Supervised remote sensing image classification using KNN and SVM

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Abstract

Land-use and land-cover information offers comprehensive insights into the Earth's surface characteristics. Remote sensing (RS), a pivotal technology within large-scale Earth-observing systems (EOS), plays a vital role in acquiring land-use and land-cover information. One of the most commonly employed techniques for analyzing land-cover information using RS images is pixel-level classification. In this project, we exploited various supervised classification algorithm, including K-Nearest Neighbor (KNN) and Support Vector Machine (SVM), for remote sensing image classification. Principal component analysis (PCA) was investigated as well due to the intrinsic high-dimensionality of the RS dataset used in this study. Qualitative and quantitative results illustrate that SVM performed better than KNN without using PCA.

1. Introduction

Remote sensing (RS), a technique enabling non-contact access to ground-level Earth data, represents a powerful tool for large-scale monitoring [1-3], particularly in regions seldom visited by human presence. It has been an extremely tool in a variety of fields, such as land-use/land-cover monitoring [4], invasive vegetation detection [5], target detection [6], and environment measurements [7]. A widely adopted methodology for extracting insights into diverse land cover types is image classification. This technique involves the assignment of pre-defined labels to each pixel within a RS image. The derived land cover information significantly contributes to an enhanced comprehension of the physical and chemical characteristics of the earth surface, leading to notable accomplishments in this domain. Hudson et al. utilized an iterative self-organizing data analysis technique (ISODATA), an unsupervised classification algorithm, to investigate land-use and land-cover characteristics within floodplain environments. They conducted their analysis using satellite remote sensing images acquired by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor system [7]. Eniolorunda et al. proposed a similar classification scheme, utilizing ISODATA as the primary classifier [8]. In their work, Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Lands Imager (OLI) imagery served as the foundational remote sensing data sources. While those aforementioned unsupervised classification algorithms do not rely on prior information, which can be time-consuming to acquire, it needs additional labor cost for post-processing procedure to obtain semantic label information, as that label information is not considered in the step of model training and needs to be determined manually through visual interpretation.

Therefore, in this project, we proposed to investigate supervised machine learning models for RS image classification. Specifically, we exploited two classification models, including K-Nearest Neighbor (KNN) and Support Vector Machine (SVM), and applied them on a benchmark RS dataset. Furthermore, as there are hundreds of spectral bands within our selected dataset, we chose to utilize Principal Component Analysis (PCA) as the dimensionality reduction algorithm to reduce the number of input features. Our assumption is that the classification performance obtained from SVM will be better than that of KNN.

2. Methodology and dataset

2.1 KNN

KNN is a straightforward and intuitive classification algorithm that operates based on instance-based learning. In KNN classification, when provided with a new data point, the algorithm determines its class by analyzing the classes of its nearest neighbors in the feature space. It calculates the distance (commonly using Euclidean distance) between the new data point and all other data points in the training dataset. The KNN algorithm then identifies the k nearest neighbors based on these distances. For classification, it considers the majority class among these k neighbors and assigns that class label to the new data point. The choice of the number of neighbors (k) is a critical parameter influencing the algorithm's performance, as smaller values may lead to more flexible boundaries and potential overfitting, while larger values may result in smoother decision boundaries but could oversimplify the classification model. Overall, KNN doesn't involve explicit training; instead, it relies on stored data and distance calculations to classify new data points based on their proximity to existing labeled data points.

2.2 SVM

SVM is a powerful supervised learning algorithm used for classification tasks. SVM aims to find the optimal hyperplane that best separates different classes in a high-dimensional feature space. Given a set of labeled training data, SVM works by mapping the input data into a higher-dimensional space using a kernel function, allowing for nonlinear separation of classes. It then seeks the hyperplane that maximizes the margin, which is the distance between the hyperplane and the nearest data points of each class, called support vectors. The objective is to find the hyperplane that not only separates the classes but also maximizes the margin, thus improving its generalization ability on unseen data. SVM is effective in handling both linearly separable and nonlinearly separable datasets by utilizing different kernel functions, such as linear, polynomial, radial basis function (RBF), or sigmoid, to map the data into higher dimensions, enabling complex decision boundaries for accurate classification.

