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A meta-learning approach for selecting image segmentation algorithm

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ABSTRACT

Image segmentation is a key issue in image processing. New image segmentation algorithms have been proposed in the last years. However, there is no optimal algorithm for every image processing task. The selection of the most suitable algorithm usually occurs by testing every possible algorithm or using knowledge from previous problems. These processes can have a high computational cost. Meta-learning has been successfully used in the machine learning research community for the recommendation of the most suitable machine learning algorithm for a new dataset. We believe that meta-learning can also be useful to select the most suitable image segmentation algorithm. This hypothesis is investigated in this paper. For such, we perform experiments with eight segmentation algorithms from two approaches using a segmentation benchmark of 300 images and 2100 augmented images. The experimental results showed that meta-learning can recommend the most suitable segmentation algorithm with more than 80% of accuracy for one group of algorithms and with 69% for the other group, overcoming the baselines used regarding recommendation and segmentation performance.

1. Introduction

Image segmentation is one of the most studied problems in computer science [15,42]. Besides, it is also one of the most challenging tasks to be automatically performed [12,33,34,43]. As stated by [15], segmentation is usually a step in an image processing chain or pipeline. When the image segmentation step is inadequate, it harms the performance of the whole pipeline. Although additional operations can reduce the drawbacks of a poor quality segmentation, they will increase the pipeline size and complexity [18]. Therefore, the selection of the most suitable segmentation algorithm can improve the image processing performance as a whole.

Additionally, adapting the *No free lunch* theorem often used in Machine Learning (ML) [37], no segmentation algorithm will be the most suitable for every image. The authors believe that look for the most suitable segmentation algorithm for each image would be the best alternative. However, this alternative has a high computational cost. A similar alternative with lower cost would be to recommend, if not the best, at least a suitable segmentation algorithm for each new image. This paper proposes and experimentally investigates a Machine Learning (ML)-based recommender system to deal with this task [12,31,41].

A similar problem occurs when recommending the most suitable ML algorithm for a new dataset. This problem has been successfully investigated using Meta-learning (MtL) [8,19]. MtL is a ML approach to learn from previous ML experiences. For such, each algorithm induces a meta-model able to map description of a dataset by a set of meta-features to the performance of a set of ML algorithms when applied to this dataset.

MtL has been successfully employed to select the best algorithm, or ranking a set of algorithms, for a new dataset [9,16,27–29].

In image analysis, MtL has also been applied to image segmentation [5,12], to object detection and localisation [2], and to search similar images [39]. Campos et al. [12] addressed the algorithm recommendation problem for image segmentation. The authors used MtL to recommend one among three conventional image segmentation algorithms for three restricted scenarios [21,26,36].

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Their study did not include the most recent image segmentation approaches [4,22,24,38]. Furthermore, the authors employed hundreds of images from each image domain. However, in most real-life image segmentation, it is only possible to deal with a few images.

In this study, we investigate the use of MtL to recommend segmentation algorithms for a new image. For such, we describe each image by a set of meta-features extracted from itself. These meta-features should provide the necessary information to allow the recommendation of suitable segmentation algorithms. In order to deal with trade-offs associated with the automatic image processing system, segmentation performance and computational complexity, the algorithms used in this work were separated into two groups: Gradient-based [24] and Machine Learning-based [4,22,38]. The experiments were conducted using a well-known database of segmentation benchmarking, the Berkeley Segmentation Dataset and Benchmark (BSDB500). This dataset was already used in several tasks, mainly for the evaluation of new segmentation algorithms [1,4,25,32]. In our experiments, three supervised classification algorithms, Random Forest (RF), Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost), were evaluated as meta-learners. Their predictive performances were compared with two different baselines (`OneR` and `Random`).

This paper is structured as follows. Related work is reviewed in Section 2. The materials and methods are covered on Section 3. Experimental results are presented and analysed in Section 4. Finally, main conclusions and future work directions are discussed in Section 5.

