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COMPARATIVE ANALYSIS OF CLASSIFICATION METHODS FOR HIGH-RESOLUTION OPTICAL SATELLITE IMAGES

High-resolution satellite image classification is used in various applications, such as urban planning, environmental monitoring, disaster management, and agricultural assessment. Traditional classification methods are ineffective due to the complex characteristics of high-resolution multichannel images: the presence of shadows, complex textures, and overlapping objects. This necessitates selecting an efficient classification method for further thematic data analysis. In this study, a comprehensive assessment of the accuracy of the most well-known classification methods (parallelepiped, minimum distance, Mahalanobis distance, maximum similarity, spectral angle map, spectral information difference, binary coding, neural network, decision tree, random forest, support vector machine, K-nearest neighbour, and spectral correlation map) is performed. This study comprehensively evaluates various classification algorithms applied to high-resolution satellite imagery, focusing on their accuracy and suitability for different use cases. To ensure the robustness of the evaluation, WorldView-3 satellite imagery, known for its exceptional spatial and spectral resolution, was utilized as the dataset. To assess the performance of these methods, error matrices were generated for each algorithm, providing detailed insights into their classification accuracy. The average values along the main diagonal of these matrices, representing the proportion of correctly classified pixels, served as a key metric for evaluating overall effectiveness. Results indicate that advanced machine learning approaches, such as neural networks and support vector machines, consistently outperform traditional techniques, achieving superior accuracy across various classes. Despite their high average accuracy, a deeper analysis revealed that only some algorithms are universally optimal. For instance, some methods, such as random forests or spectral angle mappers, exhibited strength in classifying specific features like vegetation or urban structures but performed less effectively for others. This underscores the importance of tailoring algorithm selection to the specific objectives of individual classification tasks and the unique characteristics of the target datasets. This study can be used to select the most effective method of classifying the earth's surface, depending on the tasks of further thematic analysis of high-resolution satellite imagery. Furthermore, it highlights the potential of integrating machine learning-based approaches to enhance the accuracy and reliability of classification outcomes, ultimately contributing to more practical applications.

Keywords: High-resolution optical satellite images, geoinformation systems, classification, supervised classification methods, unsupervised classification methods, confusion matrices.

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ПОРІВНЯЛЬНИЙ АНАЛІЗ МЕТОДІВ КЛАСИФІКАЦІЇ ОПТИЧНИХ СУПУТНИКОВИХ ЗОБРАЖЕНЬ ВИСОКОЇ РОЗДІЛЬНОЇ ЗДАТНОСТІ

Класифікація супутникових зображень високої роздільної здатності використовується в різноманітних сферах, таких як міське планування, екологічний моніторинг, боротьба зі стихійними лихами та оцінка сільського господарства. Традиційні методи класифікації є неефективними через складні характеристики багатоканальних зображень високої роздільної здатності: наявність тіней, складні текстури та взаємне перекриття різних об'єктів. Це зумовлює необхідність вибору ефективного методу класифікації для подальшого тематичного аналізу даних. У цьому дослідженні проводиться комплексна оцінка точності найбільш відомих методів класифікації (паралелепіпед, мінімальна відстань, відстань Махаланобіса, максимальна подібність, карта спектрального кута, розходження спектральної інформації, двійкове кодування, нейронна мережа, дерево рішень, випадковий ліс, метод опорних векторів, K-найближчий сусід і карта спектральної кореляції). Для проведення оцінки використано супутникові знімки високої роздільної здатності космічного апарату WorldView-3. Для усіх досліджуваних методів класифікації побудовано матриці помилок. Аналіз результатів дозволив зробити висновок, що нейронні мережі та метод опорних векторів мають вищу загальну точність класифікації порівняно з іншими методами. Частина розглянутих методів, при загальній низькій точності класифікації, продемонструвала високу точність виділення окремих класів, зокрема, таких як рослинність та об'єкти міської забудови. Результати роботи можуть бути використані для вибору найбільш ефективного методу класифікації земної поверхні в залежності від завдань подальшого тематичного аналізу даних супутникової зйомки високої роздільної здатності.

Ключові слова: Оптичні супутникові зображення високої роздільної здатності, геоінформаційні системи, класифікація, контрольовані методи класифікації, неконтрольовані методи класифікації, матриці помилок.

