A new synergistic approach for crop discrimination in a semi-arid region using Sentinel-2 time series and the multiple combination of machine learning classifiers

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Abstract. Accurate monitoring of agricultural lands and crop types is a crucial tool for sustainable food production. Therefore, to provide reliable and updated crop maps, the improvement of satellite image classification approaches is essential. In this context, machine learning algorithms present a potential tool for efficient and effective classification of remotely sensed data. The main strengths of machine learning algorithms are the capacity to handle data of high dimensionality, and mapping classes characterized by strong complex dynamics. The main objective of this work was to develop a new synergistic approach for crop discrimination in the semi-arid region of Chichaoua province, located in the Marrakesh-Safi region, Morocco, using high spatio-temporal resolution imagery and a multiple combination of machine learning classifiers. This approach was developed based on 10m spatial resolution open access Sentinel-2 (S2) images and machine learning algorithms. The atmospherically corrected S2 images were accessed through the Theia Land Data Center. Reference dataset was collected from a field survey carried out during the 2018 agricultural season in order to train the classifiers. Artificial Neural Networks, Support Vector Machine, K-Nearest Neighbors, Bagged Trees, Naive Bayes, Discriminant Analysis and Decision Trees classifiers were trained over the study area and the accuracy metrics, mainly Overall Accuracy (OA) and Kappa coefficient (K), were assessed. The trained models were single classifiers to build the ensemble classifier system. The obtained results showed high OA and K values up to 96% and 0.95 respectively, achieved by the developed approach. Therefore, based on these results, the approach we developed using the combination of multiple classifiers has a significant impact on crop classification quality.

1. Introduction
Satellite imagery is widely and extensively used for land cover and land use classification, crop identification, and thematic mapping at both local and global scales. This large use of remotely sensed
data is due to its advantages, mainly represented by repeatable observation, large region coverage, multi/hyper spectral records, and multi-resolution. It is significant that, with the development of satellite data acquisition technology, remote sensing images can be acquired with high spatio-temporal resolution by various sensor types [1]. These characteristics combined with classification techniques allow a great potential to obtain satellite image information. As shown in Table 1, recently supervised machine learning (ML) classifiers, such as artificial neural networks (ANN), support vector machine (SVM), decision tree (DT), random forest (RF), maximum likelihood (ML) are the algorithms most used to extract information from remote sensing imagery [2]-[6]. The use of these techniques based on satellite imagery for crop discrimination is not an easy task, in particular for semi-arid areas. Such areas are strongly characterized by heterogeneous agricultural landscapes that decrease the classification accuracy results [7]-[9]. Therefore, several studies as shown in Table 1, use the multiple classifier system as a solution to generate a single result from the combination of many ML classifiers, in order to improve the crop classification performance [10]-[12]. Multiple classifier combination, also called ensemble classifier, has become a widely used tool to achieve efficient classification results in many fields [13], [14]. Bagging and boosting are the most used approaches for combining ML classifiers [15]-[18]. Many previous studies have demonstrated that the majority voting method is an effective strategy to build an ensemble classifier [19], [20]. In the present work, we developed a new pixel-based classification approach, based on a synergy between high spatio-temporal resolution S2 time series and multiple classifier combination of two categories of supervised ML algorithms. Generative algorithms called NB and discriminative ones namely: DT, SVM, KNN, BT, ANN, and DA, are implemented and combined to create an ensemble classifier using the majority voting strategy. The study aimed to discriminate the dominant crop types over a semi-arid area located in Chichaoua region in central Morocco in high spatial resolution of 10m. In addition, this paper tested the developed crop discrimination approach and evaluated the classification results obtained through the multiple classifier combination.

This paper is organized as follows: an introduction into ML classifiers combination and crop type mapping; an implemented approach section, which describes the in-situ measurement and the satellite imagery dataset, as well as the developed approach for the multiple classifier combination; a results section, presenting the main crop classification results for both single and ensemble classifiers, and their performance assessment. Finally, discussion, conclusion, and a perspectives section, provide an in-depth discussion of the results obtained and the concluding remarks.

