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Evidential two-step tree species recognition approach from leaves and bark

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Abstract

The contribution of this paper is twofold. First, this paper aims at developing an intelligent system that emulates the decision-making ability of a botanist expert in the recognition of tree species from their leaves and bark. The main challenges of this recognition problem are related to the high diversity of trees in nature, the interspecies similarity and the intra-species variability. Therefore, similarities between species cause several confusions during recognition. The proposed decision system is designed to solve this complex problem of tree species recognition by reasoning with knowledge sets where the inference engine is based on belief functions theory, which reduces confusion between species and achieves greater accuracy. Secondly, this paper proposes a practical solution that can be embedded in the user's smartphone without any need for an internet connection. Therefore, our approach is adapted for smartphone limits, i.e. limits related to memory and computation capacity. Once in nature, everybody should appreciate the idea of having a mobile application that reflects the skills and know-how of a botanist. Building an application to make the potential of tree species recognition accessible and easy to use is a challenging problem. From methodological perspectives, the suggested method is a two-step recognition approach that identifies the leaf in a first step and refines the results using the bark in the second step. In fact, the first step is used to reduce the dimensionality of the problem through the identification of a subset of most probable species. The second step is performed using a modified evidential *k* Nearest Neighbors (EkNN) algorithm that recognizes the bark from the output of the first step. A set of experiments on real-world data is presented in order to study the accuracy of the proposed solution against existing ones.

Keywords: Tree species recognition, two-step classification, theory of belief functions, mass estimation, k nearest neighbors.

1. Introduction

Tree species recognition is the problem of identifying the species of a given tree. This task may be easy for a botanist who has strong knowledge about trees. However, a novice or a lover of the trees universe may have difficulties. This paper is part of the ReVeRiES project that seeks to develop a mobile application that recognizes tree species without needing an internet connection. Indeed, the application will be used in nature, forests, mountains where an internet connection is not available. Such a condition makes an application like Pl@ntNet (Goëau et al., 2013), for example, unusable as it is connected to a web server where all the computations are done. We note that the computation capacities of a smartphone are not yet fully developed, this specificity imposes some conditions on the proposed approach. In fact, it must be light, fast and give results with a good recognition rate. Besides, the application must be able to explain all recognition steps and the characteristics used to identify the

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tree, which makes this task challenging. Consequently, the main purpose of this paper is to develop an approach that has all the properties listed above.

The tree species recognition from leaves and bark is a challenging task. In fact, there is a large variety of tree species in nature. Furthermore, we find trees belonging to different species, but they look very similar which make their identification more delicate. In addition, we find trees in the same species but that look different. Let us consider some examples. Fig. 1 presents three leaves photos, leaves (a) and (b) are different, but they belong to the Broussonetia papyrifera L'Héro Vent species. Leaves (b) and (c) look similar, but they belong to two different species, Broussonetia papyrifera L'Héro Vent and Carpinus betulus L respectively. These problems are present for bark too. Fig. 2 presents similar bark belonging to four different species which are (from left to right) Acer campestre L., Acer opalus Mill., Aeculus hippocastanum L. and Liquidamber styraciflua L. respectively. Fig. 3 presents different bark belonging to the same species, the Acer Campestre L. species. The interspecies similarity problem generates conflict between similar species, which leads to misclassification. Also, the intraspecies variability is a crucial problem as it makes the recognition more delicate. In this paper, we use the theory of belief functions (Dempster, 1967; Shafer, 1976) to manage the confusion between the species.

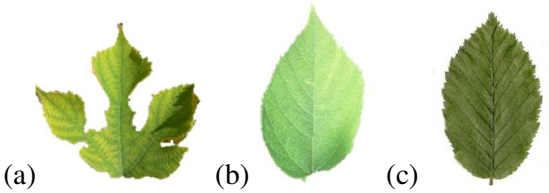


Fig. 1: Leaves (a) and (b) are different but they belong to the Broussonetia papyrifera L'Héro Vent species, leaves (b) and (c) are similar but they belong to two different species, (c) belongs to the Carpinus betulus L species

Fig. 2: Similar bark belonging to four different species which are (from left to right) Acer campestre L., Acer opalus Mill., Aeculus hippocastanum L. and Liquidamber styraciflua L. respectively

