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Automatic classification of native wood charcoal

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ABSTRACT

This paper presents an image-based method for automatic identification of native wood charcoal species. For this purpose, handcrafted features based on two configurations of the Local Binary Patterns (LBP) along with state-of-the-art machine learning classifiers and representation learning using Convolutional Neural Networks were evaluated. In addition, an image database composed of 44 species of wood charcoal was built and made available for research purposes, making possible future benchmark and evaluation. The experiments have shown that similar results can be obtained using shallow and deep representations. The best results of the handcrafted and automatic learned features were 93.9% and 95.7% of recognition rate, respectively.

1. Introduction

Charcoal is an energetic source used in different segments of iron-work, metallurgic, cement industry, and others, being important economically and historically in Brazil. According to Davrieux et al. in (Davrieux et al., 2010), Brazil consumed more than 33 million cubical meters of charcoal, making it one of the biggest consumers as well as producers of this fuel in the world. Historically, in Brazil, wood from native forests was the main source used to produce charcoal, but today a combination of stricter environmental regulation and increased enforcement has increased the use of wood from planted forests (Yazdani et al., 2012). However, in certain regions, wood is still often carbonized from illegally cut trees. In such cases, enforcement of logging rules is hampered due to the difficulty of identifying the species, making it necessary to obtain more information on the intrinsic characteristics of carbonized wood to enable species identification (Nisgoski et al., 2014).

Usually, the identification of the charcoal is based on its anatomical characteristics which demand specialists in wood anatomy. However, few reach good accuracy in classification due to the time it takes for their training. To overcome such a limitation, some studies have been reported in the literature. The main line of investigation explores the fact that charcoal is a biocarbon produced by the carbonization of wood, a process which leads to a formation of a solid residue with an increased content of carbon element. With that in mind, the idea is to use a proper source of radiation to excite the wood surface to analyze the emitted spectrum. Near Infra-red spectroscopy (Labbé et al., 2006; Nisgoski et al., 2015; Ramalho et al., 2017) and Reflective spectroscopy in the Medium Infra-red region (Davrieux et al., 2010) are examples of the spectrum-based processing systems.

Another approach is the image-based, where some characteristics of the wood are extracted and analyzed to discriminate the species. Such a pattern recognition strategy has been successfully applied to forest species classification by several authors for both macroscopic and microscopic images (Kobayashi et al., 2015; Yadav et al., 2017; Yusof et al., 2013). After the release of public datasets of forest species (Martins et al., 2013; Paula Filho et al., 2014), some researchers have reported outstanding results using different textural descriptors and also deep learning techniques (Andrearczyk and Whelan, 2016; Hafemann et al., 2014).

However, the research on automatic classification of native wood charcoal is quite limited (Gonçalves and Scheel-Ybert, 2016; Nisgoski et al., 2014), mostly because of the lack of a robust public available dataset. To close this gap, in this work we introduce a wood charcoal database composed of 44 species. This database has been built in collaboration with the Laboratory of Wood Anatomy at the Federal University of Parana (UFPR) in Curitiba, Brazil, and it is available upon request for research purposes.[1] The database introduced in this work makes future benchmark and evaluation possible.

In order to establish some baseline for further comparison, in this work we have assessed two configurations of the Local Binary Patterns (LBP) along with state-of-the-art machine learning classifiers. We also have evaluated representation learning using Convolutional Neural Networks. In our experiments we have observed similar results using handcrafted features and representation learning. Both representations

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[1] https://web.inf.ufpr.br/vri/databases/charcoal

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1574-9541/

Table 1
Forest species dataset.

ID	Family	Species	Images for training	Images for test
1	Apuleia	molaris	6	6
2	Aspidosperma	populifolium	6	6
3	Astronium	gracile	6	6
4	Byrsonima	coriaceae	6	6
5	Calophyllum	brasiliensis	6	6
6	Cecropia	glaziovii	6	6
7	Cecropia	sciadophylla	6	6
8	Cedrelinga	catenaeformis	6	6
9	Cochlospermum	orinoccense	6	6
10	Combretum	leprosum	6	6
11	Copaifera	langsdorfii	6	6
12	Croton	argyrophylloides	6	6
13	Diplotropis	purpurea	6	6
14	Dipteryx	odorata	6	6
15	Enterolobium	schomburgkii	6	6
16	Erisma	uncinatum	6	6
17	Goupia	glabra	6	6
18	Hieronyma	laxiflora	6	6
19	Hymenaea	courbaril	6	6
20	Hymenolobium	petraeum	6	6
21	Jacaranda	copaia	6	6
22	Jatropha	mutabilis	6	6
23	Licaria	cannela	6	6
24	Luitzelburgia	auriculata	6	6
25	Mezilaurus	itauba	6	6
26	Mimosa	scabrella	6	6
27	Ocotea	leucoxylon	6	6
28	Ocotea	odorifera	6	6
29	Ocotea	porosa	6	6
30	Parkia	pendula	6	6
31	Pera	glabrat	6	6
32	Piptadenia	communis	6	6
33	Poeppigia	procera	6	6
34	Poincianella	bracteosa	6	6
35	Qualea	paraensis	6	6
36	Sapium	glandulatum	6	6
37	Schefflera	morototoni	6	6
38	Sclerolobium	paniculatum	6	6
39	Tabebuia	alba	6	6
40	Trattinnickia	burseraefolia	6	6
41	Vatairea	guianensis	6	6
42	Vatairea	paraensis	6	6
43	Vochysia	densiflora	6	6
44	Vochysia	maxima	6	6