2. Implemented Methodology
This section explains the different work procedures involved in implementing the approach of combination of multiple classifiers. The fusion and combination of ML algorithms is a key attribute to our approach to crop discrimination. Both training samples and seven ML classifiers run in an ensemble framework that efficaciously incorporates information from dataset extracted from multi-temporal S2 imagery. Our implemented approach involves seven single classifications. Each ML classifier is trained and evaluated to extract accuracy metrics (OA and K). Based on the accuracy metrics, the best ML classifiers are selected and combined to build our multiple classifier system. Figure 1 shows the different steps involved in the implemented approach.
Table 1. Summary of previous studies of crop classification.

| Study | Year | Sensor          | Number of images | Number of classified crops | Classifiers       | OA (%)     | Location         |
|-------|------|-----------------|------------------|---------------------------|-------------------|------------|------------------|
| [27]  | 2016 | World-View-2    | 2                | 10                        | Multiple NN       | Not defined| Denmark          |
| [32]  | 2017 | PolSAR          | 1                | 11                        | DT                | 84.89%     | Netherland      |
|       |      |                 | 1                | 5                         |                   | 92.59%     | Denmark          |
|       |      |                 | 1                | 7                         |                   | 86.87%     | Canada           |
| [21]  | 2016 | LandSat-8 & SPOT-4 | 8              | 18                        | RF, SVM           | 79.40%     | Canada           |
| [1]   | 2018 | Sentinel-1 & LandSat | 18            | 1                         | SVM, RF           | 90.40%     | China            |
| [14]  | 2018 | RapidEye        | 1                | 1                         | SVM, XGBoost, Bagging, RF, ANN, KNN | 98.9%     | Japan            |
| [34]  | 2019 | Sentinel-1      | 33               | 16                        | NB, KNN, DA, RF, SVM | 43%       | Pakistan         |
| [5]   | 2018 | Indian Pines    | 1                | 8                         | RF, SVM, ANN, DT, KNN | 94.40%     | India            |
| [12]  | 2018 | LandSat         | 11               | 1                         | ANN, SVM, DT, KNN  | 90.23%     | China            |
| [24]  | 2017 | Sentinel-1      | 26 for 2014, 55 for 2015, 22 for 2016 | 5 | NB, RF, Maximum Likelihood (ML) | Not defined | Germany          |
2.1. Data collection phase

2.1.1. Study area and ground truth data. The study area is an agricultural area located in the Chichaoua province, Marrakesh-Safi region in central Morocco (Figure 2). It is characterized by a semi-arid Mediterranean climate with a mean annual precipitation of 250 mm [24]. The study area is mostly flat. The major land cover classes dominant in this area are: annual crops, mainly cereals (wheat and barley), as well as vegetables and melons; tree plantations including permanent trees (olives and oranges) and deciduous trees (apricots and grapes); as well as significant areas left fallow or uncultivated.
The vegetation development in this area is affected by a great inter-annual and intra-annual heterogeneity [7], therefore, the land cover maps require annual updates. Effort was directed towards the development of land cover classification methods based on remote sensing data. On April 2018, a field survey was carried out to collect a ground truth dataset. Detailed information was recorded for six thematic classes namely: cereals (Cr), watermelon (Wr), olive trees (OlvT), orange trees (OrgT), deciduous trees (DecT) and fallow (Fl). A seventh class belonging to non-crops (NC) was considered, including built-up and bare soil samples. The latter was identified using Google Earth and a total of 145 ground truth plots were defined for the seven thematic classes.

2.1.2. Satellite imagery dataset. Optical S2 imagery was exploited for the present study. Twenty six S2 images were acquired from November 2017 to August 2018 over our study area. Each image was received as a tile covering an area of 100 x100 km2 at level 2A (L2A). This level provides products atmospherically in GeoTIFF format. Therefore, no corrections have been required. The S2 sensor acquires data in 13 spectral bands with three spatial resolutions 10m, 20m and 60m. For the present work, two bands were exploited with 10 m spatial resolution bands (band 4 and band 8). Due to cloudiness, only one to two acquisitions have been used for some months. Detailed information about the acquisition dates of earth observation data is illustrated in Table 2. S2 earth observation data are freely downloaded from Theia Land Data center [25].