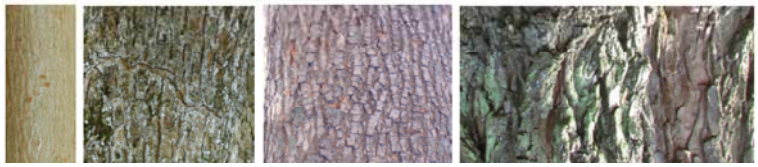


Fig. 3: Different bark belonging to the same species, Acer Campestre L. species

In literature, several recognition techniques like deep neural network (Joly et al., 2014), SVM (Horaisová & Kukal, 2016; Lin & Herold, 2016), kNN (Novotný & Suk, 2013), Random Forest (Harrison et al., 2018; Othmani et al., 2013), etc. have been used. Deep neural networks are not applicable in our case. In fact, they need high computational capacities that are not provided by smartphones. SVM is a classification technique that searches to identify linear separators between the species. However, the interspecies similarity generates many confusions between species, which make them non-linearly separable. kNN is a simple classification technique that identifies the species through its similarities with the k nearest labeled trees. The problem with this classifier is that the selected nearest neighbors have almost the same distance from the unknown species with different labels. We consider this problem as an indicator of the kNN confusion in identifying the right species. Random Forest is an ensemble classifier composed of a set of decision trees. The output of the random forest classifier is a list of species ordered according to a probability distribution that associates a probability that it is the right one to each species. Usually, the species with the greatest probability is

the right one. However, in most cases we have a subset of species with almost the same probability value, this is due to the confusion of the classifier in identifying the right species. To remedy these issues, we use the theory of belief functions. In fact, it is useful to manage confusion and to make a more reliable decision.

The theory of belief functions, also called evidence theory, provides a mathematical framework for imprecise, uncertain and conflictual information. In fact, it supplies a set of tools for imperfect information modeling and fusion in order to reduce the impact of the imperfection and to make a more reliable decision. Furthermore, the theory of belief functions is efficient in managing confusion. Indeed, it allows the modeling of all the confusions the system can have while identifying species due to its similarities with other species. This confusion between species is translated to the system ignorance in the process of specie identification. This theory models such information through the consideration of the union of the hypothesis (possible species in this case) instead of considering them separately.

The main objective of this paper is to describe how Dempster-Shafer's (DS) theory of belief function can be used for managing uncertainty in a decision system, which can be seen as an expert system. Therefore, the practical criteria (interpretation, imprecision/uncertainty, consistency, computation and calculus) which are necessary if an expert system is to be implemented in practice are present in our methodology. For more details about the theoretical foundations of the relevance of belief functions theory in expert systems framework, the reader is invited to consult the following references (Gordon & Shortliffe, 1985) and (Shafer, 1987).

To provide an overview of the work that is presented here and to explain the reasoning behind our approach, we begin by detailing the motivation for the proposed approach. The developments that are inherent to our methodology will be detailed in the next sections. In this paper, a more viable methodological and implementation approach is proposed for the design of a decision system for the recognition of tree species. From a methodological point of view, due to the presence of conflict information, the originality of the proposed decision system that imitates a botanist expert is not based on conventional "If-Then" rules, but on belief function concepts for treating and combing the available conflictual information. From an implementation point of view, the recognition tree species system must be embedded in a smartphone (real-time operations with limited on-board computational resources and without an Internet connection). In this framework, the proposed solution must be adapted for smartphone capacities and improves the running time compared to the existing solutions.

To achieve these methodological and implementation goals, an evidential two-step classification approach for tree species identification from leaf and bark is proposed. The first step uses a random forest classifier to recognize the leaf characteristics and select a small set of most probable species. This step is useful to reduce the dimensionality of the problem. The second classification step uses a modified EkNN to recognize the bark from the result of the first step. Then, a mass distribution estimation process is introduced. The idea of the two-step classification exists in literature. However, it was used to extend the training set. We find the work of (Lian et al., 2015) that introduces an evidential two-step classification strategy. Indeed, they partitioned the testing set into two subsets. Next, they used their approach to classify the first subset, then they injected the recognized samples into the training set. Finally, they used the resulting training set to recognize the rest of the samples. Their solution consists of enriching the training set with part of the testing examples to better recognize the rest of the training set. It is not applicable in our case as it does not address any of the problems mentioned above. The novelty of our approach is that it models the confusions between similar species and considers them as a partial ignorance between these species, thus it puts them in the same focal element. This solution considers that there is confusion between two or more species if their distance to the unknown species is almost the same. This methodology of conception reduces the computing recognition time and allows its adaptability to be run with the limited capacities of smartphones.