2. Related work

MtL has been successfully used for algorithm selection [3]. In the last years, it has been applied to solve a variety of problems in Computer Vision. In [41], the authors proposed a learning-based approach to select image segmentation algorithms. The approach was explored with SVM for modelling a recommender based on 9000 images. The recommender was compared with the manual selection of thresholding algorithms (Otsu, enhanced histogram, region growing and Kapur's maximum entropy). Although the results presented a high predictive performance, only grayscale synthetic images, described by their histogram values, were used in the experiments. Thus, the contributions were limited to specific scenarios using simple image segmentation algorithms, with low applicability to real-life images.

A novel framework for intracellular image segmentation based on effective algorithm selection was proposed by [31]. When recommending an algorithm for a new image, the system compares the segmented regions with user-supervised regions based on similarity measures. The authors' framework was able to recommend suitable algorithms using intensity and texture meta-features (pixel intensity and normalised moment), as well as to define the hyperparameter of each segmentation algorithm. Although the authors presented a segmentation solution based on SVM and Approximated Nearest Neighbour (ANN), the contribution was limited to a very specific domain. They explored just two image features with two types of hyperparameter settings.

In [5], MtL was used to identify the best set of hyperparameter values to perform watershed segmentation. The authors used hierarchical clustering to identify similar images. They used only nine images of different types (biological images, faces, and animals). If an image was considered similar to a well-segmented image, it was segmented using the same hyperparameter values used for that image. The authors used meta-features from image descriptions (statistical and texture features). In order to improve performance, they computed particular weight values to the statistical and texture features. In our work, we explored the image feature importance to understand the meta-features contribution and use this information to automate the segmentation recommendation task.

MtL was successfully used to select segmentation algorithms in [12]. In the experiments, the authors applied 3 segmentation algorithms to 4 image datasets. According to the results, MtL was able to select suitable segmentation algorithms. However, the datasets were limited to restricted domains, which does not allow a generalisation to other image domains. Besides, the segmentation evaluation was subjective, provided by domain experts, increasing the cost of the framework.

[2] proposed a framework to generalised object detection and localisation based on MtL. The authors reported AdaBoost as the most promising meta-learner, when compare with Decision Stump (DS) and SVMs. Their framework did not include hyperparameter tuning. The Experiment was run on three different datasets, with a total of 2242 images. Despite the high performance and the identification of the most relevant meta-features, the proposed framework presented a high computational cost. Besides, the experiments were restricted to only three application domains.

A variant of the Particle Swarm Optimization (PSO) meta-heuristic using MtL was proposed by [39]. The authors investigated the problem of searching for satellite images by similarity in a dynamically changed problem space. They took advantage of transfer learning, a MtL technique that transfer knowledge acquired in a dataset to model another dataset. The obtained results were explored in a ML perspective of a single application domain (satellite imaging), without a general contribution to image processing. Different from the other works, the authors explored shape descriptors as meta-features.

It is possible to identify relevant contributions in different domains for image segmentation algorithm recommendation. However, most of the proposed approaches are restricted to a single application domain. Further, they do not explore new segmentation algorithms. Finally, the importance of image features was not taken into account. Table 1 summarises the main aspects of the related works highlighting important comparison items. In this work, we investigate the use of MtL for image segmentation algorithm recommendation using novel image segmentation algorithms. We also use image features in the recommendation process and perform experiments with images from several different domains.

3. Materials and methods

The experiments carried out in this paper assess the use of MtL to recommend image segmentation algorithms. Fig. 1 presents the modelling task, exploring previously acquired knowledge from similar tasks, while Fig. 2 illustrates the recommending step. Further subsections describe in details each one of their components.

In the modelling task, a set of images are segmented by a group of image segmentation algorithms (A) and characterised by *meta-features*" (C). Next, each segmented image is evaluated using the benchmark method proposed by [24], which computes the F-score evaluation measure using a ground-truth boundary map (B). The benchmark/evaluation step defines the "*meta-targets*", the classes/labels to be predicted by the MtL recommender system. This process generates a meta-dataset.

Finally, ML algorithms ("*meta-learners*") are applied to a training subset of the meta-dataset to induce a "*meta-model*". The meta-model maps the relations between the meta-features and the meta-target. Thus, as illustrated in Fig. 2, the meta-model can be applied to a new image, represented by the values of its meta-features, and return the most suitable image segmentation algorithm for that image.