achieved results around 95% of recognition rate.

The remaining of this paper is organized as follows: Section 2 presents the protocol used to built the proposed database of wood charcoal images. Section 3 describes the strategies used to represent the charcoal classification problem, where handcrafted and automatic representation were used. Section 4 presents the experimental protocol used to assess such different representations using the constructed wood charcoal database, and also the best results observed for each strategy. Finally, Section 5 presents our conclusions and future work.

2. Database

The wood charcoal database presented in this work contains 44 forest species with 12 images each as shown in Table 1. This balanced dataset were cataloged by the Laboratory of Wood Anatomy at the Federal University of Parana in Curitiba, Brazil. The trees were cut in a natural forest, and disks were extracted from the diameter at breast height (DBH), with a thickness of about 8 cm. Twelve samples were obtained from each species, with dimensions of $2 \times 2 \times 5$ cm. Each sample was wrapped in aluminum foil and carbonized in a muffle furnace (Q318S, Quimis), with a final temperature of 450C and a heating rate of 1.66C min^{-1}. The carbonized material remained at the final temperature for two hours. The images were obtained directly from the carbonized material, without coating, with a tabletop microscope (TM-1000, Hitachi).

The images were obtained in grayscale and stored in TIFF (Tagged Image File) format with no compression and resolution of 1280×1040 pixels. Fig. 1 shows some samples of the database.

3. Features

In this section, we present the feature sets we have used to train the classifiers. Section 3.1 describes the handcrafted textural descriptors, while Section 3.2 gives the details about the CNN used to automatically extract the representation from the charcoal images.

3.1. Handcrafted features

Along with Grey Level Co-occurrence Matrices (Haralick, 1979), LBP is likely the most used texture descriptor, which first emerged in the 1990s. As stated in (Kylberg and Sintorn, 2013), at first LBP was introduced as a local contrast descriptor and a further development of the texture spectra. Shortly afterward, it was shown to be interesting as