Introduction

In the modern world, satellite technologies are essential for monitoring the environment, observing changes in natural and anthropogenic landscapes, and various industries such as agriculture [1] and forestry, urban planning, and land management [2]. In particular, high-resolution optical satellite images provide detailed information about the Earth's surface [3], crucial for accurate analysis and decision-making [4]. The relevance of researching high-resolution optical satellite image classification methods [5] is due to the increasing demands for data processing accuracy and speed in various applications. The classification of optical satellite images involves considering various factors such as the spectral characteristics of objects, spatial resolution, data heterogeneity, and the influence of atmospheric conditions. Additionally, computational resources are essential as processing high-resolution images requires significant power. This study aims to perform a comparative analysis of the accuracy of various methods for classifying high-resolution optical satellite images. The results of this study will contribute to the development of satellite image classification methodology and improve practical solutions in remote sensing.

Related works

Traditional methods of classifying images with high spatial resolution, such as supervised and unsupervised classification, and methods using artificial neural networks are usually based on the spectral characteristics of the image [6]. However, these methods have significant limitations, such as low classification accuracy, limited spatial information, and the "salt and pepper" effect, manifesting in numerous classification errors and incomplete class coverage. In particular, the spectral features of images do not always allow for accurate distinction between objects with similar spectral characteristics, which leads to classification errors and incorrect interpretations. According to studies [7, 8], which achieved an overall accuracy of 0.91 and a Kappa index of 0.88, traditional methods can be effective but still have significant limitations in conditions of complex ground coverage or when processing high-resolution images. Paper [9] discusses classification methods used to analyze historical maps. Among the main problems of satellite image processing are low contrast, incorrect selection of the segmentation threshold, and errors in pixel interpretation during change detection [10-12]. These difficulties greatly complicate the application of classification methods in real-world conditions. One of the ways to solve these problems is to use machine learning, which allows for effective data-driven decision-making and adaptation to changes. The quality of the input images and the complexity of their characteristics determine the choice of processing methods, and the development of hybrid approaches to improve the reliability of existing methods is currently a relevant area.

More modern approaches and intense learning methods have gained popularity due to their numerous advantages over traditional methods. In particular, Convolutional Neural Networks (CNNs) allow for the automatic extraction of important spatial and spectral features without requiring manual feature selection, significantly improving classification accuracy. They can also combine spectral features with additional information, such as texture features or data from other sensors, allowing more accurate results. However, as noted in [13-15], these methods have limitations, including high data and computing requirements and high time complexity during the training phase. Although deep learning [16, 17] significantly improves classification accuracy, it requires large amounts of data and significant computing resources, an essential factor to consider when choosing a method.

Purpose

This article aims to study the effectiveness of high-resolution image classification methods.

The tasks of the study are: a comparative analysis of the effectiveness of high spatial resolution image classification methods, identification of their limitations; conducting experimental studies for the WorldView-3 high-resolution satellite image; evaluation of high-resolution image classification methods using metrics (Accuracy, Precision, Recall, F1).

The results allow the user to choose the most effective method for classifying high-resolution images for solving a specific thematic task.

Considered classification algorithms

This article analyzes the following algorithms: a parallelepiped, a minimum distance, the Mahalanobis distance, the maximum probability, the spectral angle mapper, the spectral information divergence, a binary coding, a neural network, a random trees, a support vector machine, K-nearest neighbor; a spectral correlation mapper.

The parallelepiped classification algorithm uses a simple decision rule. It is applied when the spectral brightness values of various objects do not overlap significantly and the number of object classes is small. The algorithm operates as follows: within the spectral feature space, regions in the shape of parallelepipeds (or rectangles in two-dimensional space) are defined to encompass the brightness values of objects in each class. The boundary values are determined visually using two-dimensional spectral feature plots. Each pixel's spectral features are then compared with these boundary values. If a pixel's brightness falls within one of the defined ranges, it is assigned to the corresponding class. Pixels that do not fit into any range remain unclassified. If a pixel's brightness falls within multiple ranges, it allows for classification possibilities. This algorithm is often integrated with more complex techniques to separate objects with non-overlapping brightness values, followed by further processing of the remaining areas [18].