Table 1
Summary of related studies applying recommendation for image segmentation tasks. Fields without information in the related study are marked with a hyphen.

Task	# of algorithms	# of images	Image features	Image domains	Evaluation criteria	Feature analysis	Reference
Segmentation Algorithm Selection	4	9000	Histogram	Synthetic	Manual	–	[41]
	2	6	Intensity, Boundary	Intracellular	Automatic	–	[31]
	3	366	Color, Intensity, Texture, Histogram, Image quality	Chicken, Cloud, Wound	Manual	•	[11]
Hyperparameter recommendation	1	9	Statistical, Texture	Biological, Faces, Animals	Manual	•	[5]

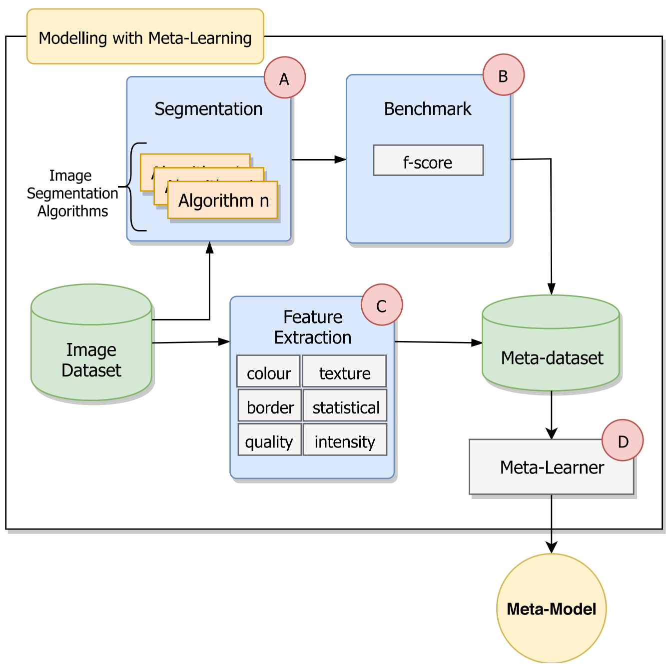

Fig. 1. General modelling overview of the framework.

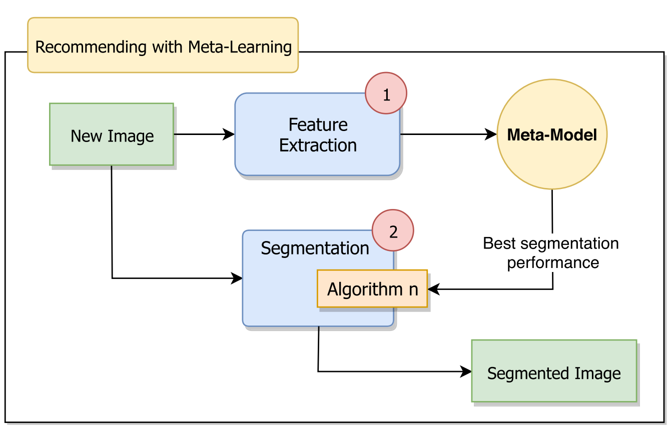

Fig. 2. Meta-learning system to recommend image segmentation algorithms.

3.1. Meta-dataset

For the experiments, we used the Berkeley Segmentation Dataset and Benchmark (BSDB500) [23]. The BSDB500 is widely known and used for evaluating segmentation algorithms [1,4,24,30]. This dataset is composed of 500 real images separated into three disjoint groups: training (200 images), test (200 images) and validation (100 images). In the experiments, the validation and test set were combined into a set of 300 images for meta-learning purposes. Since the training set was used to build the ML-based segmentation algorithms, they were not used in the next experiments.

To improve the generalisation of the induced meta-models, we created additional learning examples by means of image augmentation. For each original BSDB500 image, we created 7 different distortions by rotating and flipping the image. We made rotations with 90, 180 and 270 degrees around the origin, and flipped the original and rotated images horizontally. At the end, our meta-dataset was composed by $300 + (300 \times 7) = 2400$ images (meta-examples).