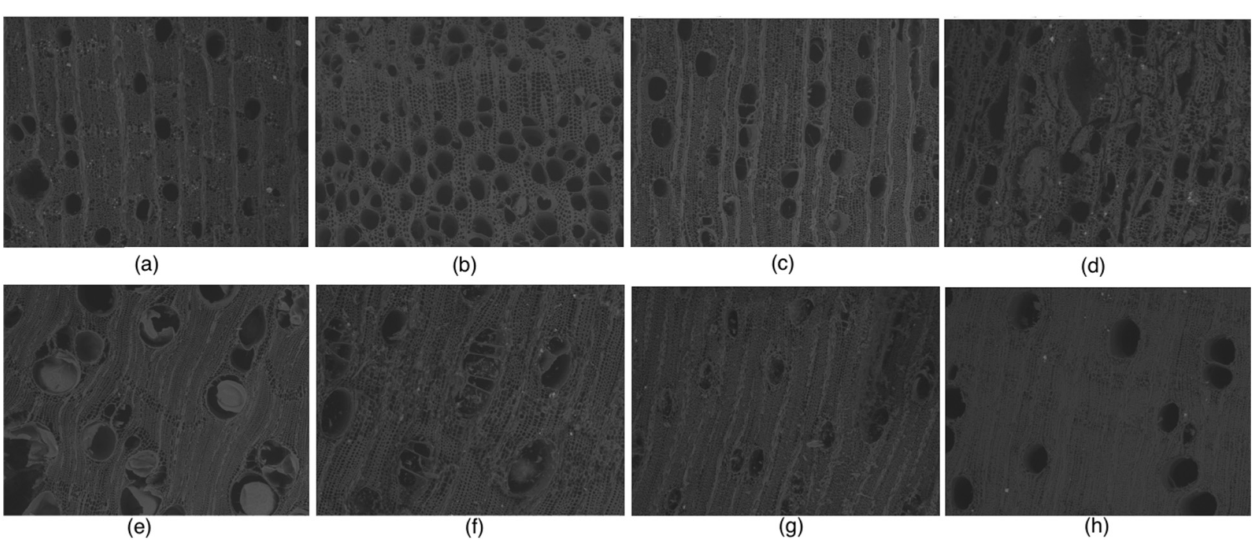


Fig. 1. Samples of the database: (a) Apuleia molaris, (b) Aspidosperma populifolium, (c) Astronium gracile, (d) Byrsonima coriaceae, (e) Calophyllum brasiliensis, (f) Cecropia sciadophylla (g) *Copaifera langsdorfii*, (h) *Hymenaea courbaril*.

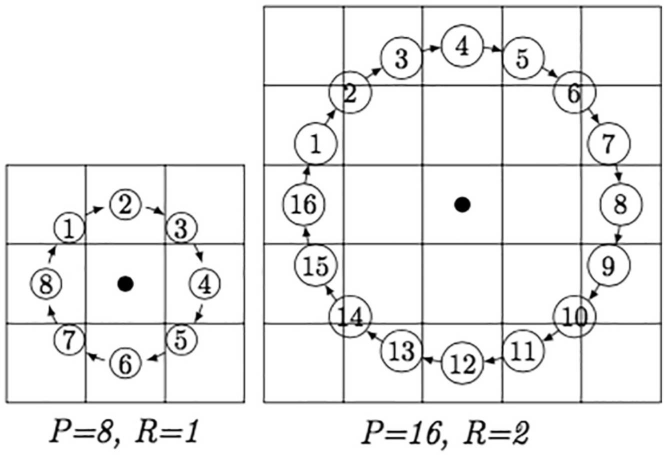


Fig. 2. LBP distribution.

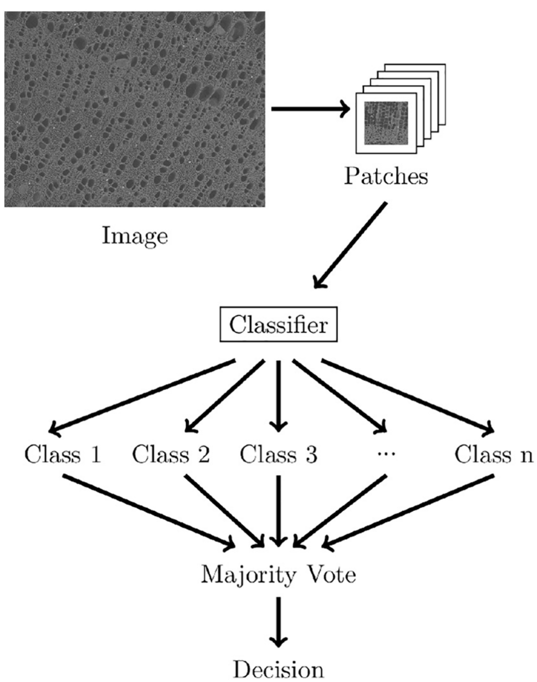


Fig. 3. The testing procedure adopted in this work.

Table 2
Recognition rates for the classifiers trained with the hand-crafted features.

Classifier	Feature set	
	$LBP_{(8,\ 1)}$	$LBP_{(16,\ 2)}$
RF	90.4 ± 4.7	88.4 ± 4.1
Linear SVM	92.7 ± 4.7	93.4 ± 5.1
RBF SVM	92.8 ± 4.5	93.9 ± 5.1

a texture descriptor (Ojala et al., 1996) and has become widely used since then (Nanni et al., 2012).

In a more simplistic way, LBP works as follows. A histogram is computed with the distribution of the binary configurations of the pixels of the image, based on thresholding the surrounding window of each pixel when the intensity of the neighborhood pixel is below or above the center value. In the most simple implementation of LBP, 3 × 3 windows can be considered and a 256 bin histogram can be generated given the 2^8 possible combinations of the binary windows. In (Ojala et al., 2002), Ojala et al. extended the LBP descriptor to other neighborhood sizes. To compute LBP, it is considered a neighborhood with circular symmetry of a radius R with P neighbors equally separated (Fig. 2). The LBP descriptor presents 2^P different binary patterns which can produce a histogram of frequency as feature vector.