The remainder of this paper is organized as follows: Section 2 states and discusses the related works. Section 3 presents a background on the theory of belief functions. Section 4 details the

proposed two-step recognition system. Section 5 discusses the experiments and the results. Finally, Section 6 concludes the paper.

2. Related works

In this paper, a tree species recognition approach from leaf and bark is introduced. The main purpose is to get a light and efficient approach that can be run on a smartphone. Consequently, smartphones running capacities create some constraints on the proposed approach. Besides, the proposed solution treats the confusion between species in order to obtain accurate recognition. In this section, we present some related works that searches to recognize tree species.

2.1. Tree organ identification

The problem of tree species recognition is widely studied in literature. Most of the existing works focuses on attribute extraction from the tree organs photos to which they then apply a classification technique like kNN (Novotný & Suk, 2013), SVM (Horaisová & Kukal, 2016; Lin & Herold, 2016), Random Forest (Harrison et al., 2018; Othmani et al., 2013), Neural Network (Yang et al., 2017; Horaisová & Kukal, 2016), etc. Table 1 presents a summary of some existing tree organ identification approaches.

Many works seek to identify the tree species using attributes extracted from its leaf photo. Then, (Harrison et al., 2018) used long-wave infrared to extract parameters from the leaves of twenty-six species. These attributes were later used as input for a random forest classifier. The authors achieved a good error rate of less than 10%. However, long-wave infrared technique cannot be run on a smartphone.

The authors of (Horaisová & Kukal, 2016) worked on 2D binary leaf images. They proposed two methods for parameter extraction based on the 2D Fourier power spectrum. Then, they applied a kernel SVM and a self-organizing neural network for leaf recognition. Besides, they used a dataset containing 13 leaf species having a uniform background photo from ImageCLEF 2013 dataset. They obtained a classification rate of about 85%. In the work of (Yang et al., 2017), the authors extracted 7 features from leaf photos using the 2-level wavelet transform. Next, they used a back-propagation neural network classifier for leaf recognition. They tested their solution on a dataset containing 90 images of leaves from three different species and they achieved a recognition rate of 90%. These solutions were shown to be performant on datasets containing just a few species and there is no guarantee that they work on a larger scale where several species similarities may appear and create confusion.

Table 1 : A comparison between tree organs identification approaches

Approach	Technique	Parameters	Organ	Recognized species
(Harrison et al., 2018)	Random forest	Long-wave infrared	Leaf	26 species
(Horaisová & Kukal, 2016)	Kernel SVM and a self-organizing neural network	2D Fourier power spectrum	Leaf	13 species, uniform background
(Novotný & Suk, 2013)	kNN	Fourier descriptors	Leaf	153 species, uniform background
(Yang et al., 2017)	Back-propagation neural network	2-level wavelet transform	Leaf	3 species
(Othmani et al., 2013)	Random forest	Terrestrial laser scanning technique	Bark	5 species
(Lin & Herold, 2016)	SVM	Static terrestrial laser scanning	Tree structure	4 species

The authors of (Novotný & Suk, 2013) used Fourier descriptors to extract parameters from leaf photos. They then applied a kNN classifier for the recognition step. They tested their approach on a dataset that included 153 species with solid white background. They obtained classification rates of 88%. However, this solution is performant on solid white background leave photos and there is no guarantee that it works with natural background photos. Besides, they did not treat the confusions between similar species.

Few works search to recognize tree species from bark photos. We find for example the work of (Othmani et al., 2013). They used a terrestrial laser scanning technique to extract a 3D description of the bark texture. Subsequently they applied a random forest classifier on the extracted attributes. They tested their approach on a dataset containing samples from five species. They obtained an error rate less than 2%. Some other works search to recognize tree species from the hole tree structure, like the work of (Lin & Herold, 2016). In fact, the authors used the static terrestrial laser scanning to extract features describing the tree structure. Next, they applied a classification model based on SVM. However, these approaches are not suitable to be run on a mobile. In fact, these works use feature extraction techniques that cannot be run on a mobile like the terrestrial laser scanning technique.