Eight different segmentation algorithms were applied to each image from BSDB500 dataset. The performance obtained by these algorithms were used to define the target feature for each meta-instance in the meta-dataset. Thus, the value of the target of each meta-instance is one of the eight possible labels (segmentation algorithms).

3.2. Meta-features

The description of each image by the meta-features produced one meta-instance in the meta-dataset. A meta-feature is a function that extracts a relevant characteristic from an image. The description of each image by a set of meta-features produces a vector of numerical values. In this paper, we extracted 98 meta-features from each image. These meta-features can be organised into five groups:

- Colour-based [20]: Simple statistical measures from colour channels;
- Border-based: Statistical measures obtained after applying border-detector filters;
- Histograms [6]: Statistics from histograms of colour and intensity;
- Texture [17]: Values from the texture of an image using Fast Fourier Transform (FFT) and Local Binary Patterns (LBP) methods; and
- Image Quality [40]: Quality assessment metrics.

A list of all meta-features used in our experiments can be seen in Table 2.

3.3. Meta-targets

The value of the meta-target indicates which image segmentation algorithm is the most suitable for a given image. The eight segmentation algorithms applied to each image can produce segmentation with different qualities and demand different processing times.

As the main goal of this paper is to recommend the best algorithm for each new image, we avoided the comparison of algo-

Table 2
Category, acronym and description of meta-features used in the experiments.

Category	Acronym	Description
Colour-based	cor_*	Spearman correlation value between * channels pairwise (RGB, HSV and Intensity).
	mean_*	Mean of the * channel (RGB, HSV)
	std_*	Standard deviation of the * channel (RGB, HSV and Intensity)
	entropy_I	Entropy of the Intensity Channel
Image Quality	SNM	Statistical Naturalness Measure
	EME	Measure of Enhancement
Border	nump_sobel	Number of white pixels in a Sobel Image
	hu_sobel[1–7]	Hu Moments of Sobel Image
	hu_canny[1–7]	Hu Moments of Canny
Histogram	std_hist_*	Standard deviation of the histogram of * channel (RGB, HSV and Intensity)
	kurt_hist_*	Kurtosis of the histogram of * channel (RGB, HSV and Intensity)
	skew_hist_*	Skewness of the histogram of * channel (RGB, HSV and Intensity)
Texture	lbp [0–9]	LBP Vector
	com_entropy	Entropy of Co-occurence Matrix
	com_inertia	Inertia of Co-occurence Matrix
	com_energy	Energy of Co-occurence Matrix
	com_correlation	Correlation of Co-occurence Matrix
	com_homogeniety	Homogeneity of Co-occurence Matrix
	FFT_energy	Energy of FFT
	FFT_entropy	Entropy of FFT
	FFT_intertia	Inertia of FFT
	FFT_homogeneity	Homogeneity of FFT

Table 3
Meta-datasets of each group, the meta-targets and the number of times (and %) they were the most suitable in the group.

Meta-Dataset	Meta-Target	Number of Wins	Number of Meta-examples	Percentage of Wins
Gradient-based	CGTG	1495	170	62.29
	BGTG	331	170	13.79
	TG	202	170	8.42
	CG	193	170	8.04
	BG	179	170	7.46
ML-based	gPb-ucm	1348	170	56.17
	SPC	879	170	36.63
	gPb	173	170	7.21

rithms with very different computational complexities. Thus, we divided the segmentation algorithms into two groups:

- ML-based algorithms: Includes the algorithms with high computationally complexity, in this study: Sparse Code Gradients (SPCs) [38], Global Probability of Boundary (gPb) [22] and Global Probability of Boundary Ultrametric Contour Maps (gPBucm) [4]. These algorithms are based on ML;
- Gradient-based algorithms: algorithms with low complexity, based on Colour, Texture and Brightness Gradients: Colour Gradient (CG), Texture Gradient (TG), Brightness Gradient (BG), Colour/Texture Gradient (CGTG), Brightness/Texture Gradient (BGTG) [24].