Some texture patterns are more common than others, thus they are called uniform patterns. For example, in a neighborhood of 8 neighbors and radius equal to 1, the uniform patterns correspond to nearly 90% from all patterns. However, in a neighborhood of 16 neighbors and radius equal to 2, the uniform patterns represent about 70% of all patterns. The local binary pattern is considered uniform if there are up to a maximum of two transitions between zero and one, otherwise the pattern is considered non-uniform. More precisely, in a neighborhood of P neighbors the operator LBP_U produces a feature vector with $P * (P - 1) + 3$ components. The $P * (P - 1) + 2$ of them describe different uniform patterns and the last one describes all non-uniform patterns from the texture (Ojala et al., 2002).

Over the years, though, several variations of LBP have been proposed, with several purposes such different sampling techniques to effectively capture characteristics of certain features, or improving robustness to noise (Chen et al., 2013; Liu et al., 2016; Zhao et al., 2012). In this work, we have performed experiments with several descriptors but our best results were achieved with $LBP_{(8,\ 1)}$ (256 features) and $LBP_{(16,\ 2)}$(65,536 features).

3.2. Representation learning

Representation learning or feature learning has become a field in itself in the machine learning community. The main idea to learn representation from the data hence avoiding feature engineering. Representation learning using deep CNN has been explored in several applications yielding substantial gains in various benchmarks. One example is the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). In 2012, Krizhevsky et al. (Krizhevsky et al., 2012) proposed an 8-layer CNN and achieved an error rate of 15.4% (the second best entry achieved an error of 26.2%). In 2015, Google introduced an architecture codenamed Inception (Szegedy et al., 2015), a 22-layer CNN, that reduced the error rate on the 2014 ILSVRC to about 6%. Then, researchers from Microsoft presented ResNet (He et al., 2016), a 152-layer CNN that won the ILSVRC 2015 with an incredible error rate of 3.6%.

To take advantage of these trained models, several researchers have dedicated efforts to make available algorithms to fine-tuning these models for distinct image classification tasks. This is often referred to as transfer learning (Pan and Yang, 2010) and has been an area of particular interest in the field of representation learning. A common prescription for a computer vision problem is to first train an image classification model with the ImageNet Challenge dataset, and then transfer this model's knowledge to a distinct task.

In 2016, Szegedy et al. (Szegedy et al., 2016) compared the Inception_v3 with other CNN architectures and showed that Inception_v3 achieved the lowest error rate among them. Inspired on that, in this work we have used the Inception_v3 as feature extractor for wood charcoal classification. The descriptors were provided by the pool_3 layer, which has a dimension of 2048. The pool_3 layer represents the lowest level features that have high discriminant capability if compared with other layers from the same architecture (Szegedy et al., 2016). The Inception model was used "as is", just passing the input image through a feed-forward step, and using the outputs of the aforementioned layers of the network as input for the classifier.

4. Experimental results

In our experiments the dataset was randomly divided into training (50%) and testing (50%) (see Table 1). In addition, 20% of the training set was used for validation. Since the amount of images available in the dataset is limited, we have adopted the strategy presented by Hafemann