In the minimum distance classification algorithm, each class is characterized by a mean vector representing its main spectral characteristics. For each pixel, its measurement vector is determined and compared with the mean vectors of each class to determine the spectral distances. The decision rule then classifies the pixel into the class with the closest mean vector. This classifier is appreciated for its simplicity and efficiency. It is particularly suitable for situations with limited computing resources, achieving acceptable classification accuracy and ensuring that a pixel is assigned to the most spectrally similar class. The Mahalanobis distance classifier shares similarities with the minimum distance algorithm but notably integrates the covariance matrix. Unlike the minimum distance algorithm approach, which uses the Euclidean distance, this matrix provides a more detailed and multidimensional metric for measuring the distance between data points. By integrating the covariance matrix, the Mahalanobis distance classifier effectively handles different levels of variance in the class distributions, making it more adept at handling complex spectral interdependencies in the data, thereby increasing classification accuracy and reliability. The Maximum Likelihood Classifier (MLC) uses a statistical algorithm for supervised classification. This algorithm assigns pixels to classes based on the highest estimated probability that the pixels belong to those classes. The main goal is to identify the class that maximizes this probability, thus determining the most likely class for a given pixel. MLC is widely used in remote sensing and various classification tasks due to its classification efficiency based on probabilistic logic [19].

The Spectral Angle Mapper (SAM) classifies pixels according to their spectral resemblance to reference spectra. This technique utilizes endmember spectra derived from the image or a spectral library. SAM assesses the similarity between each image pixel and a reference spectrum by computing the spectral angle, which yields values ranging from zero to one. A smaller angle signifies greater similarity, whereas a larger angle indicates less similarity [20].

Spectral Information Divergence (SID) employs a divergence measure to relate pixels to reference spectra, where a smaller divergence indicates greater similarity. A threshold can be defined, and pixels with a divergence exceeding this threshold are not classified. In contrast to Spectral Angle Mapper, which computes the spectral angle between spectra, SID treats each pixel's spectrum as a random variable. It then quantifies the probabilistic difference between two spectral vectors [21].

The binary coding classification algorithm transforms data and endmember spectra into a binary format based on whether each spectral band is below or above the average spectrum, respectively. The exclusive OR function subsequently compares each encoded reference spectrum with the encoded data spectra to generate a classification image. Pixels are categorized based on the end member with many matching bands. If a minimum matching threshold is specified, pixels that do not meet this criterion may not be classified. Artificial neural networks (ANNs) are a subset of artificial intelligence designed to mimic certain functions of the human brain, especially the ability to meaningfully label individual pixels in images. ANNs take a non-parametric approach to classification and are inherently adaptive, allowing the inclusion of additional data to improve accuracy. Structurally, ANNs consist of several layers with interconnected neurons that act as processing units. During training, ANNs analyze training samples to obtain valuable information. ANNs handle intricate classification challenges, frequently surpassing less sophisticated approaches [19].

Random trees are a collection of several decision trees. Each tree is trained on a randomly selected subset of the data set and functions as a separate decision tree. Classification decisions are made by summarizing the results by majority vote of all trees. This approach increases the stability and accuracy of classification results [22].

The Support Vector Machine (SVM) algorithm is based on statistical learning theory. It separates the data into different classes using a hyperplane that maximizes the distance between them. Data points near the hyperplane are called "support vectors". The goal of SVM is to optimize this margin to reduce misclassification errors. By establishing clear and precise boundaries, SVM effectively distinguishes between different classes in a dataset. The K-Nearest Neighbors (KNN) algorithm classifies data based on majority voting. It calculates the Euclidean distance between data points in the feature space to estimate similarity. KNN defines a parameter K to determine the number of nearest neighbors participating in the voting process. KNN does not require a special training phase. It classifies a data point by assigning it to the most common class among K-nearest neighbors. This simplicity makes KNN particularly useful when the training dataset is frequently updated or expanded [19].