2.2. Leaf and Bark information fusion to identify the tree

Some works are focused on multimodal trees identification. They studied the tree species recognition from the leaf and bark through information fusion techniques (Ben Ameur et al. 2017; Bertrand et al. 2018). The authors of (Ben Ameur et al. 2017) introduced an interesting fusion system that recognizes the leaf and the bark, then they fuse the results to obtain a more reliable identification. In fact, they have a set of characteristics extracted from leaves and bark. Next, they apply a random forest classifier on each characteristic separately. Then they use the theory of belief functions to combine the classification results of these characteristics. We note that they propose a hierarchical system based on a cascade fusion to combine leaf characteristics results in parallel to a second cascade fusion to combine bark characteristics results. Next their system fuses these two modalities together. Finally, their system recognizes the tree species from the output of the hierarchical modalities fusion. This solution is interesting, but it may be optimized. In fact, using a random forest classifier for each characteristic makes the time consumption relatively high. Besides, it did not consider the confusion between species. Indeed, it uses the consonant transformation operator (Aregui & Denoeux, 2008) to generate mass distributions from the outputs of the random forests. However, this operator is not adapted to consider a partial ignorance when we have two or more confused. We consider their solution as a baseline in our experiments.

An extension of the work of (Ben Ameur et al. 2017) was recently introduced (Jendoubi et al., 2018). This last solution has the same cascade fusion strategy as (Ben Ameur et al. 2017). The novelty of (Jendoubi et al., 2018) is that it uses an adapted evidential k nearest neighbors classifier for each characteristic. This changing reduced the complexity of the system which reduced the response time. However, it did not improve the recognition rates. Besides, this solution did not consider the confusion between species. We consider this solution as a baseline in our experiments.

Leaf and bark fusion systems was studied by (Bertrand et al. 2018). In fact, they introduced various strategies to fuse the features extracted from leaf and bark to recognize the tree. They proposed two main categories of fusion systems. The first one is the “a-priori fusion”. This solution consists of concatenating the feature vector of the leaf with a feature vector of the bark. Next, they classify the concatenated vector using a 1-vs-all Support Vector Machine classifier (SVM) with a Radial Basis Function kernel. The second one is the “a-posterior fusion”. It consists of classifying the leaf features and the bark features separately using two 1-vs-all SVM. To fuse the output of the two classifiers, they defined a weighted multiplicative fusion function of the confidence values of each species. Their function allows to sort the species using the information from the leaf and the bark. According to their experiments, this second solution is more accurate than the first one. However, this accuracy is not satisfying. Then the proposed solution improves these results the proposed two set classification principle and the processing of the confusion between species. We consider the a-posterior solution as a baseline in our experiments.

2.3. Mobile applications

Many studies provide an implementation of the tree species recognition approaches they propose. Then we find mobile applications (Cerutti et al., 2013; Phyu et al., 2012; Kumar et al., 2012; Goëau et al., 2013), web services (Goëau et al., 2013; Joly et al., 2014) and desktop applications (Hossain & Amin, 2010). Characteristics of these applications are summarized in Table 2. In this paper, we are interested in mobile application. In fact, such an application makes the species identification more accessible and easier task for the general public. Besides, the user just needs a smartphone equipped with a camera and an internet connection for some application to identify the tree species.

We identify some works that provide an online service, such an application needs a large computational power. Then, all the computations are done on a distant server. Thus, the user uses his smartphone to take a photo of the tree organ. Next, the photo is sent to the server for processing and recognition. Finally, the server sends its response to be displayed to the user. Such an application requires a reliable internet connection. However, tree species recognition applications are generally used in remote area where an internet connection may be unreliable or even unavailable. Then, the major limitation of such an application is its dependence on the internet. As an example of these applications we find Pl@ntNet (Goëau et al., 2013), CLOVER (Nam et al., 2016), LeafSnap (Kumar et al., 2012) and MOSIR (Phyu et al., 2012).

On the other hand, we find some other works that choose to run the recognition process on the device without need to any internet connection or server. We note that smartphones have some computational power limitation which limits algorithmic choices. Then the challenge of such an application is the recognition algorithm that must be efficient and fast. We note that such applications still have some classification performance limitations especially related to the recognition accuracy. Folia (Cerutti et al., 2013) and LeafView (Belhumeur et al. 2008) are two examples of these applications.