2.3 RS image utilized in this study

The image that will be exploited in this study is corrected by the Reflective Optics System Imaging Spectrometer (ROSIS) sensor over Pavia University, Italy. It consists of 610*340 pixels with 103 spectral bands. The spatial resolution of that image is 1.3 meters, and nine land-cover classes are labeled in the corresponding ground-reference data. Such an image is available on this website: https://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes. The collected image is displayed in Figure. 1.

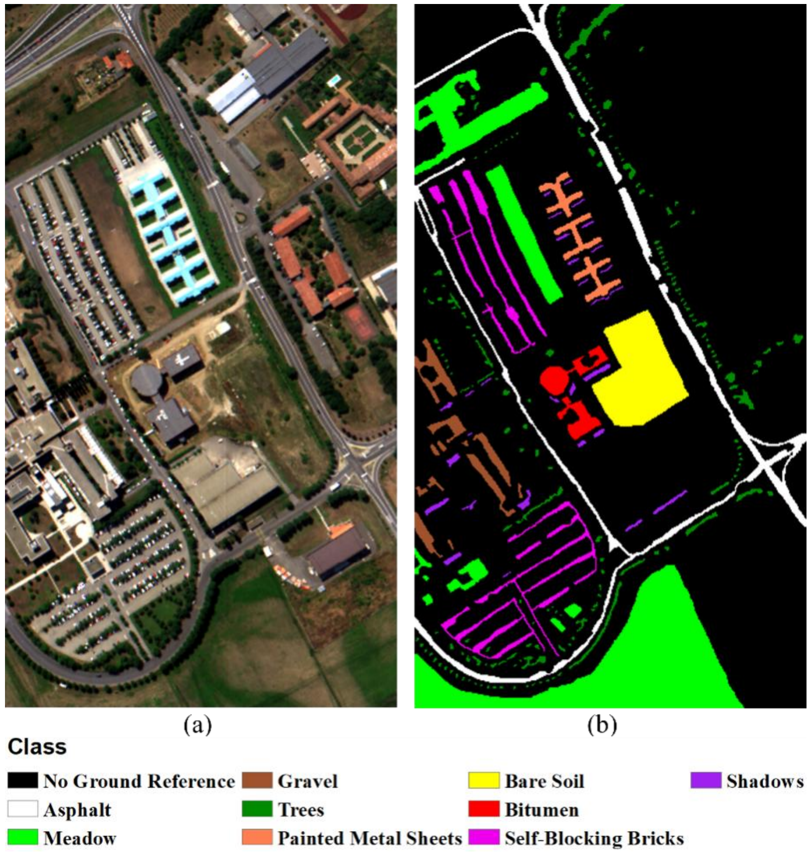

Figure 1. False-color image composites and their corresponding ground-reference data: (a) false-color composite of Pavia University image bands (R: band 55, G: band 33, and B: band 13); and (b) ground reference data (with class legend) for the Pavia University image.

3. Experimental setup and results

3.1 Experimental setup

In this study, KNN and SVM algorithms are implemented from scratch using Python. Regarding the KNN model, the hyper-parameter *k*, which represents the number of selected nearest neighbors, is set to 5. And the Euclidean distance is selected as distance measurement.

For the SVM utilized in this project, we implement linear and RBF kernel functions and evaluate their classification performance, respectively. In terms of dual form of the SVM optimalization problem, we utilize “covopt” Python package to obtain the solutions of those parameters which will be used for model prediction. Moreover, as SVM is designed natively for two-class classification problem based on maximizing margin. However, for remote sensing image classification, multi-class classification is common due to various land cover types on the Earth. Our solution is to use “One-vs-Rest” strategy, which splits multi-class classification problem into two-class classification problem per class, to ensure SVM for multi-class classification. Regarding the utilization of PCA, 5 resulting PCs are extracted as reduced feature representation.

