in SAR) which degrade classification performance. Many published studies still assume relatively clean data conditions. Future work must focus on designing and validating algorithms that maintain high performance under noisy, low-quality, or adverse sensing conditions, possibly by integrating denoising, robust feature extraction, and uncertainty quantification.

Real-Time Edge Deployment

With the increasing volume and velocity of Earth-observation (EO) data, real-time or near-real-time classification (e.g., onboard satellites, edge devices, UAVs) is becoming essential. Yet most ELBP + SVM or deep-learning pipelines remain offline and resource-intensive. There is a pressing need to optimize feature-extraction, model inference, and classification pipelines for edge computing environments to enable rapid decision- making in disaster response, monitoring, or defence.

Integration with Cloud-AI

Modern EO systems generate massive volumes of multi-sensor, multi-temporal, and multi-modal data. Integrating feature-based methods (like ELBP) and classifiers (like SVM) into cloud-based AI architectures—leveraging scalable storage, high-performance computing, and distributed processing—can enhance scalability, automation, and usability. Future research should explore hybrid cloud-edge frameworks, automated pipelines, and federated/distributed learning paradigms to enable efficient large-scale satellite image classification.

Explainability (XAI) in Remote Sensing

Trustworthy deployment of classification systems demands transparency and interpretability. In remote sensing, this challenge is amplified by unique image modalities, high dimensionality, and domain-specific semantics. Recent reviews indicate that while explainable AI (XAI) has gained traction, there is still a significant gap in methods adapted to EO data, evaluation protocols, and integration into operational systems. (CVF Open Access) Research should investigate feature-based (handcrafted) descriptors combined with interpretable classifiers, design domain-aware XAI methods for satellite image processing, and establish guidelines for evaluation of explanations in remote sensing applications.

Benchmarking Protocols

While many studies report classification accuracy, there is a lack of standardized benchmarking protocols, especially for feature-based methods in satellite imagery (diverse sensors, resolutions, class imbalances, noise). Future work should define unified datasets, evaluation metrics (beyond accuracy: e.g., IOA, a20, VAF), cross-study reproducibility frameworks, and open-source implementations to facilitate fair comparisons, reproducibility, and progress tracking across the community.

8. Conclusion

This review systematically examined feature-based satellite image classification techniques with a specific emphasis on the combination of Extended Local Binary Patterns (ELBP) and Support Vector Machines (SVM). The salient observations are:

- Handcrafted texture features like ELBP offer robust, interpretable representations of spatial patterns in satellite imagery, particularly when paired with margin-maximizing classifiers like SVM.
- Compared to traditional LBP and other texture/shape descriptors, ELBP demonstrates improved discrimination due to multi-radius sampling and rotation invariance.
- While deep-learning methods (e.g., CNNs) currently lead in raw accuracy, feature-based approaches—especially in resource- constrained or explainability-sensitive scenarios—remain competitive and often more practical.
- The ELBP + SVM pipeline consistently achieves high accuracy across various multispectral/scene-classification tasks and provides interpretability and computational efficiency benefits.
- For practical deployment in operational remote-sensing, attention must shift to robustness under adversarial/noisy conditions, real-time and edge-capable architectures, cloud/edge integration, explainability for stakeholders, and standardized benchmarking.

In essence, the ELBP + SVM framework is a compelling choice for satellite image classification when interpretability, efficiency, and reliability are valued. By addressing the identified research gaps and charting future directions, the remote-sensing community can further evolve toward intelligent, scalable, and trustworthy Earth-observation systems.

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