| Platform       | Year   | Acquisition dates |
|----------------|--------|-------------------|
| Sentinel-2A    | 2017   | 18/11, 23/11, 08/12, 23/12 |
| and Sentinel-2B| 2018   | 02/01, 22/01, 27/01, 01/02, 03/03, 23/03, 12/04, 17/04, 27/04, 02/05, 12/05, 06/06, 16/06, 26/06, 16/07, 26/07, 10/08, 15/08, 20/08, 25/08, 30/08. |

2.2. Data preparation and feature extraction phase

2.2.1. Training and validation samples
The reference dataset is randomly divided into two parts: training samples and validation samples. The latter accounts for 75 % of the total samples and the rest was used for training.

2.2.2. Feature layers
For the present work, the normalized difference vegetation index (NDVI) feature layers, were derived from S2 time series. NDVI [23] maps were derived based on the red and near infrared reflectance bands of S2 images as follows:

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]

(1)

Where NIR and RED referred to the reflectance measurements in red and near infrared bands respectively.

2.3. Single classification, accuracy evaluation and comparison phase
A set of seven ML algorithms were applied comprising two types of approaches (generative and discriminative). These algorithms are the most used in a literature review for crop classification. The machine learning and statistics toolbox of MATLAB was utilized for the present study.

2.3.1. Single classifiers
Naive Bayes classifier. NB is a probabilistic ML model that is used for the task of classification. It is a simple structure of Bayesian network (Equation 2). This method assumes that the features are statistically independent of one another and works with this assumption.

\[ P(A|B) = \frac{P(B|A)P(A)}{P(B)} \]  

(2)

Decision Tree classifier. DT is a supervised ML approach that repeatedly divides the training dataset into smaller subsets, based on tests to feature values. This algorithm classifies the pixels based on a series of binary decisions. The DT approach is a non-parametric classifier that requires no prior statistical assumptions. This approach is widely exploited for classification of remote sensing images [5], [27], [28].

Support Vector Machine classifier. SVM is a ML algorithm which is mostly used for classification problems. It is a supervised classifier which uses training samples in an input space and projects them into a high dimensional space to allow the discrimination of different classes. The algorithm aims mainly to find the optimal hyperplane which maximizes the distance between this hyperplane and the samples nearest to it. This method has been applied widely and efficiently for crop classification using satellite imagery [29]-[31].

Artificial Neural Networks classifier. ANN is a branch of artificial intelligence which refers relatively to electronic networks of neurons based on the neural structure of the human brain. It is one of the ML algorithms that can efficiently solve the classification problems. Its special strength is the ability to create dynamically complex prediction functions and emulate human thinking. Neurons (equivalent to biological axons) are the computational elements of an ANN. Those elements are organized in layers to build the block of an ANN [32]. ANNs have been widely used over decades to map crop types [5], [33].

K-Nearest Neighbor classifier. KNN is a supervised ML algorithm used for classification and regression predictive issues. This method relies on labeled input data and classifies new unlabeled data based on similarity measures, mainly distance functions. It uses training samples as a reference set to identify a subset of K training samples which are the closest to a test sample. The latter is labeled with the closest class to the K subset. The KNN classifier is characterized by easy-to-interpret output, low calculation time, and its predictive power. It is a method, belonging to the most simple and traditional classification techniques, which has been extensively used for geospatial analysis and image classification [5], [34].

Bagged Tree classifier. BT is an ensemble of decision trees for either regression or classification. Bagging stands for bootstrap aggregation. To carry out a prediction using the bagged trees method, you have to carry out a prediction from each decision tree, then simply average the predictions together to get a final prediction. Bagged or ensemble prediction is the average prediction across the sampled bootstrapped trees. This approach has been used for land cover mapping, using satellite imagery [3], [4], [32].

Discriminant Analysis classifier. DA model is a generalization of Fisher’s linear discriminant, an approach used in ML, statistics, and pattern recognition, in order to find a linear combination of features that characterizes or identifies two or more classes. Several studies used the DA classifier for remotely sensed crop mapping [4], [36], [37].