In the evaluation of the segmentation algorithms, they were assigned a continuous score between 0 and 1, according to the methodology proposed by [24]. The higher the value, the better the algorithm. The algorithm with the highest score in an image becomes the image label (meta-target) value. Table 3 presents the class distribution for each group of algorithms. It is important to mention that both scenarios are imbalanced since classes differ substantially in the number of examples because one of the algorithms is the best segmentation algorithm for a large number of images. Considering the superior number of algorithms (meta-targets) from both meta-datasets, and to deal with the high imbalanced meta-dataset, we applied under-sampling for both meta-datasets. Since the minority class in the Gradient-based (BG) had 179 wins, 170 images were randomly selected for each class. The same approach was adopted for the ML-based group. Thus, the Gradient-based meta-dasaset was composed with 850 examples (170 images $\times$ 5 algorithms.) and the ML-based with 510 examples (170 images $\times$ 3 algorithms).

3.4. Meta-learners

Three ML algorithms were used as meta-learners: RF [10], SVM [35] and XGBoost [13]. They induce models following different learning biases and have been used with success in multiple predictive tasks. They were implemented using the R language[1] and the `mlr` package[2] [7] along with their default hyperparameter values.

The predictive performance of the meta-learners was evaluated using the Leave-One-Out Cross Validation (LOO-CV) strategy. Two different baselines were also used in the experimental comparisons: a model that always recommends a unique class for the whole dataset (`OneR`) and a model that provides random recommendations (`Random`). Additionally, we used an upperbound as the ground-truth (`Truth`), related to the segmentation algo-

[1] https://www.r-project.org.
[2] https://mlr-org.github.io/mlr-tutorial/release/html/index.html.

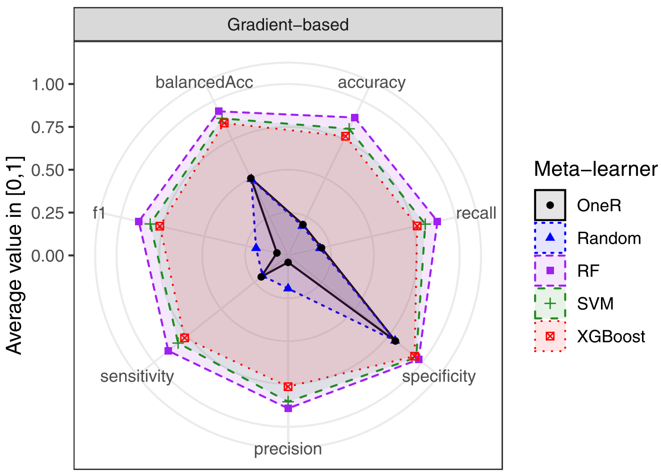

Fig. 3. Performance of the meta-models for Gradient-based algorithms.

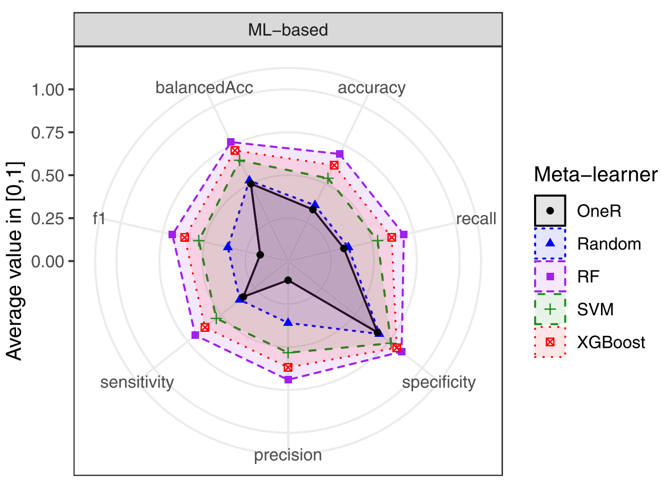

Fig. 4. Performance of the meta-models for ML-based algorithms.

rithm that obtained the best segmentation performance according to [24].