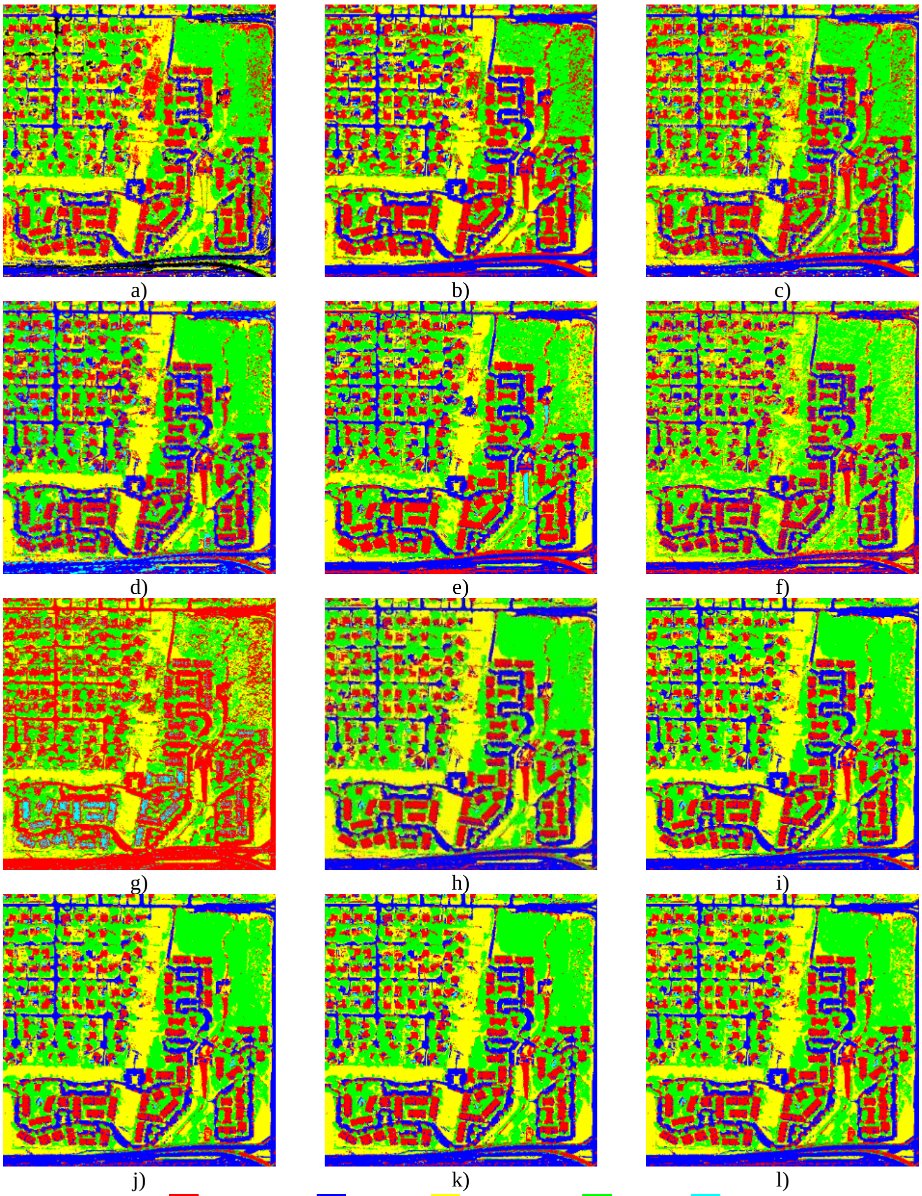
The Spectral Correlation Mapper (SCM) algorithm assigns pixels to the class with the highest correlation. It is a modified version of the Spectral Angle Mapper classifier, which uses spectral angles to classify pixels. The SAM algorithm was found to produce shading effects by determining only the direction of the vector, not the magnitude. SCM solves this by normalizing the data and centering the mean of the two spectra, thus overcoming the shortcomings of SAM [23].

Results

In supervised classification, satellite images undergo classification using predefined input or training data [20]. Establishing training data involves defining class types for classification and selecting representative areas, which are differentiated by color to indicate the respective classes on the image. The identified classes for the image are as follows: buildings (marked in red), roads (marked in blue), land plots (marked in yellow), trees (marked in green), and pools (marked in cyan). Next, the training sample areas for each class are delineated using the corresponding colors on the image. The selected areas for training samples, created for a high-resolution WorldView-3 satellite image, are shown in Figure 1.