2.3.2. Accuracy assessment. There are various methods to analyze and evaluate the performance and the accuracy of satellite image classification. The accuracy is assessed by comparing the results of classification to ground truth data. Generally speaking, the accuracy of the land cover maps extracted
from remotely sensed data was assessed using K and OA. K is an accuracy metric used to assess statistical differences between classifications (Equation 3).

\[ K = \frac{\sum_{i=1}^{k} X_{ii} - \sum_{i=1}^{k} (G \cap C)}{N^2 - \sum_{i=1}^{k} (G \cap C)} \]  

(3)

OA represents the percentage of correctly classified pixels or objects, which corresponds to commission and omission errors [38]. Equation 4 illustrates the formula of OA.

\[ OA = \frac{\sum_{i=1}^{k} (X_{ii})}{\sum_{j=1}^{k} \sum_{i=1}^{k} (X_{ij})} \]  

(4)

Where k is number of rows and columns in error matrix; i is the class number; N is the total number of classified values compared to truth values; Xii is the number of values belonging to the truth class i that have also been classified as class i (i.e., values found along the diagonal of the confusion matrix); Xij the number of values belonging to the truth class j that have been classified as class i; Ci is the total number of predicted values belonging to class i; Gi is the total number of truth values belonging to class i. Besides K and OA, accuracy assessment of individual classes can be computed in a similar manner.

Two other metrics are used: The producer’s accuracy (PA). It is calculated by dividing the number of correct pixels in one class divided by the total number of pixels, as derived from ground truth data (Equation 5).

\[ PA = 100\% - O_e(\%) \]  

(5)

The user’s accuracy (UA). If the correct classified pixels in a class are divided by the total number of pixels that were classified in that class, this measurement is called UA (Equation 6).

\[ UA = 100\% - C_e(\%) \]  

(6)

Where

Oe is error of omission;
Ce is error of commission.

For the present work, the four accuracy metrics of each of the used ML algorithms were calculated using confusion matrix results.

2.4. Selection of the best Classifiers and Combining multiple classifiers phase

The evaluation and comparison of the classification results of each ML classifier is carried out based on the performance metrics calculated in the previous step to create multiple classifier combinations. Firstly, the seven single classifiers were used to create the multiple classifier combination, based on the major voting method. Then a classifier selection process was processed to choose the best classifiers to combine, according to the classifiers reaching high accuracy values, and eliminating the classifiers with low results from the multiple classifier system for each iteration. The single classifiers utilized for the six combinations are presented in Table 3.
3. Results

3.1. Single classifications results
Table 4 shows the confusion matrix and performance metrics of each of the seven ML classifiers. In addition, the PA and UA of all classes are presented and compared for each classifier, as illustrated in Figure 3(a-b). The classification results vary widely from generative to discriminative approaches, while the generative classifier reached the lower performance metrics. These results indicated that the ANN classifier produced the highest performance metrics, whereas the lowest result was obtained for the single classifier NB followed by the SVM classifier. 3.2. Comparison of machine learning classifications
The comparison of the obtained OA and K values of the single classifications showed that the best results achieved by the ANN classifier (OA = 95.08 % and K = 0.941), followed by KNN algorithm (OA = 93.85 % and K = 0.926). All statistical results are presented in Table 4. As can be seen in Figure 3, the PA values of all classes, obtained for ANN, are the highest, except for the olive trees where the best value was achieved by KNN classifier. Also, the UA’s values obtained by ANN are the highest, compared to the other algorithms. NB algorithm yielded the lowest accuracy metrics (OA = 70.68 % and K = 0.653) followed by SVM classifier (OA = 79.39 and K = 0.752). A large difference between the PA and UA was observed for four classes; non-crop (with lowest values of PA = 21.74 % and UA = 54.40 %); fallow (with lowest values of PA = 52.43 % and UA = 75.90 %); olive trees (with lowest values of PA = 57.44 % and UA = 38.52 %), and cereals (with lowest values of PA = 75.09 % and UA = 56.96 %).