Seven evaluation metrics were used to assess the predictive performance of the induced models: Accuracy, Balanced per class accuracy, Precision, Recall, F-score (f1), Sensitivity and Specificity.

4. Experimental results and discussion

The predictive performances obtained by the three meta-learners in the test subset of the two meta-datasets are presented as a radar chart in Figs. 3 and 4. In these figures, each line represents a meta-model and each vertex accounts for a different performance measure. The larger the area in the radar chart, the better the meta-model.

Regarding the Gradient-based meta-datasets, the radar charts shows that the meta-models outperformed the baselines. The best segmentation algorithm was not recommended only in 51 out of 850 meta-instances (6%). All meta-models overcame the `OneR` and `Random` baselines for both datasets. It is also possible to see in the results (Table 4) that RF obtained the best results with 89% of accuracy, precision, and recall and 0.89 of F-score.

The predictive performances for the ML-based meta-dataset show that in the ML-based group, considering all meta-models, only in 109 out of 510 (21.3%) meta-instances the best image segmentation algorithm was not recommended. This reduction, when compared with the Gradient-based meta-datasets, occurred because the predictive performance of the baselines are closer to the predictive performance of the ML-based segmentation algorithms. The results also show that the meta-model induced by RF obtained the best predictive performance, with 69% of accuracy, precision, and recall and 0.69 of F-score, as in Table 5.

The superiority of the MtL recommending system regarding the baselines was confirmed by statistical tests. We used the Friedman test, with a significance level of $\alpha = 0.05$. The null hypothesis is that the recommendation by the meta-models and by the baselines are similar. Anytime the null hypothesis is rejected, the Nemenyi post hoc test can be applied, stating that the performance of the two approaches are significantly different if their corresponding average ranks differ by at least a Critical Difference (CD) value. When multiple algorithms are compared in this way, a graphic representation can be used to represent the results with the CD diagram, as proposed in [14].

Considering the Gradient-based set, the meta-models (RF, SVM, XGBoost) were compared with `Truth` (expected algorithm suggestion), the use of the single segmentation algorithms as `OneR` (CG, TG, BG, CGTG and BGTG), and the random selection of segmentation algorithm for each image (Random), using their F-Score values as performance metric. This analysis is shown in Fig. 5, using the results from the Nemenyi test.

As shown in Fig. 5, the RF meta-model is connected to the `Truth` baseline at the top of the ranking. Thus, this meta-model recommends the best segmentation algorithm, which is statistically similar to `Truth`. In sequence, RF, SVM, XGBoost are connected, supporting the benefit of using MtL in comparison to select a specific algorithm to the whole dataset. When applying a single segmentation algorithm (`OneR`), CGTG and BGTG were superior to the others. In particular, the CG, TG and BG algorithms were similar to a random choice of algorithms, presenting the worst F-score performance.

Evaluating the ML-based recommending using `Truth`, meta-models (RF, SVM, and XGBoost), `OneR` (gPb-ucm, SPC and gPb) and `Random`, Fig. 6 shows that no solution was similar to the expected `Truth` value. However, the meta-model recommending results were superior to `Random` or `OneR` with RF providing the best recommendations, with similar results for SVM and XGBoost.

Finally, the segmentation performance obtained by the segmentation algorithms recommended by meta-models was superior to always using the same segmentation algorithm or a segmentation algorithm randomly chosen. Regarding the predictive performance of the meta-models, RF induced the best meta-models in both sets of segmentation algorithms. Moreover, when recommending Gradient-based algorithms, RF was similar to the ground-truth solution.

4.1. Relative feature importance

It is also possible to assess the importance of each image feature for the induction of the meta-models by using the RF Feature Importance metric. This inner RF's metric is calculated by permuting the values of a feature in the Out-of-Bag (OOB) examples and recalculating the OOB Error. In this way, if substituting the values of a feature by random values results in error increase, this feature was considered important. Otherwise, if the error decreases, the resulting importance is negative, and the feature is considered not important [10].

We used the RF Feature Importance to investigate the contribution of each feature in selecting segmentation algorithms. Fig. 7 shows the feature importance for both datasets. In the Gradient-

Table 4
Gradient-based predictive performance.