Fig.1. Selected areas for training samples from the WorldView-3 satellite image

The results of supervised classification from the WorldView-3 satellite image were obtained using methods such as Parallelepiped, Minimum Distance, Mahalanobis Distance, Maximum Likelihood, Spectral Angle Mapper, Spectral Information Divergence, Binary Encoding, Neural Networks, and Support Vector Machine (SVM) with various kernels (Linear, Polynomial, Radial Basis Function, and Sigmoid), is illustrated in Figure 2. These methods demonstrate differing levels of accuracy and clarity for the specified classes: buildings, roads, land plots, trees, and pools. The Parallelepiped method produces distinct but fragmented lines for roads, and Minimum Distance generates blurry paths with false classifications. Mahalanobis Distance and Maximum Likelihood improve clarity and continuity, with Maximum Likelihood achieving the most consistent results. Neural Networks and SVM (Radial Basis Function kernel) also provide accurate and continuous road lines. Spectral Angle Mapper and Spectral Information Divergence yield clear, albeit slightly blurred, representations, while Binary Encoding and other SVM variants perform similarly with minor interruptions and errors. The Parallelepiped method defines regions with some inaccuracies for land plots, while the Minimum Distance results in indistinct boundaries. Mahalanobis Distance improves clarity, but Maximum Likelihood provides the most precise delineation. Neural Networks, SVM (Radial Basis Function kernel), and other SVM variants demonstrate similarly high accuracy with minimal boundary errors. Spectral similarity methods and Binary Encoding deliver moderately accurate results with minor deviations.



Legend: – buildings; – roads; – land plots; – trees; – pools.

Fig.2. Classification results of methods for the WorldView-3 satellite image: a) Parallelepiped; b) Minimum distance; c) Machalanobis distance; d) Maximum likelihood; e) Spectral Angle Mapper; f) Spectral Information Divergence; g) Binary Encoding; h) Neural Net; i) Support Vector Machine with Linear kernel; j) Support Vector Machine with Polynomial kernel; k) Support Vector Machine with Radial Basis Function kernel; l) Support Vector Machine with Sigmoid kernel

The classification of trees reveals that the Parallelepiped method defines areas with reasonable accuracy, though occasional misclassifications occur. The Minimum Distance method results in blurred boundaries, while the Mahalanobis Distance approach improves delineation, albeit with minor inaccuracies. The Maximum Likelihood method and Neural Networks produce the most precise and accurate outlines, as do Support Vector Machine (SVM) variants with Radial Basis Function kernels. Spectral Angle Mapper and Binary Encoding methods yield satisfactory results, though with slightly less defined contours. The parallelepiped method effectively delineates areas for pools, but it needs some accuracy. Minimum Distance results in indistinct regions, while Mahalanobis Distance improves clarity. Maximum Likelihood, Neural Networks, and SVM (Radial Basis Function kernel) achieve precise and clear boundaries. Spectral similarity and Binary Encoding methods are moderately accurate, with minor deviations, while other SVM kernels deliver reliable results with minimal errors.

In summary, advanced machine learning approaches, particularly Neural Networks and SVM with Radial Basis Function kernels, consistently outperform traditional classification accuracy and boundary clarity across all classes.

Discussion

To assess the quality of the classification results, it is crucial to define rigorous quality metrics and compare the obtained classification images with reference images. To create the reference image, each pixel was manually labeled according to land cover classes (buildings, roads, land plots, trees, and water bodies), allowing for an accurate representation of the visual characteristics of the objects. It enabled a comparison with the results of automatic classification algorithms, facilitating an assessment of their accuracy. The comparison uses a confusion matrix, where the rows and columns correspond to the pixel colors present in the obtained and reference images, respectively. The intersection of each cell in the matrix quantifies the percentage of pixel matches for corresponding colors. The diagonal elements of the confusion matrix indicate the percentage of correctly classified pixels for each color class, providing a direct measure of classification accuracy. In addition to evaluating overall accuracy, analyzing off-diagonal elements reveals which object classes are frequently misclassified, offering insights into specific challenges within the classification process. To identify the optimal classification method, the average values along the main diagonal of the confusion matrix are compared across different classification methods implemented in various software products. Figure 3 illustrates detailed confusion matrices for each classification method, systematically showcasing their comparative performance.