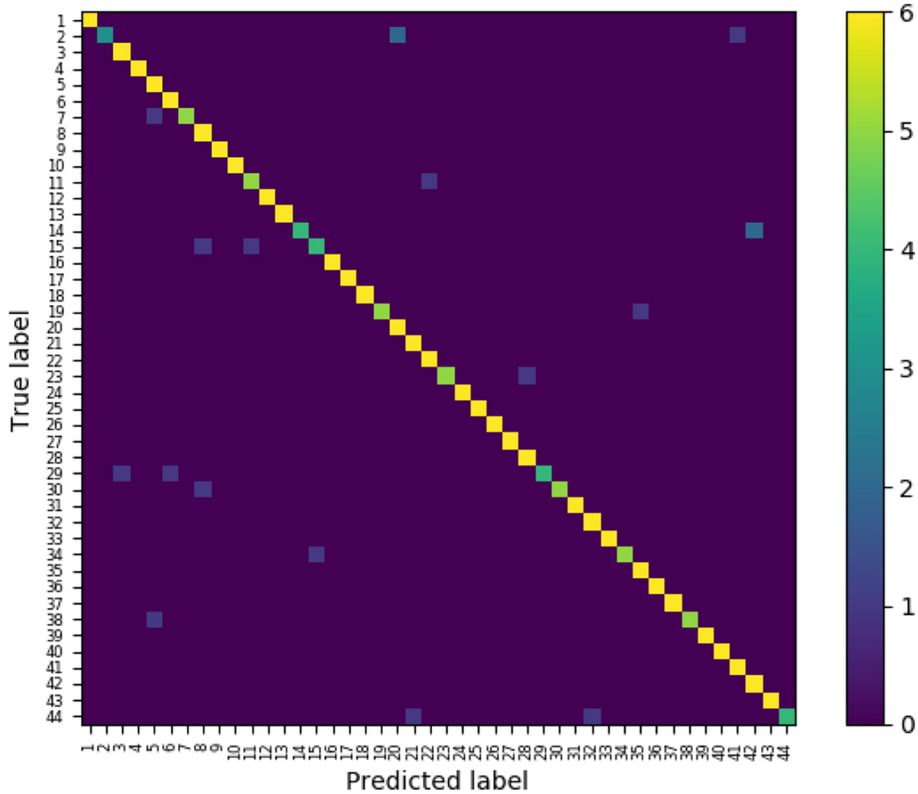
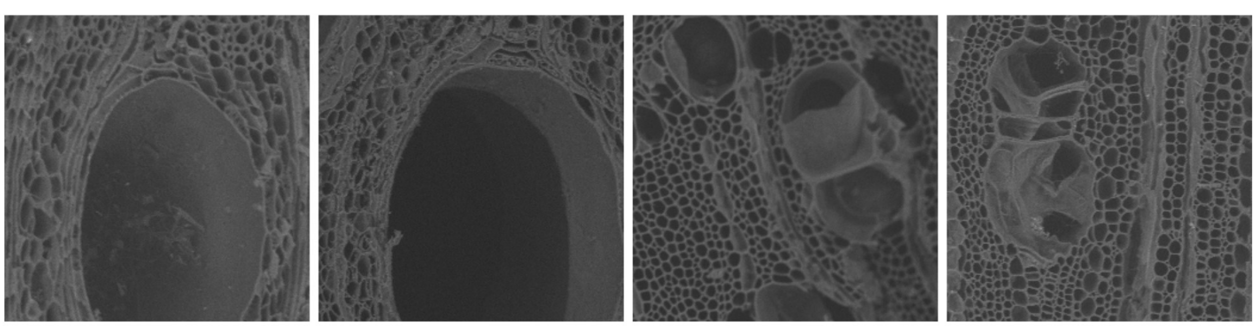


Fig. 4. Confusion matrix for the Linear SVM trained with $LBP_{(16,\ 2)}$.



(a) (b) (c) (d)

Fig. 5. Some confusions: (a) Parkia pendula (class 30), (b) Cedrelinga catenaeformis (class 8), (c) Ocotea porosa (class 29) and (d) Astronium gracile (class 3).

et al. (Hafemann et al., 2014), where the original image is divided into several sub-images called patches. In this case, the main premise is that these patches can contain enough information to train a model, then an appropriated set of patches is extracted from each image. In this work we have empirically investigated different number of patches and the best results were observed using 80 random patches of 256 × 256 pixels extracted from each image. The patch size was chosen based on two observations: i) the input from Inception_v3 must to be squared, and ii) Martins et al. (Martins et al., 2013) and Paula Filho et al. (Paula Filho et al., 2014) achieved better results to recognize forest species using LBP descriptor and patches of 341 × 256 pixels, and 326 × 244 pixels, respectively.

To classify a given input image, the same idea is used, i.e., a number of random patches are extracted from the image and individually submitted to the classifier. Then, all classifier's decisions are combined through majority voting to produce a final decision. This is exemplified in Fig. 3.

The recognition rate that we used for evaluation purpose in this work is given by Eq. 1. This is always computed on the testing set with N images. We call N_{rec}, the images from this set that were correctly classified by the recognition system. The results are average of ten trials, in which the training and testing were randomly divided into 50–50%.

$$\text{Recognition rate} = \frac{N_{rec}}{N} \times 100 \tag{1}$$

4.1. Handcrafted features

To assess the handcrafted features, we have used several state-of-the-art classifiers, however, the best results were achieved with Support Vector Machines (SVM) and Random Forests (RF). For the SVM, both Linear and RBF kernels were considered. In the case of the RBF, the parameters C and γ were determined through a grid search on the validation set. In the case of the RF, the best results were yielded with 50 trees and $\sqrt{M}$ features randomly picked at each node in test set. M is the number of features from the feature vector. Table 2 reports the recognition rates using $LBP_{(8,\ 1)}$ and $LBP_{(16,\ 2)}$.