Meta Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1	Balanced Accuracy
SVM	82%	0.82	0.95	0.85	0.82	0.82	88%
RF	**89%**	**0.89**	**0.97**	**0.89**	**0.89**	**0.89**	**93%**
XGBoost	77%	0.77	0.94	0.76	0.77	0.76	85%
Random	19%	0.19	0.79	0.19	0.19	0.19	49%
OneR	2%	0.20	0.80	0.04	0.20	0.06	50%

Table 5
ML-based predictive performance.

Meta Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1	Balanced Accuracy
SVM	53%	0.53	0.76	0.53	0.53	0.53	65%
RF	**69%**	**0.69**	**0.84**	**0.69**	**0.69**	**0.69**	**76%**
XGBoost	61%	0.61	0.80	0.61	0.61	0.61	71%
Random	36%	0.36	0.68	0.36	0.36	0.36	52%
OneR	33%	0.33	0.66	0.11	0.33	0.16	50%

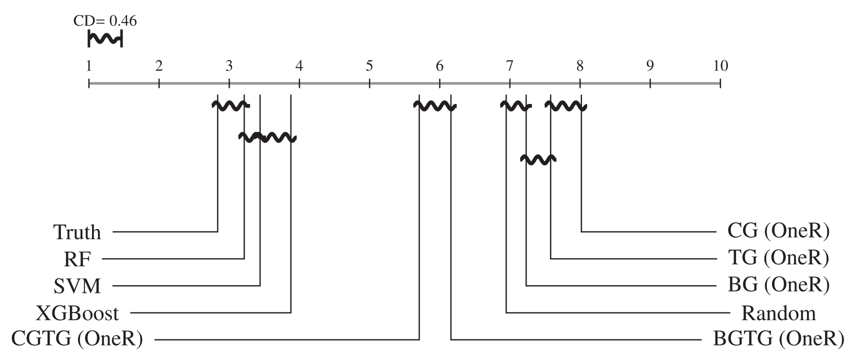

Fig. 5. Comparison of the F-Score values obtained by meta-models when recommending Gradient-based segmentation algorithms according to the Nemenyi test. Groups of meta-learners that are not significantly different (α= 0.05 and CD = 0.46) are connected.

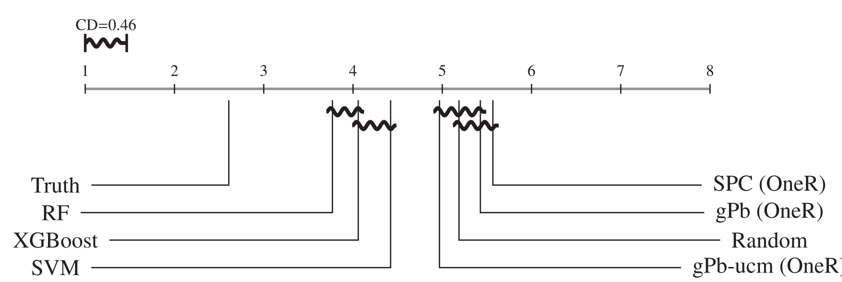

Fig. 6. Comparison of the F-score values obtained by meta-models when recommending ML-based segmentation algorithms according to the Nemenyi test. Groups that are not significantly different (α= 0.05 and CD = 0.46) are connected.

based meta-dataset, the Texture and Colour meta-features were considered the most important, especially FFT Entropy (12.88), Mean (13.99) and Standard Deviation of Blue Channel (12.01), and Standard Deviation of Saturation Channel (14.184). Once the Gradient-based algorithms are grounded on information from Texture and Colour attributes of image regions to segment images, their selection makes sense.

ML-based segmentation algorithms were suggested by meta-models with high meta-feature importance (>20) from *mean_h* (25.77), *cor_hs* (22.86), *skew_hist_H*(22.01), *kurt_hist_H*(21.22) and *lbp_3*(20.73). Some of them are extracted from *H* colour channel and histogram. However, the high importance of meta-features from LBP Vector (Texture category) suggests that a more precise segmentation algorithm, supported by ML-based, requires a plural of image descriptors. Another example was *SNM* from Image Quality (twentieth most important with 16.79 of importance), which was more important than other colours, histogram and intensity features.