Table 2: Tree species recognition applications and their characteristics (Waldchen & Mader, 2017)

Name	Application type	Organ	Background	Recognized species	Analysis
LeafView (Belhumeur et al. 2008)	Mobile	Leaf	Plan	About 500	Offline
LeafSnap (Kumar et al., 2012)	Mobile	Leaf	Plan	184	Online
Folia (Cerutti et al., 2013)	Mobile	Leaf	Natural	108	Offline
CLOVER (Nam et al., 2016)	Mobile	Leaf	Plan	-	Online
MOSIR (Phyu et al., 2012)	Mobile	Flower	Plan	-	Online
Pl@ntNet (Goëau et al., 2013; Joly et al., 2014)	Web/Mobile	Multi organ	Plan	16,675	Online
Chloris (Hossain & Amin, 2010)	Desktop	Leaf	Plan	32	Offline

Another classification of the existing mobile application can be done according to the recognized tree organs. We note that most applications are used to recognize the leaf of the tree (Cerutti et al., 2013; Kumar et al., 2012). Few applications recognize the flower like MOSIR (Phyu et al., 2012). Finally, we find Pl@ntNet (Goëau et al., 2013) that recognizes all tree organs.

Pl@ntNet (Goëau et al., 2013; Joly et al., 2014) is a robust application that gives good recognition rates. It uses a convolutional neural network (CNN) to select a set of most likely species. In a second step, they apply a k nearest neighbors classifier in order to reject less likely species from the result of the CNN. However, this application needs high computational capacities that are done on a distant server. Then it is dependent to the internet connection, but the internet is not always given in the nature where the application will usually be used. We consider their solution as a baseline in our experiments.

In the literature, there is only one mobile application that explains how to recognize tree species in a natural environment to the user, which is Folia (Cerutti et al. 2011; 2013). This application imitates the botanists' strategy and uses the same characteristics they use to recognize trees. However, the current version of Folia recognizes only photos of leaves. Besides, the recognition rate of Folia does not exceed 50% for the first returned species. Then, we are looking to improve the recognition rate through the consider of the bark modality and the reduction of the confusion between similar species. We consider the Folia classifier as a baseline in our experiments.

3. Background

The theory of belief functions, also called Dempster-Shafer theory or Evidence theory, was first introduced by Dempster (Dempster, 1967) in 1967 and then it was detailed by Shafer (Shafer, 1976) in 1976. This theory attracted a great of attention as it presents flexibility in information modeling and fusion. Besides, it is useful to model the uncertain and imprecise information.

The theory of belief functions is used in this paper to model the confusion that can appear between species due to the interspecies similarity. Furthermore, it can reduce the impact of these problems. In fact, this theory is useful to represent the confusion that may appear between similar species. Besides, it allows fusing information from many sources to obtain a more reliable one which allows taking a good decision about the species.

Let $\Omega=\{c_1,c_2,\cdots,c_n\}$ be a frame of discernment of n possible decisions. The mass function m is defined on subsets of Ω and verifies:

$$\sum_{A\subseteq\Omega} m(A)=1 \tag{1}$$

It allows representing the pieces of information coming from a given source and describing a given problem. The subset A is called a focal element if $m(A)>0$. When $A=\Omega$, then A models the total ignorance. Indeed, the total ignorance helps to model the cases where we have no information or we have several confusions, then all the hypotheses in the frame of discernment are possible. Besides, when $A\subset\Omega$ and A is not a singleton then we say that A models partial ignorance. It is useful when we have some information about a disjunction of the hypothesis, but we are not able to have a preference between them. Then we can represent the case where we have a confusion between some similar species through the definition of a focal element on the union of them.

The theory of belief functions provides a mathematical framework for information fusion. Besides, it proposes a wide variety of tools adapted for many types of information having distinct sources or even indistinct ones. Furthermore, some information fusion tools are useful to reduce partial ignorance (confusion). Then, as a result, we obtain refined information with less confusion and more confidence.

To fuse information from distinct sources, the theory of belief functions presents many combination rules among them the Dempster's Rule (Dempster, 1967) defined as:

$$m_{1\oplus 2}(A)=\begin{cases}\dfrac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1-\sum_{B\cap C=\emptyset} m_1(B)m_2(C)}, & \emptyset\neq A\subseteq\Omega\\ 0 & \text{if } A=\emptyset\end{cases} \tag{2}$$

through this rule, the conflict value, i.e. empty set mass, is proportionally distributed on the focal elements of the resulting BBA. Also, we find the conjunctive rule of combination (CRC) (Smets, 1993) defined as:

$$m_{1\otimes 2}(A) = \sum_{B\cap C=A} m_1(B)\, m_2(C), \forall A \subseteq \Omega \tag{3}$$

The CRC does not distribute the conflict. The CRC is useful to reduce partial ignorance while combining pieces of information. Indeed, it used to consider the intersection of the focal elements which leads to more refined and certain information. In the next section, we detail the proposed two-step tree species recognition approach.