In order to evaluate classification performance quantitatively, all ground-reference data is randomly split into training and testing sample sets. In this project, we randomly select 20% samples per class as training data, with the remaining ground-reference data used as testing data. Furthermore, two quantitative indices are also adopted for the evaluation, including overall accuracy (OA), and the Kappa coefficient (Kappa).

3.2 Experimental results

First, we evaluated classification performance of KNN and SVM using the original spectral features. The quantitative results are shown in Table 1. We can observe that SVM-RBF achieved best classification performance, with OA=93.32%, and Kappa=91.15%. KNN can obtain promising results, where OA-88.10% and Kappa=83.91. However, SVM-linear cannot produce similar classification performance compared with other two approaches. From the classification maps shown in Figure 2, similar phenomenon can be observed as well, where those misclassified pixels located in the central part of the image are eliminated in the classification map derived from SVM-RBF. And SVM-linear produces the worst classification maps compared with the other two maps.

Table 1. Classification results (in unit of %) of Pavia University image using the original spectral features

	KNN	SVM-linear	SVM-RBF
OA	88.10	32.13	93.32
Kappa	83.91	23.82	91.15

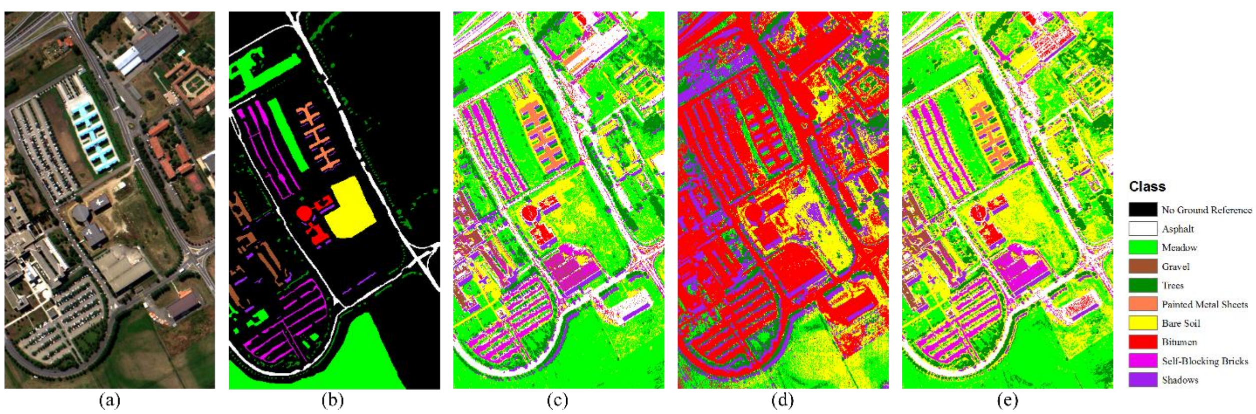

Figure 2. Classification maps of Pavia University image using the original spectral features: (a) false-color composite of Pavia University image bands (R: band 55, G: band 33, and B: band 13); (b) ground reference data; (c) KNN result; (d) SVM result using linear kernel; and (e) SVM result using RBF kernel.

Second, we applied PCA for dimensionality reduction, then selected first 5 PCs as the input data for KNN and SVM, instead of utilizing the original spectral features. The quantitative classification results are illustrated in Table 2. Different from those results obtained by utilizing the original spectral features, we notice that KNN combined with PCA produces best classification accuracies, with 85.42% OA and 80.23% Kappa. And compared with Table 1, OAs decrease for KNN and SVM-RBF, where OA of SVM-linear increases from 32.13% to 42.24%. Manual interpretation of the classification maps shown in Figure 3 enables us to draw the same conclusion. For those maps of RBF-RBF in Figure 3 (e) and Figure 2 (e), many “Asphalt” pixels are misclassified as “Bitumen”, leading to lower classification accuracies. Meanwhile, even though the OA of SVM-linear increases from 32.13% to 42.24%, the classification map shown in Figure 3 (d) still contains much more misclassified pixels.