In both meta-datasets, the border meta-features (*hu_sobel*{1.7} and *hu_canny*{1.7}) had low importance at the point of being removed from the meta-features without compromising the results.

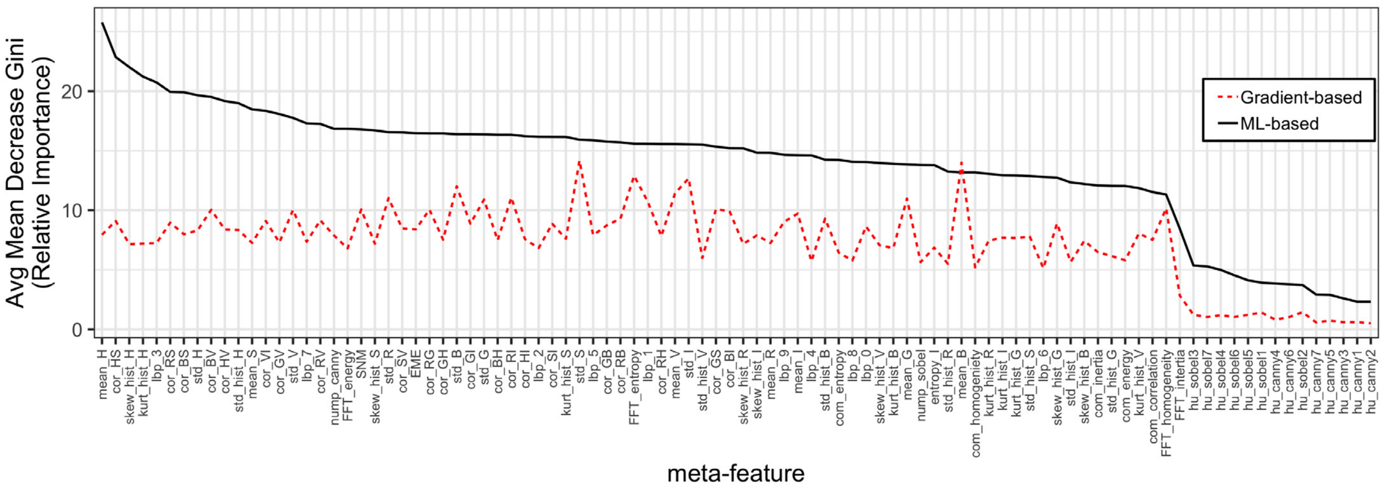

Fig. 7. Average relative importance of the meta-features obtained from RF importance. The names of the meta-features in the x-axis follow the acronyms presented in Tables 2 sorted by the most important features for the ML-based set.

5. Conclusion

This paper presented a framework to recommend segmentation algorithms using Meta-learning (MtL) for automatic image segmentation. In the experiments carried out, for each image, two segmentation algorithms were suggested, from a set of 8 algorithms, one from a group with more computationally costly solutions (ML-based) and another from a group with less complex and faster techniques (Gradient-based). Experiments were performed with 2400 images, from general domains, 300 from the BSDB500 dataset and 2100 augmented images.

Three Machine Learning (ML) algorithms were compared for meta-model induction. The meta-models produced by the RF algorithm presented the best predictive performance for both groups of segmentation algorithms. The predictive performance obtained by the meta-models induced by the SVM and XGBoost were not as high as those from RF algorithm, but were superior to both baselines for all images: the `OneR` and `Random` models.

This paper also investigated the importance of the meta-features given by the RF algorithm. The results of the analysis performed highlight colour and histogram meta-features as the most important for Gradient-based segmentation algorithms. The analysis also showed that the recommendation of the ML-based segmentation algorithms considered important meta-features from different categories. As future work, we intend to use features extracted using Convolutional Neural Networks (CNN), instead of handcrafted features. We believe that these meta-features will increase the predictive performance. CNNs could also be used to evaluate if a segmentation was adequate or not. Finally, we plan to increase the number of segmentation algorithms in future experiments.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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