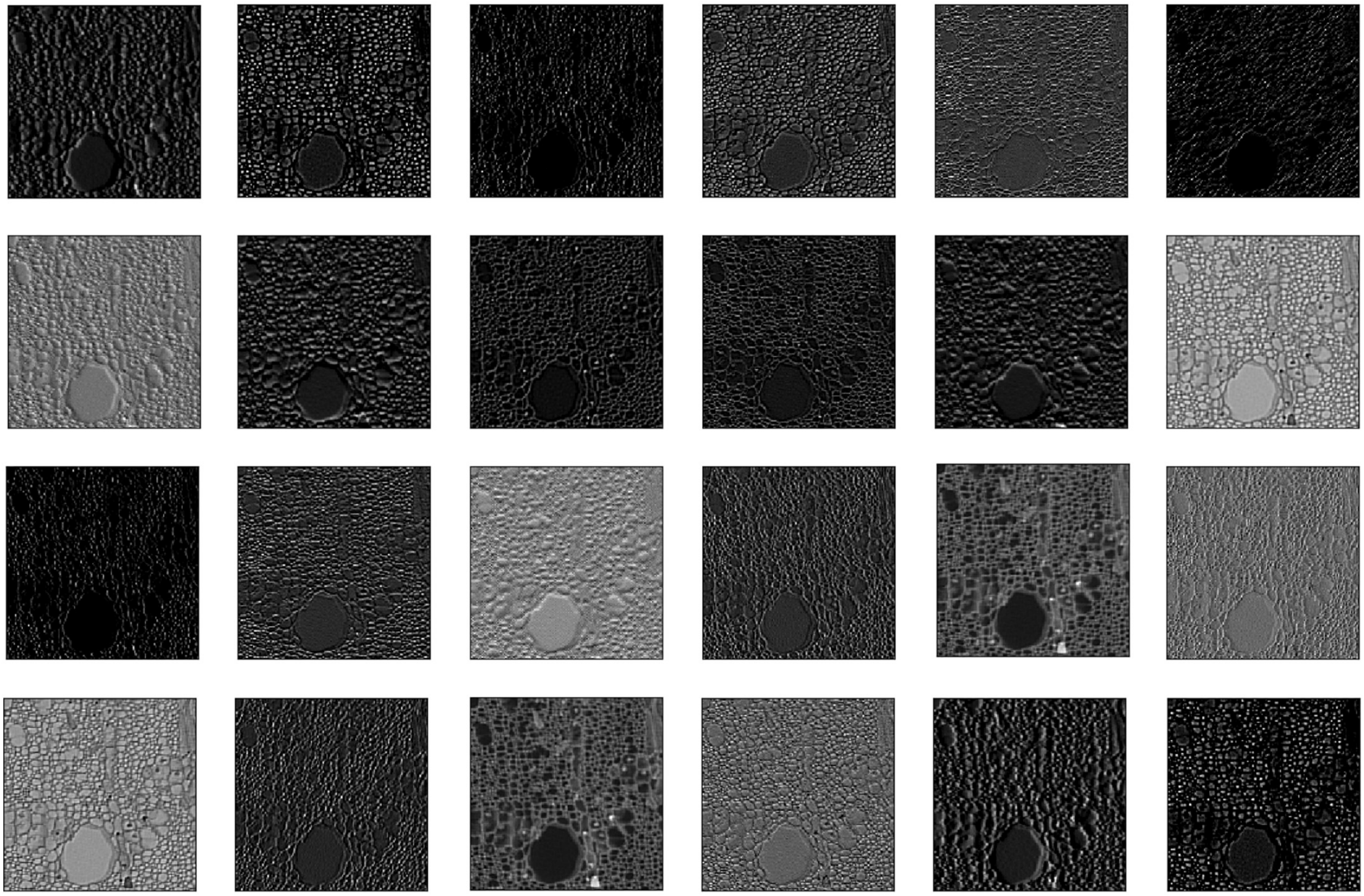


Fig. 6. Examples of the images created in the activation layer of the CNN.

Table 3
Recognition rates for the classifiers trained with the representation learning (Inception).

Classifier	Inception
RF	93.9 ± 4.0
Linear SVM	95.7 ± 4.7

The SVMs trained with $LBP_{(16, 2)}$ achieve a slightly better result than the same classifiers trained with $LBP_{(8, 1)}$, however with a considerable large feature vector (65,536 versus 256). Fig. 4 shows the confusion matrix for the Linear SVM trained with the $LBP_{(16, 2)}$ features. Some examples of the misclassifications are presented in Fig. 5. Two confusions found very often occur between classes 30 Parkia pendula (Fig. 5a) and 8 Cedrelinga catenaeformis (Fig. 5b), and classes 29 Ocotea porosa (Fig. 5c) and 3 Astronium gracile (5d). In both cases, the species have as prominent attribute large vessels and also similar texture patterns.