To compare the obtained matrices, we will use the average value of all values of the main diagonal of the matrix calculated as [23]:

$$\bar{c} = \frac{\sum_{i=1}^{N} c_i}{N}, \tag{1}$$

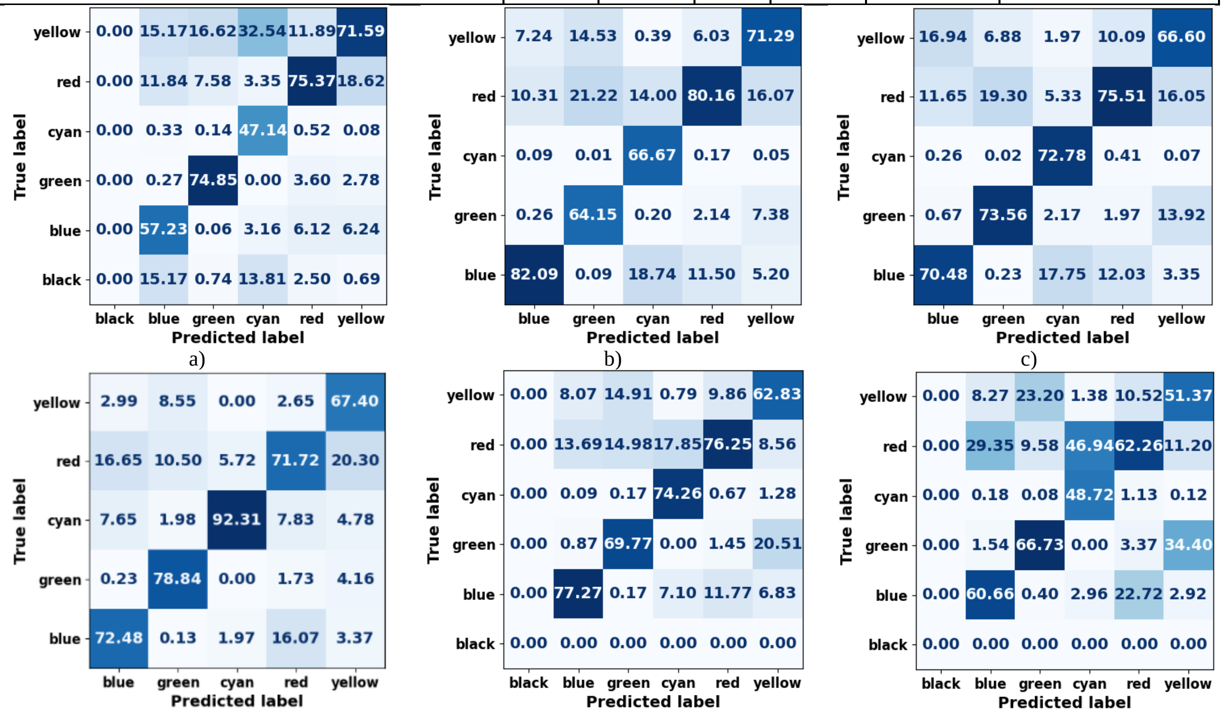
where N – the number of classes; i – the variable, $i=1...N$; c_i – the accuracy of the i-th class.

The accuracy for each class of each method and the calculated average accuracy are presented in Table 1.

Table 1

Average accuracy metrics for classification algorithms

Algorithm Name	blue	green	cyan	red	yellow	Average accuracy
Support Vector Machine with Polynomial kernel	82.27	84.40	85.21	74.20	81.00	81.42
Support Vector Machine with Radial Basis Function kernel	82.47	84.23	84.22	74.71	81.17	81.36
Neural Net Classification Logistic Activation	79.10	82.80	84.22	77.70	82.56	81.28
Support Vector Machine with Linear kernel	81.23	84.88	85.21	73.98	80.23	81.11
Support Vector Machine with Sigmoid kernel	80.22	82.11	76.73	76.06	77.54	78.53
Maximum likelihood	72.48	78.84	92.31	71.72	67.40	76.55
Minimum distance	82.09	64.15	66.67	80.16	71.29	72.87
Spectral Angle Mapper	77.27	69.77	74.26	76.25	62.83	72.18
Machalanobis Distance	70.48	73.56	72.78	75.51	66.60	71.79
Parallelepiped	57.23	74.85	47.14	75.37	71.59	65.24
Spectral Information Divergence	60.66	66.73	48.72	62.26	51.37	57.95
Binary Encoding	0.00	54.15	28.99	71.81	61.85	43.36



a) b) c)
d) e) f)

