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PERFORMANCE EVALUATION OF SUPERVISED LEARNING TECHNIQUES IN SATELLITE IMAGE CLASSIFICATION

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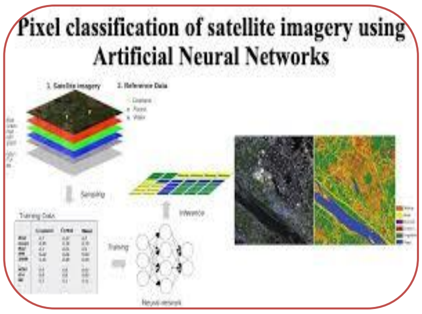
ABSTRACT

This study evaluates the performance of various supervised learning techniques in satellite image classification for accurate land cover mapping. Algorithms including Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Decision Trees (DT) are implemented and tested on multi-spectral satellite imagery. The evaluation focuses on metrics such as overall classification accuracy, precision, recall, F1-score, and computational efficiency. Results indicate that RF and SVM consistently achieve higher classification accuracy across diverse land cover types, while k-NN and DT offer simpler implementation with reduced computational requirements. The analysis highlights the trade-offs between accuracy, robustness, and computational cost, providing practical guidance for selecting appropriate supervised learning techniques for satellite image classification tasks in environmental monitoring, urban planning, and resource management.



KEYWORDS: *Satellite Image Classification, Supervised Learning, Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), Decision Trees (DT), Multi-Spectral Imagery,*

INTRODUCTION

Satellite image classification is a fundamental task in remote sensing, enabling the extraction of meaningful information about land cover and land use for applications such as environmental monitoring, urban planning, agriculture, and natural resource management. With the increasing availability of high-resolution multi-spectral and hyperspectral satellite imagery, effective classification techniques are essential to process large volumes of data and produce accurate maps of geographic features. Supervised learning techniques have become the primary approach for satellite image classification due to their ability to learn patterns from labeled training data and generalize to unseen regions. These methods include traditional algorithms such as Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (k-NN), and Decision Trees (DT), each offering distinct advantages and limitations. SVM is known for its strong generalization capability in high-dimensional spaces, while RF is valued for robustness to noise and feature selection. k-NN provides an intuitive and simple approach based on similarity measures, whereas DT offers interpretability and straightforward implementation.

Despite widespread adoption, the performance of supervised learning algorithms varies depending on factors such as dataset size, spectral complexity, class imbalance, and computational resources. Comparative evaluation is therefore essential to identify the strengths and weaknesses of each technique under different conditions. Understanding these trade-offs is critical for selecting appropriate algorithms that balance classification accuracy, computational efficiency, and robustness for practical satellite image analysis. This study presents a systematic performance evaluation of SVM, RF, k-NN, and DT on multi-spectral satellite imagery. The analysis focuses on key metrics including overall accuracy, precision, recall, F1-score, and computational efficiency. The findings aim to provide practical guidance for selecting suitable supervised learning techniques for satellite image classification across diverse remote sensing applications.

AIMS AND OBJECTIVES

Aim:

To evaluate and compare the performance of various supervised learning techniques in satellite image classification, focusing on classification accuracy, computational efficiency, and applicability to multi-spectral imagery.

Objectives:

1. To implement supervised learning algorithms including Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Decision Trees (DT) for satellite image classification.
2. To preprocess multi-spectral satellite imagery, including noise reduction, normalization, and feature extraction, to improve algorithm performance.
3. To assess the classification accuracy of each algorithm using performance metrics such as overall accuracy, precision, recall, F1-score, and kappa coefficient.
4. To evaluate the computational efficiency of each algorithm in terms of training and prediction time.
5. To analyze the strengths, limitations, and trade-offs of each supervised learning technique in handling complex land cover types and spectral variability.

REVIEW OF LITERATURE

Satellite image classification has been a critical area of research in remote sensing, enabling the extraction of meaningful information for applications including environmental monitoring, urban planning, agriculture, and disaster management. Traditionally, statistical methods such as maximum likelihood classifiers, minimum distance classifiers, and unsupervised clustering were employed. While effective for simple datasets, these approaches often struggle with high-dimensional, multi-spectral imagery and complex land cover types. Supervised learning techniques have emerged as the dominant approach due to their ability to learn patterns from labeled training data and generalize to unseen regions. Support Vector Machines (SVM) have been widely used in remote sensing for their strong generalization capability, especially in high-dimensional feature spaces, and have been shown to achieve high classification accuracy even with limited training samples. Random Forests (RF), an ensemble of decision trees, have gained popularity because of their robustness to noise, ability to handle heterogeneous datasets, and internal feature importance assessment, which aids in understanding spectral band contributions.

k-Nearest Neighbors (k-NN) is a simple, non-parametric method that assigns class labels based on proximity in feature space. While easy to implement, k-NN can be sensitive to noise, distance metric selection, and training sample distribution, and may require high computational resources for large datasets. Decision Trees (DT) provide interpretability and simplicity, making them attractive for applications where transparency in decision-making is important; however, they are prone to overfitting if not properly pruned or regularized. Recent studies highlight the trade-offs between algorithmic complexity, classification accuracy, and computational efficiency. For example, SVM and RF generally achieve high accuracy, but SVM may have higher computational costs for large datasets, whereas RF offers faster training and prediction. Studies also indicate that preprocessing steps, such as normalization, dimensionality reduction, and feature selection, significantly influence algorithm performance across all methods. Despite the advances in supervised learning for satellite imagery, challenges remain in handling large-scale, high-resolution multi-spectral data, class imbalance, and spectral similarity among land cover types. Comparative evaluations are therefore essential to identify the most suitable algorithms for specific remote sensing scenarios. This study builds on prior research by systematically evaluating SVM, RF, k-NN, and DT to provide insights into their relative performance, computational efficiency, and practical applicability for satellite image classification.