4.2. Representation learning

To be able to compare the discriminative power of representation learning with the handcrafted features, we used the Inception_v3 to extract features of the image patches and train the same classifiers used in the previous experiments. Therefore, the same hyper-parameters used to train the classifiers with handcrafted features were used here. As stated before, we have used the "pool_3" layer, which produces a vector with 2048 features. The experiments were performed using the Tensor Flow 1.3.[2]. Fig. 6 shows some examples of the images created in the activation layer of the CNN. As we can see, it is able to highlight the same features in several different ways.

As we can observe from Table 3, the features extracted from the "pool_3" layer of the Inception model offer good discrimination power producing slightly better results than those we have observed with the hand-crafted features. In other words, the CNN trained to discriminate a 1000 classes of objects is able to learn a powerful representation, which compares to the state-of-the art textural descriptors such as LBP.

All the results reported so far consider the combination through majority voting of 80 patches. However, the same performance can be achieved using a considerable smaller number of patches, hence reducing the computational cost for classification. Fig. 7 shows the accuracy from the number of patches ranging from 1 to 80 for both Linear SVM and RF classifiers trained with Inception features. In the case of the Linear SVM the performance of 95% is achieved with 9 patches and no further improvement is observed afterwards. The RF needs more information (around 40 patches) to reach the performance reported in Table 3.

Fig. 8 shows the confusion matrix for the Linear SVM trained with the Inception features. Some examples of the misclassifications are presented in Fig. 9. Two confusions found very often occur between classes 28 Ocotea odorifera (Fig. 9a) and 5 Calophyllum brasiliensis (Fig. 9b), and classes 36 Sapium glandulatum (Fig. 9c) and 8 Cedrelinga catenaeformis (9d). In both cases, the species have as prominent attribute large vessels and also similar texture patterns.

5. Conclusion

In this paper we dealt with the challenging problem of automatic

[2] https://www.tensorflow.org/

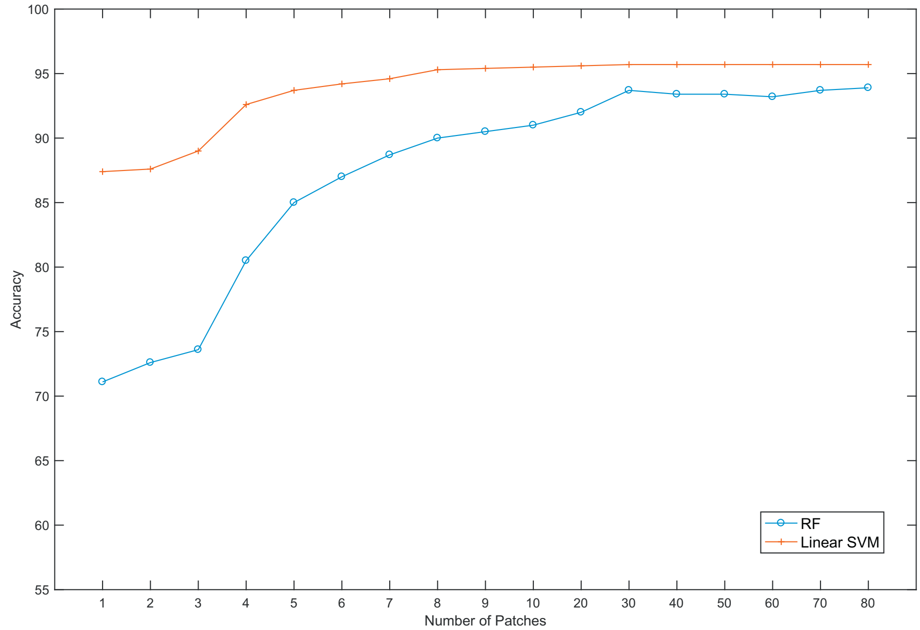


Fig. 7. Accuracy versus number of patches.