3.2. Selection and performance assessment of the best multiple classifier combination
In order to select the best multiple classifier combination, different and multiple combinations were created based on the majority voting strategy. Table 5 illustrates the PA and UA of the thematic classes.
Table 4. Accuracy metrics of single classifiers for 7 classes; DecT: Deciduous trees, OrgT: Orange trees, OlvT: Olive trees, Cr: Cereals, Wm: watermelon, Fl: Fallow, NC: Non-Crop.

|          | Single classifications |          |          |          |          |          |          |
|----------|------------------------|----------|----------|----------|----------|----------|----------|
|          | PA         | UA         | PA         | UA         | PA         | UA         | PA         | UA         | PA         | UA         |
| DecT     | 96.49      | 100.00     | 98.68      | 99.34      | 98.90      | 94.53      | 96.93      | 97.36      | 90.79      | 94.09      | 96.04      | 100.00     | 78.29      | 97.01      |
| OrgT     | 99.01      | 98.32      | 98.31      | 99.15      | 100.00     | 95.69      | 98.03      | 94.95      | 94.51      | 94.64      | 94.93      | 92.97      | 78.73      | 84.19      |
| OlvT     | 95.85      | 96.85      | 97.23      | 92.43      | 91.00      | 87.38      | 83.74      | 88.97      | 80.62      | 79.52      | 81.98      | 78.38      | 57.44      | 38.52      |
| Cr       | 93.43      | 96.09      | 87.54      | 93.36      | 82.58      | 94.68      | 90.31      | 87.00      | 83.04      | 74.53      | 91.70      | 66.03      | 75.09      | 56.96      |
| Wm       | 98.08      | 100.00     | 99.52      | 100.00     | 100.00     | 98.56      | 98.56      | 99.04      | 89.57      | 98.5       | 100.00     | 96.15      | 86.58      |           |
| Fl       | 94.82      | 91.85      | 91.10      | 88.52      | 88.76      | 90.56      | 91.59      | 87.08      | 77.60      | 75.90      | 86.61      | 75.90      | 52.43      | 86.17      |
| NC       | 93.14      | 91.79      | 84.70      | 85.68      | 82.88      | 85.41      | 80.59      | 90.28      | 63.24      | 72.51      | 21.74      | 85.94      | 69.18      | 54.40      |
| OA       | 95.08      | 93.85      | 92.62      | 91.92      | 83.98      | 79.39      |           |           |           |           |           |           |           |           |
| K        | 0.941      | 0.926      | 0.911      | 0.903      | 0.808      | 0.752      | 0.653      |           |           |           |           |           |           |           |

Table 5. Accuracy metrics of different Multiple classifier combinations.

|          | Multiple classifier combinations |          |          |          |          |          |          |
|----------|----------------------------------|----------|----------|----------|----------|----------|----------|
|          | PA         | UA         | PA         | UA         | PA         | UA         | PA         | UA         | PA         | UA         | PA         | UA         |
| DecT     | 97.59      | 100.00     | 98.03      | 99.55      | 98.90      | 99.12      | 99.34      | 99.34      | 99.56      | 97.84      | 99.78      | 99.34      |
| OrgT     | 99.15      | 96.97      | 99.86      | 96.07      | 99.58      | 98.61      | 99.86      | 96.46      | 99.72      | 98.47      | 99.72      | 97.66      |
| OlvT     | 92.39      | 93.03      | 89.27      | 95.91      | 95.85      | 95.85      | 90.66      | 97.04      | 96.89      | 96.89      | 93.43      | 98.18      |
| Cr       | 95.16      | 90.46      | 96.89      | 90.32      | 97.58      | 93.07      | 96.89      | 93.33      | 95.50      | 96.50      | 96.89      | 92.41      |
| Wm       | 99.52      | 100.00     | 100.00     | 100.00     | 99.52      | 99.52      | 100.00     | 100.00     | 99.52      | 100.00     | 99.04      | 100.00     |
| Fl       | 94.50      | 87.69      | 85.95      | 85.82      | 95.15      | 91.02      | 95.79      | 90.24      | 94.98      | 92.01      | 95.31      | 85.86      |
| NC       | 81.05      | 95.17      | 76.94      | 98.25      | 85.39      | 95.90      | 84.93      | 97.13      | 87.21      | 94.32      | 78.31      | 96.62      |
| OA       | 94.32%     | 94.15%     | 95.94%     | 95.61%     | 96.21%     | 94.78%     |           |           |           |           |           |           |           |
| K        | 0.932      | 0.955      | 0.929      | 0.951      | 0.947      | 0.955      | 0.937      |           |           |           |           |           |           |
for the six multiple classifier combinations that have been created. The single classifiers utilized for the combinations with their OA and K metrics are presented in Table 4. As can be seen in Table 5, an analysis of the OA and K metrics of the created combinations showed that C3 (ANN, KNN, DT, DA and BT) has the best improved results (OA = 95.94 % and K = 0.951) compared to the highest accuracy metrics of single classifiers (ANN classification with OA = 95.08 % and K = 0.941). With the combination of three ML algorithms C2 (ANN, KNN and DA), the crop classification performance accuracy is slightly improved and reached the maximum values (OA = 96.21 % and K = 0.955).