4. Recognition System

In this paper, we present a solution for tree species recognition from photos of leaves and bark taken with a smartphone. Besides, we follow the recognition process of the botanist and we consider a set of morphological features that he uses to identify the tree species. Then, from leaf photo, we have a feature vector that describes the polygonal model, the apex, the base and the margin of the leaf. From the bark photo, we extract a second vector that describes the color hue H of the HSV space, the texture (Gabor) space and the vertical and the horizontal orientation of the bark texture. These feature vectors were described in more details in some previous works (Bertrand et al. 2018; Cerutti et al., 2011; 2013).

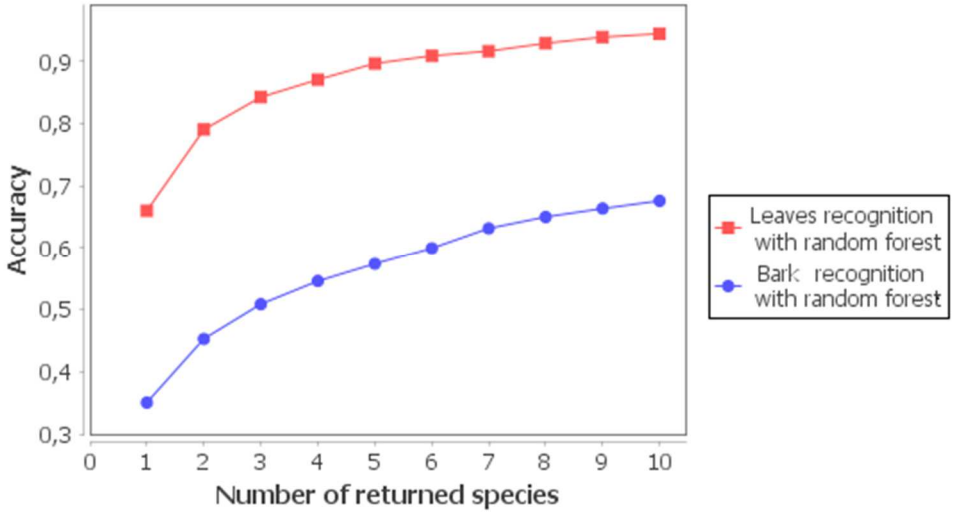


Fig. 4: Accuracy of leaves recognition compared to bark recognition using a random forest classifier

The high species diversity in nature is an important challenge among the challenges of the tree species recognition problem. For example, in France there are about 140 species[2], in Australia, there are 24,000 species[3]. In fact, this is a real issue for most existing machine learning techniques as most of them are adapted for a smaller scale. Then, comes the idea behind the proposed two-step recognition system. It consists of applying a first classification step to reduce the problem dimensionality. In fact, this step selects a small set of N species having a high probability that the good species is among them. Next, the second classification step refines the output of the first classification step in order to identify the good species from the set of N species. This system allows the consideration of two different organs, in this paper we used the leaf and the bark.

To identify the best tree organ to be used in the first step of the proposed system, we made the experiment of Fig. 4 that compares the accuracy of the leaves in recognizing the tree to the bark using

[2]IGN Institut National de l'information Géographique et forestière. https://inventaire-forestier.ign.fr/spip.php?rubrique87

[3]https://www.australia.com/en/facts-and-planning/australias-plants.html

the random forest classifier. We fixed N to 10, then, the system returns the most probable ten species (horizontal axis). According to Fig. 4, the leaf photo is more discriminant to recognize the tree. In fact, using the leaf characteristics, the probability that the good species is among the first ten returned species is about 93%. However, this probability is less than 70% when we use bark characteristics. Thus, using the leaf characteristics, we can select a reduced set of most probable species that has the minimum loss probability. In fact, it is generally harder to identify the tree from its bark only, because similarities between bark are extremely present, e.g. the reader can refer to Fig. 2 for example, which makes their identification from a set of attributes extracted from their photo non-discriminating. Consequently, we consider the leaf characteristics to reduce the search space in the first step and the bark characteristics to refine the results of the second step of the proposed two-step classification approach.