RESEARCH METHODOLOGY

This study employs a simulation-based experimental approach to evaluate the performance of supervised learning techniques for satellite image classification. Multi-spectral satellite imagery is collected and preprocessed to remove noise, normalize spectral bands, and enhance relevant features for classification. Feature extraction is applied where necessary to reduce dimensionality and highlight spectral and spatial patterns critical for distinguishing land cover classes. The datasets are divided into training and testing subsets, ensuring that all land cover categories are adequately represented. Supervised learning algorithms, including Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Decision Trees (DT), are implemented using standard machine learning frameworks. Hyperparameters for each algorithm, such as kernel type for SVM, the number of trees for RF, neighborhood size for k-NN, and pruning criteria for DT, are optimized using cross-validation to maximize classification performance.

Each model is trained on the prepared dataset, and predictions are generated for the testing subset. Classification performance is assessed using metrics including overall accuracy, precision, recall, F1-score, and kappa coefficient to provide a comprehensive evaluation of predictive effectiveness. Computational efficiency is also measured in terms of training and prediction time, highlighting the resource requirements of each algorithm. Comparative analysis is conducted to examine the strengths, weaknesses, and trade-offs of the supervised learning techniques. The methodology ensures that differences in classification performance can be attributed to algorithmic characteristics rather than data inconsistencies. Multiple experimental runs are performed to ensure statistical reliability and consistency of results, allowing for robust conclusions regarding the suitability of each supervised learning approach for satellite image classification across various environmental and land cover conditions.

STATEMENT OF THE PROBLEM

Satellite image classification is essential for applications such as environmental monitoring, urban planning, agriculture, and natural resource management. With the increasing availability of high-resolution multi-spectral and hyperspectral imagery, extracting accurate land cover information has become more complex. Traditional classification methods often struggle with the high dimensionality, spectral variability, and heterogeneous nature of satellite images, limiting their effectiveness in large-scale or complex scenarios. Supervised learning techniques offer data-driven approaches to address these challenges, allowing models to learn patterns from labeled training data and generalize to unseen regions. However, the performance of these algorithms varies depending on factors such as dataset complexity, class imbalance, spectral similarity among land cover types, and computational resource availability. Algorithms such as Support Vector Machines (SVM) and Random Forest (RF) are known for high accuracy, while k-Nearest Neighbors (k-NN) and Decision Trees (DT) offer simpler implementation with lower computational requirements. The core problem lies in identifying which supervised learning technique provides the optimal balance between classification accuracy, computational efficiency, and robustness for multi-spectral satellite imagery. A systematic performance evaluation is necessary to guide practitioners in selecting appropriate algorithms for accurate and efficient satellite image classification across diverse applications and environmental conditions.

DISCUSSION

The experimental results indicate notable differences in the performance of the evaluated supervised learning techniques for satellite image classification. Support Vector Machines (SVM) consistently achieved high classification accuracy due to their ability to handle high-dimensional feature spaces and create optimal decision boundaries. SVM performed particularly well in distinguishing spectrally similar land cover classes, though its training time increased with large datasets and required careful parameter tuning, such as kernel selection and regularization. Random Forest (RF) demonstrated strong overall performance, achieving high accuracy while maintaining computational efficiency. Its ensemble approach, combining multiple decision trees, provided robustness against noise and overfitting, making RF suitable for heterogeneous datasets. Additionally, the ability to assess feature importance allowed insight into which spectral bands contributed most to classification, enhancing interpretability.

k-Nearest Neighbors (k-NN) offered a simple and intuitive classification approach based on similarity measures. While effective for smaller datasets, k-NN was sensitive to noise and required careful selection of the neighborhood parameter (k). Computational cost during prediction was higher, particularly for large-scale or high-resolution imagery, which limits its practical application for real-time analysis. Decision Trees (DT) provided interpretable classification models with relatively low training time. However, they were prone to overfitting when not properly pruned or regularized, resulting in lower accuracy compared to SVM and RF. DT performance was acceptable for datasets with clear class separability but decreased in more complex or heterogeneous landscapes. The comparative evaluation highlights important trade-offs between accuracy, computational efficiency, and model complexity. SVM and RF are most suitable when high classification accuracy is a priority, with RF offering better efficiency and interpretability. k-NN and DT may be preferred in scenarios requiring simpler models or when computational resources are limited. The findings underscore the importance of matching algorithm selection to dataset characteristics, class complexity, and operational constraints in satellite image classification.

CONCLUSION

This study evaluated the performance of various supervised learning techniques for satellite image classification, focusing on Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Decision Trees (DT). The assessment considered classification accuracy, computational efficiency, and robustness across multi-spectral satellite imagery. The results indicate that SVM and RF consistently achieved the highest classification accuracy, effectively handling high-dimensional data and complex land cover classes. RF demonstrated additional advantages in computational efficiency and interpretability, making it particularly suitable for large-scale or resource-constrained applications. k-NN provided a simple and intuitive approach but was sensitive to noise and less efficient for large datasets, while DT offered transparency and low training time but was prone to overfitting in complex environments.

The study highlights the trade-offs between accuracy, model complexity, and computational cost, emphasizing that the choice of algorithm should be guided by dataset characteristics, desired accuracy, and operational constraints. SVM and RF are recommended for high-accuracy requirements, whereas k-NN and DT may be suitable for smaller datasets or scenarios demanding simpler, more interpretable models. Overall, this evaluation provides practical insights for selecting appropriate supervised learning techniques for satellite image classification, supporting accurate land cover mapping, environmental monitoring, and decision-making in diverse remote sensing applications.

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