In Figure 4 (a-b), the evolution of PA and UA metrics for the seven classes are compared and analyzed for each combination. As can be seen in the graph of PA evolution, low values were recorded for non-crop class for all combinations compared to the other classes (with lowest value of PA = 76.94 % achieved by C2 and highest value PA = 87.21 % reached by C5). Whereas for the UA evaluation graph, the fallow class depicted low values compared to the other classes (with lowest value of UA = 85.82 % achieved by C2 and highest value UA = 92.01 % reached by C5). The best multiple classifier combination achieved high PA and UA values exceeding 92 %, for all classes except the non-crop as was the case for the other combinations.

![Figure 4. Evolution of PA (a) and UA (b) by class for each multiple classifier combination](image)

### 4. Discussion and conclusion

In this paper, the aim of study was to classify 5 dominant crop types over a semi-arid area using combined ML algorithms. The generative algorithm Naïve Bayes, and discriminative ones, mainly DT, SVM, ANN, KNN, BT and DA are trained and evaluated for crop discrimination. Focusing on the results of single classifications, we noticed that the discriminative approach, ANN compared to the rest of ML classifiers, provided the most accurate results (OA = 95.08 % and K = 0.941 ), and all the classes achieved PA and UA accuracies greater than 91 %. Whereas the worst result, was obtained for NB algorithm (with an OA of 70.68 % and K of 0.653) and for non-crop, olive trees and cereals the PA and UA accuracies are lower than 76 %, especially for olive trees with PA = 57.44 % and UA = 38.52 %. SVM and DT also showed low crop discrimination results with OA less than 80 %. The combination of the ML algorithms reflect the highest crop discrimination results showed in OA = 96.21 % and K = 0.955. Previous studies were carried out to map the spatial distribution of crop types over the same study area. Simonneaux [7], based on LandSat TM imagery, classified four land cover classes namely, bare soil, annual crops, trees on annual understory and trees on bare soil and the classification results were about 83.7 % and 0.78 for OA and K respectively. On the one hand, there was confusion between trees on annual understory and annual crops and, on the other hand, between trees on bare soil and trees on annual understory. Compared to our approach, the discrimination between three tree types, olive, orange and deciduous trees, is achieved with very good PA and UA accuracies. However, the existence of mixed crops (trees on annual crops) is not taken into consideration because of the lack of sufficient ground
truth samples for each type of tree. Two other studies [8], [9] were performed where the highest obtained performance metrics did not exceed 85 % of OA value. For both studies, the olive tree was the confused class. The misclassified pixels were mainly confused with bare soil class, which can be explained by the low density of some olive tree samples (including bare soil). Another misclassified class according to [9] was cereals because of the confusion with bare soil. This misclassification is owing to the use of rainfed cereal samples gathered with irrigated ones. The rainfed cereal pixels were confused with those of bare soil to decrease the PA and UA accuracies. In conclusion, the new synergistic approach based on the high spatio-temporal resolution images of S2 and the multiple combination of ML algorithms developed in this paper, improved the crop discrimination by 10 % compared to previous studies. However, other issues such as the discrimination of irrigated cereals from rainfed ones, and the identification of annual crops mixed with trees are still challenges for this new approach, in such a way as to evaluate its effectiveness.

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