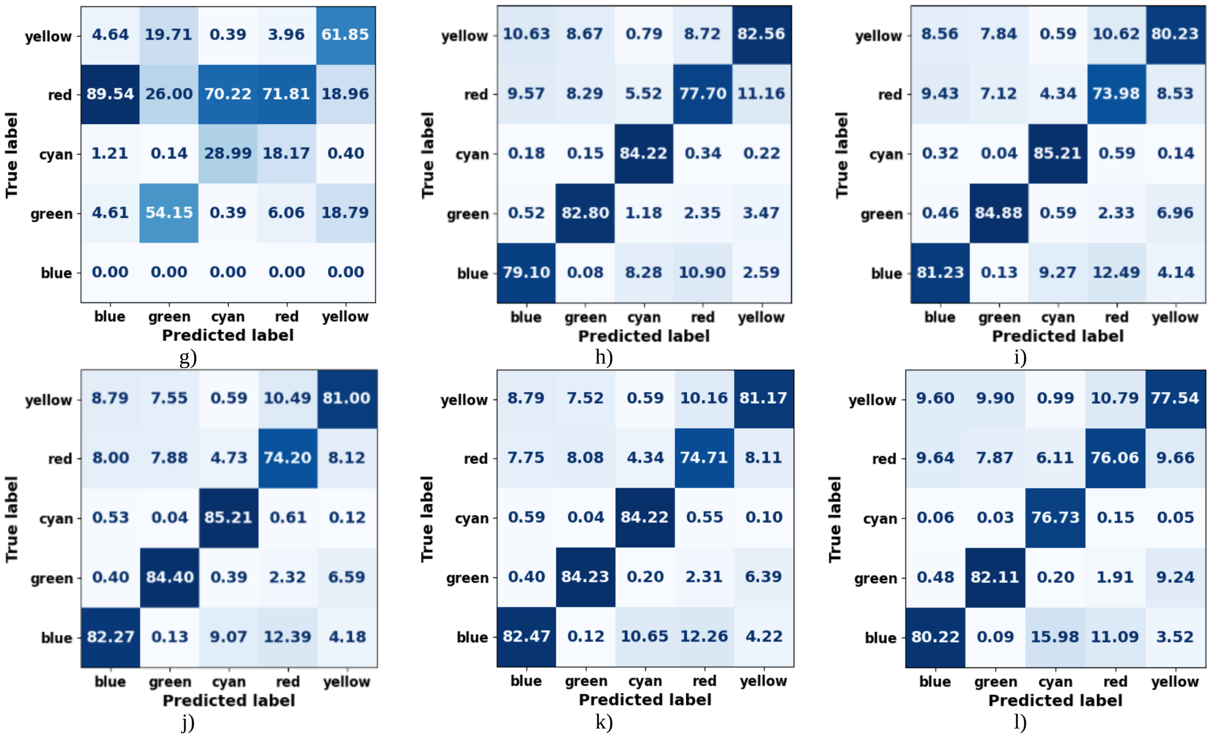


Fig.3. Confusion matrix for classification methods: a) Parallelepiped; b) Minimum distance; c) Machalanobis distance; d) Maximum likelihood; e) Spectral Angle Mapper; f) Spectral Information Divergence; g) Binary Encoding; h) Neural Net; i) Support Vector Machine with Linear kernel; j) Support Vector Machine with Polynomial kernel; k) Support Vector Machine with Radial Basis Function kernel; l) Support Vector Machine with Sigmoid kernel.

Table 1 shows that the most accurate algorithms are the Support Vector Machine (SVM) and Neural Network Classification. Their average accuracy values differ by less than one percent, except for the SVM with a Sigmoid kernel. Other algorithms exhibit lower accuracy, ranging from three to thirty-five percent less. Binary Encoding performed the worst, failing to classify a single pixel of the road class. To evaluate the effectiveness of the methods considered in this paper in the context of image classification based on satellite data, Table 2 shows the following metrics: accuracy, precision, recall, and F1-measure [22].