Table 2. Classification results (in unit of %) of Pavia University image using the first 5 PCs

	KNN	SVM-linear	SVM-RBF
OA	85.42	42.24	80.37
Kappa	80.23	30.16	73.91

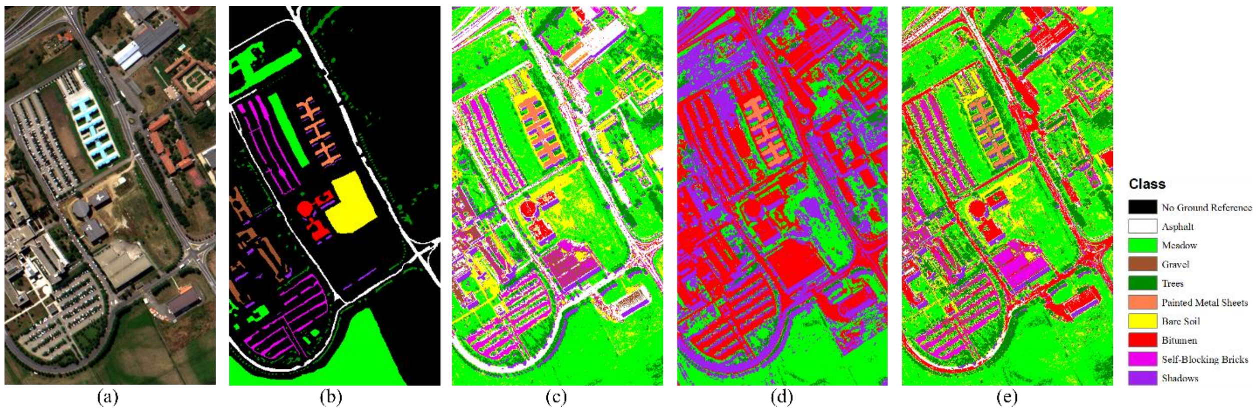

Figure 3. Classification maps of Pavia University image using the first 5 PCs: (a) false-color composite of Pavia University image bands (R: band 55, G: band 33, and B: band 13); (b) ground reference data; (c) KNN result; (d) SVM result using linear kernel; and (e) SVM result using RBF kernel.

4. Conclusion and discussion

For this project, we investigated the applications of KNN and SVM on remote sensing image classification. Experimental results demonstrate that SVM-RBF and KNN achieve the best classification results utilizing original spectral features and PCA resulting features, respectively. Moreover, it is notable that exploiting PCA cannot yield higher classification accuracies for KNN and SVM-RBF. For this case, there are two possible reasons: (a) non-linear relationships: PCA assumes linear relationships between features. If the underlying data relationships are non-linear, PCA might not effectively capture these complex relationships. In such a case, nonlinear dimensionality reduction techniques like t-distributed stochastic neighbor embedding (t-SNE) or manifold learning methods might be more suitable; and (b) optimal features for classification: The original features used for classification might already be highly informative and relevant for the specific classification task at hand. In such cases, reducing dimensionality through PCA might discard valuable discriminatory features, leading to a decrease in classification accuracy.

Furthermore, there are several constraints that have been well addressed and can be addressed in the future. The first one is the memory cost when classifying all pixels using SVM to obtain land-cover mapping result. The main reason comes from the matrix calculation of SVM model, where the size of that matrix depends on the number of pixels. Predicting labels for all pixels of my dataset at the same time will yield "out-of-memory" issue. In order to overcome such a memory issue, our solution is to classify those pixels line-by-line and combine those classification results together to generate final land-cover mapping. The second is the distance calculation utilized in KNN. In this project, we adopted the Euclidean distance as the distance measurement. Other distances, such as spectral angel mapping (SAM), Mahalanobis distance, and Hausdorff distance, can be considered for further investigations. Third, those hyper-parameters utilized in KNN and SVM, such as *k* representing the number of selected neighbors and *gamma* in the RBF kernel, can be optimized by employing cross-validation.

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