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# EVOR-STACK: A label-dependent evolutive stacking on remote sensing data fusion

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ABSTRACT

Land use and land covers (LULC) maps are remote sensing products that are used to classify areas into different landscapes. Data fusion for remote sensing is becoming an important tool to improve classical approaches. In addition, artificial intelligence techniques such as machine learning or evolutive computation are often applied to improve the final LULC classification. In this paper, a hybrid artificial intelligence method based on an ensemble of multiple classifiers to improve LULC map accuracy is shown. The method works in two processing levels: first, an evolutionary algorithm (EA) for label-dependent feature weighting transforms the feature space by assigning different weights to every attribute depending on the class. Then a statistical raster from LIDAR and image data fusion is built following a pixel-oriented and feature-based strategy that uses a support vector machine (SVM) and a weighted k-NN restricted stacking. A classical SVM, the original restricted stacking (R-STACK) and the current improved method (EVOR-STACK) are compared. The results show that the evolutive approach obtains the best results in the context of the real data from a riparian area in southern Spain.

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## 1. Introduction

Remote sensing is an important discipline for many tasks such as resource management [1], environmental monitoring [2] and disaster response [3]. For a long time, machine learning techniques have been used to improve remote sensing performance and applicability. In addition, the use of active sensors such as LIDAR (light detection and ranging) has recently spread to improve the classical remote sensing products [4], which were mainly based on images. This change involves a data complexity increase and makes artificial intelligence systems and data fusion techniques even more important for extracting meaningful information from remote sensing data.

Remote sensing knowledge can be gathered in several products, among which land use and land covers (LULC) maps are arguably one of the most important. LULC maps are based on a classification of the terrain depending on its morphologic or functional characteristics, and they are a very remarkable tool in the development of policies to manage the natural environment. Automatic pixel classification, which is generally supervised, is usually the first step to extract maps from remote sensing data. Several techniques from machine learning have been used in this context with satisfactory results, e.g., k-NN [5], Naive Bayes [6] and SVM [7].

Although the validity of machine learning has been widely demonstrated in the remote sensing context, more research is needed to fulfil the standard requirements of many remote sensing products, and especially for LULC maps [8]. Thus, the final classification has to maintain not only the global accuracy that is the general standard but also satisfactory partial accuracies for every label. Thus, some researchers [9,10] have started to exploit hybrid artificial intelligence systems [11] based on optimization techniques (genetic algorithms) and classical machine learning applied to remote sensing data.

Evolutionary computation is usually used to search optimal weighting for both structural and functional aspects to improve the predictive models for machine learning. In supervised machine learning, there are essentially three main areas of weighting application: support vector machine optimization, artificial neural networks (training and topology) and feature weighting.

Support vector machines (SVMs) are learning algorithms proposed by Vapnik [12,13]. A SVM constructs one or more hyperplanes in a high-dimensional space by means of a kernel function. Therefore, the kernel function election and its proper parametrization are critical for the performance of the classifier. Many authors have used evolutionary computation to solve this problem with pure [14] or real-coded [15] genetic algorithms. Other authors have also explored the use of genetic programming for kernel assembling [16] or developed hybrid algorithms [17], which usually have an evolutionary module in a first level and a SVM applied for classification in a second one.

Artificial neural networks (ANNs) consist of a simulation of the structures and behaviour of biological neural systems by means of mathematical models [18]. Evolutionary computation has been used to train the set of neural network parameters and to design its structure. From the viewpoint of training the network, the common

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approach is to create the genome by encoding the weights of the connections. This may be done by typical bit-based encoding, but there are also more efficient proposals [19]. The main problem with the approaches based on genetic algorithms is the lack of efficient crossover operators because it is difficult to establish which functional parts of the network are to be exchanged. For this reason, other techniques based on genetic programming have been more successful [20]. There have also been several studies on evolutionary computation applied to the design of neural network architecture and weighting optimization. In these cases, the fitness function is usually multi-objective [21] because it must take into account different aspects (structural and functional) of the network.

Techniques that use genetic algorithms to find a set of weights for the feature space, allowing greater accuracy in the classification process, are common in the literature [22]. The usual individual encoding is a set of real values that represent the weights of each feature. The fitness is defined by the classification process itself. Therefore, the search process can be viewed as a global task in which the optimal weights are considered in terms of their features regardless of the label assigned to each instance. Moreover, the use of several evolutionary techniques (genetic algorithms and evolutionary strategies) for both instance selection and feature weighting has proven possible [23], and an optimal weight searching dependent on each label has recently been tested [24] with good results in biomedicine.