The Binary Encoding method showed the lowest results with an accuracy of 0.52, which indicates that this approach is ineffective for recognizing classes in these images. The Machalanobis Distance method achieved significantly better results, particularly an accuracy of 0.62, due to its ability to distinguish classes well based on distances in a multidimensional space. The Maximum Likelihood and Minimum Distance methods showed similar results, with an accuracy of about 0.64, indicating their ability to work effectively with the classical approach to classification based on probabilities or distances. The Neural Net method demonstrated high results with an accuracy of 0.86, which confirms the effectiveness of modern machine learning methods for classifying complex data. The Support Vector Machine methods, including Linear Kernel, Polynomial Kernel, Radial Basis Function (RBF) Kernel, and Sigmoid Kernel, showed almost identical results, with accuracies ranging from 0.77 to 0.84. They all showed high precision and F1-measure values, indicating their effectiveness in classification using different kernels. The Spectral Angle Mapper and Spectral Information Divergence methods showed average results with about 0.63 and 0.60 accuracy, indicating moderate spectral classification effectiveness.

Table 2

Average accuracy metrics for classification algorithms

Algorithm Name	**Accuracy**	**Precision**	**Recall**	**F1**
Binary Encoding	0.52	0.55	0.52	0.50
Machalanobis Distance	0.62	0.68	0.62	0.61
Maximum Likelihood	0.64	0.70	0.64	0.62
Minimum Distance	0.63	0.69	0.63	0.62
Neural Net	0.86	0.83	0.86	0.85
Parallelepiped	0.63	0.69	0.63	0.62
Spectral Angle Mapper	0.63	0.69	0.63	0.61
Spectral Information Divergence	0.60	0.65	0.60	0.58
Support Vector Machine (Linear Kernel)	0.77	0.73	0.77	0.75
Support Vector Machine (Polynomial Kernel)	0.79	0.74	0.78	0.76
Support Vector Machine (RBF Kernel)	0.87	0.84	0.87	0.86
Support Vector Machine (Sigmoid Kernel)	0.84	0.79	0.81	0.84

Conclusions

In this study, we conducted a comprehensive comparative analysis of various classification methods applied to high-resolution optical satellite images. These images present complex challenges due to their diverse spectral signatures, intricate textures, shapes, spatial dependencies, and temporal variations. Our research focused on evaluating the effectiveness of several supervised classification techniques, including traditional algorithms such as Parallelepiped, Minimum Distance, Mahalanobis Distance, and Maximum Likelihood, alongside machine learning and deep learning methods like Spectral Angle Mapper, Spectral Information Divergence, Binary Coding, Neural Network, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbor, and Spectral Correlation Mapper.

Experiments were conducted using authentic high-resolution satellite images obtained from the WorldView-3 satellite. The evaluation was based on rigorous quality metrics, prominently the confusion matrix, to assess classification accuracy across different methods. Our findings indicate that Neural Network and Support Vector Machine algorithms consistently outperformed other methods, demonstrating superior capability in accurately classifying diverse features within high-resolution satellite imagery. These algorithms excelled in capturing nuanced spectral and spatial information, enhancing classification accuracy across various classes such as buildings, roads, land plots, trees, and pools.

Evaluation of the efficiency of high-resolution satellite image classification methods showed that the Binary Encoding method was the least efficient (accuracy 0.52). At the same time, Neural Net (0.86) and SVM with different kernels (0.77 – 0.84) provided the best results. Classical approaches, such as Mahalanobis Distance (0.62), Maximum Likelihood, and Minimum Distance (about 0.64), showed moderate efficiency. The Spectral Angle Mapper and Spectral Information Divergence methods (0.60 – 0.63) demonstrated limited capabilities for spectral classification. The highest accuracy was provided by neural networks and SVM, confirming their effectiveness for analyzing complex data.

Furthermore, the analysis of error matrices highlighted the variability in algorithm performance across different classes. While average values along the main diagonal provided an overall measure of classification success, individual class analyses underscored the importance of selecting appropriate algorithms tailored to specific classification tasks. This research contributes to advancing methodologies for satellite image classification, emphasizing the significance of machine learning and deep learning approaches in enhancing the efficiency and accuracy of remote sensing applications. Future studies could explore hybrid approaches and incorporate more advanced deep learning architectures to refine high-resolution satellite imagery analysis classification outcomes.

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