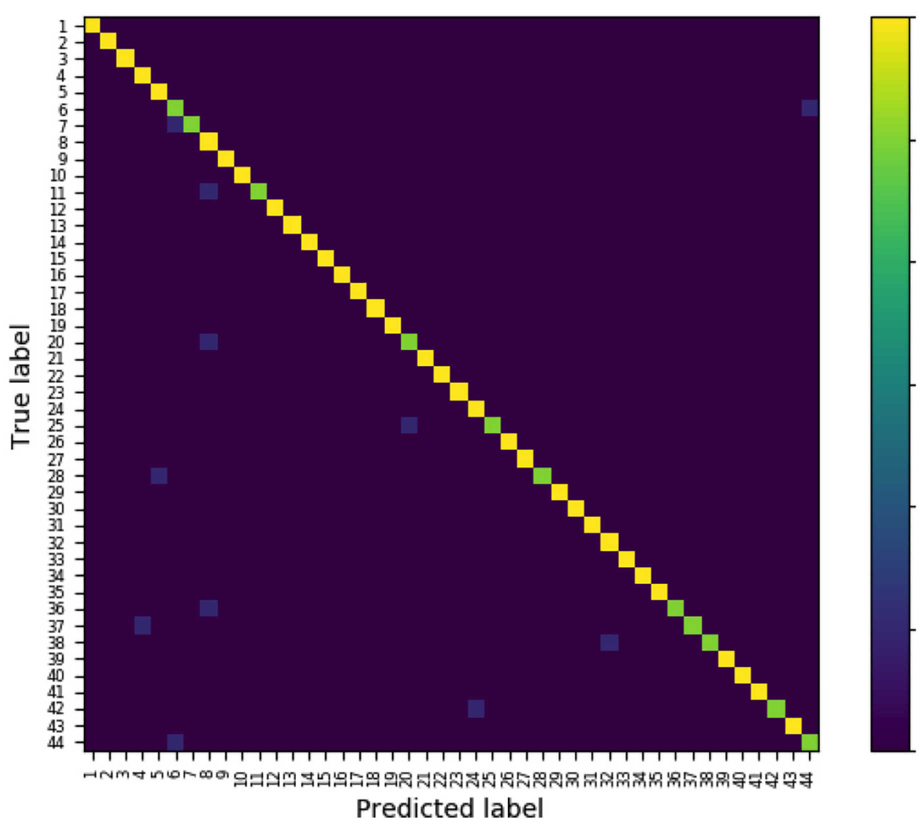
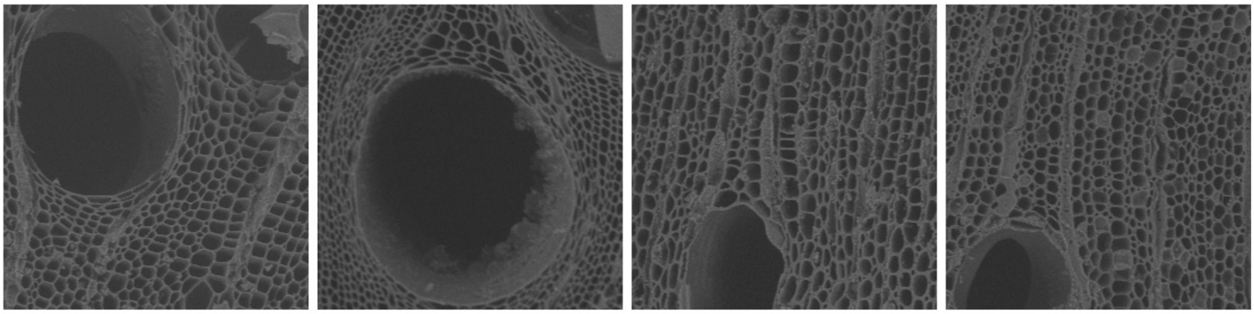


Fig. 8. Confusion matrix for the Linear SVM.

classification of native wood charcoal. For this purpose, we introduced a new database which is composed of images related to 44 different species of wood native charcoal. In addition, different methods were evaluated in the context of handcrafted and automatic feature learning. To assess the handcrafted features, we have used different state-of-the-art classifiers, however, experiments have shown that the best results were achieved with Support Vector Machines (SVM) and Random Forests (RF). These shallow methods were compared with a deep learning method by using the Inception_v3 convolutional neural network. This deep method was based on transfer learning, in which the Inception_v3 is used as a feature extractor. We have observed very promising results using handcrafted features and representation learning, being the best results 93.9% and 95.7% of recognition rate, respectively.

The set of experiments performed in this work also provide the baseline results for the introduced charcoal image database, which may



(a) (b) (c) (d)

Fig. 9. Some confusions: (a) Ocotea odorifera (class 28), (b) Calophyllum brasiliensis (class 5), (c) Sapium glandulatum (class 36) and (d) Cedrelinga catenaeformis (class 8).

minimize the gap related to the lack of a robust public dataset in the field of automatic classification of native wood charcoal, making possible future benchmark and evaluation.

Further work can be done to explore other handcrafted and automatic features or even the combination of them using multiple classifiers. Due the wide application of Convolution Neural Networks as a classifier to solve different tasks, it can also be assessed and explored as an end-to-end solution for the wood charcoal classification problem. In addition, the proposed method can be assessed using other forest species besides the proposed ones. Therefore, the creation of other public available datasets of wood charcoal using different forest species is also encouraged.

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