With all this in mind, this work can be seen as a new application of hybrid artificial intelligence system [25] which combined the application of ensembles in remote sensing [26,27] that takes advantage of contextual information from multi-source (LIDAR and aerial images) data and the use of evolutive computation to improve the separability of pixels for each label. Thus, we improve a method called R-STACK [28] (based on the stacking of a SVM and multiple k-NN classifiers) with a matrix of weights obtained in the preprocessing stage [29] to give rise to a new method called EVOR-STACK for the following three purposes:

- Improve the general accuracy of an automatically generated LULC map.
- Show the quality of models when hybrid artificial intelligence systems are applied to LIDAR and imagery fusion data.
- Obtain information about what features are the most important to classify each landscape by studying the resulting weights per label.

The rest of this paper is organized as follows: Section 2 presents the study area for this work and provides a brief description of the different landscapes in the area. Section 3 provides a detailed description of the proposed method. The results and discussion are presented in Sections 4 and 5, respectively. Finally, Section 6 is devoted to summarizing the conclusions and to discussing future lines of work.

## 2. Data description

A LIDAR system is a remote sensor technology that is able to register object heights. The process starts with the emission of light (usually laser). The light impacts on a surface and its reflected signal is caught by the LIDAR system. Finally, the system measures the time elapsed from emission to reception to establish the distance between the emitter and the object that produced the return. This process gives rise to a cloud point database in which for every point, it is possible to obtain the following data: spatial position (i.e., $x$, $y$ and $z$ coordinates), intensity of return and number of returns in a sequence (if a pulse caused multiple impacts). These measurements and the RGB values in an orthophoto are used in this work to obtain statistical features on which the whole classification is based.

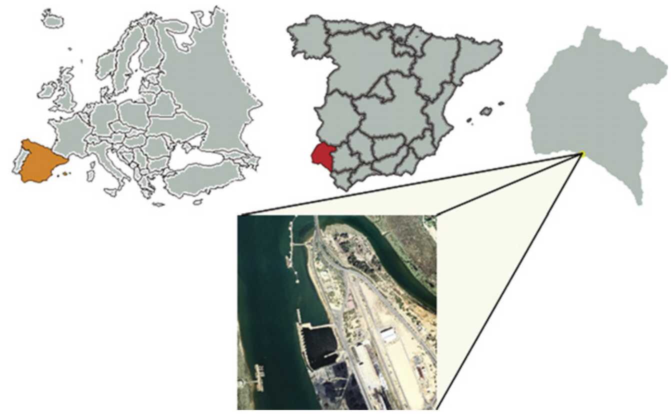

**Fig. 1.** Study area.

Our LIDAR data were collected in coastal areas of the province of Huelva (Fig. 1). The pulses were geo-referenced and correctly validated by the distributor of the data and included 1,384,875 records for an area of 1.5 km$^2$. The reported precision indicates a maximum error of 0.5 m in the $x$–$y$ positions and 0.15 m in the $z$ position. Along with the LIDAR flight, aerial photographs were taken of the area with a resolution of 0.5 m$^2$. The study area is situated in southern Spain at the mouth of the Tinto and Odiel rivers. This area is near the city of Huelva and presents a mix of urban and natural areas. The natural areas can be classified into five subclasses: watered zones, marshland and vegetation (low, middle and high). The high vegetation in the area consists of scarce trees of the genus *eucalyptus*. The middle vegetation consists of different types of Mediterranean bushes that principally surround roads and urban areas. Pastures are classified as low vegetation and include bare earth areas. The urban areas are also classified into three subclasses: roads and railways, dumps and urban areas (buildings and industrial areas).

## 3. Method

The method proposed, called EVOR-STACK (steps 4–8 in Algorithm 1), is a new contextual [30] hybrid method to improve thematic maps by means of a remote sensing data fusion, evolutionary computation and complex classifiers (ensembles) [31].

**Algorithm 1.** LULC classification method.

**input**
*l*: LIDAR data
*o*: Orthophotograhy data
**output**
*m*: LULC map
**begin**
1. Build a matrix *raster* in which every cell involves a physical position with the corresponding statistics from *l* and *o*
2. Select a training set from *raster*, called *train*
3. Label each pixel in *train* using expert knowledge
4. Execute a multi-label EA to extract the matrix *W*
5. Let *svm* be a SVM model from *train*
6. Use *svm* to classify every pixel in *raster*
7. For each pixel *p* in *raster*
   7.1. Collect the neighborhood of *p* in a set *s*
   7.2. Use *W* to modify every pixel from *s*
   7.3. Build a weighted-distance k-NN model, *knn*, from *s*
   7.4. Use *knn* to classify *p*
8. Return a map *m* with every pixel spatial position and its label
**end**

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