The proposed recognition system is presented in Fig. 5. It recognizes the tree from its leaf and bark characteristics in two main steps. The first step uses the leaf characteristics to reduce the problem dimensionality. This step is performed using a trained random forest classifier that was previously trained on a labeled dataset containing a set of leaves characteristics. Then, this first step runs the trained random forest classifier to recognize the new leaf characteristics. The result of this step is a set of N most likely species. Each species is associated with a probability that it is the right species. Thus, the number of possible species is reduced to N. This output is used in the second classification step. The random forest classifier is adapted for this first step. It is an ensemble classifier composed of a set of decision trees and it gives accurate results compared to other tested classifiers like SVM and kNN.

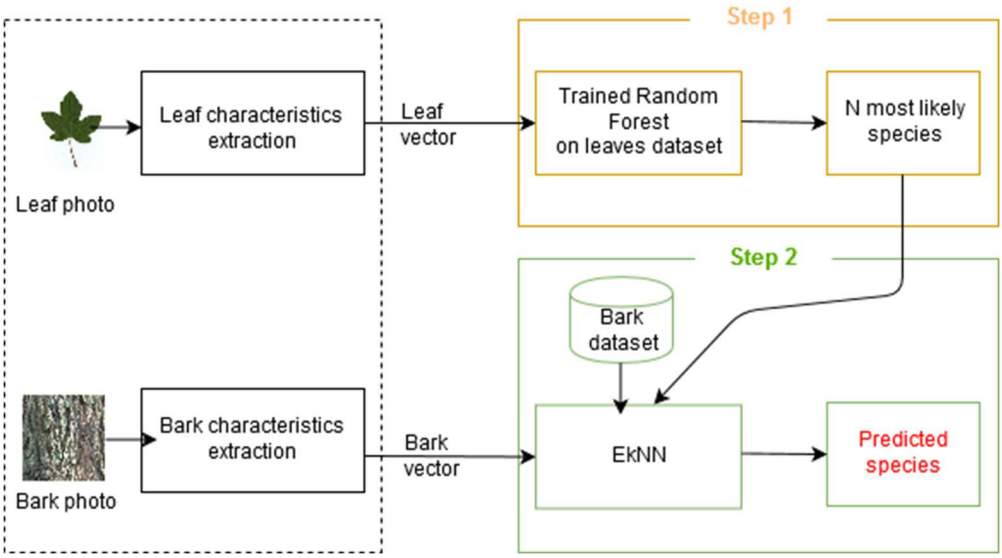


Fig. 5: Proposed tree species recognition model

We studied the output of the random forest classifier and we noticed in many cases that the returned species have almost the same probability to be the good species. Besides, the searched species is not always in the first position. Fig. 6 illustrates this problem. Indeed, in this example, the good species is the second position. Such results are obtained because there are similarities between the selected species which generate confusion between them and leads to the confusion of the random forest classifier in identifying many species. This problem leads to erroneous recognition results in many cases. The classifier predicts a similar species instead of the good one. Furthermore, the good species is selected in a later position with an almost similar probability.

The result of the first step is used to reduce the bark dataset and to adapt it to the current unknown tree. The second step uses a kNN based classification technique that needs a data sample of similar species to the unknown one. Then, we use the N most likely species obtained from the output of the first step to reduce the bark dataset. The idea here is to keep only the samples of the most likely species.

In the second step, we use the bark characteristics of the unknown tree to refine the result of the leaf characteristics (results of the first step of the system). Here we use a k nearest neighbors (kNN) based technique for classification. The idea is to select the most similar bark to the unknown bark from the sampled bark dataset. In this step, a distance-based classifier is the most adapted. In fact, the training dataset, i.e. the bark dataset, is updated from the result of the first step which makes a model-based classifier inappropriate for this step. A model-based classifier needs a learning step to create the classifier. However, the training dataset is variable, then it is not adaptable to use a pre-trained model. Thus, a distance-based classifier is the most adapted.

The proposed kNN technique in this second step is an adapted evidential kNN (EkNN) classifier to our problem. In fact, from the results of the random forest classifier, we get the set of most likely species and each of those is associated with the probability that it is the right species. Then the proposed EkNN uses this information to adjust its results. We present this algorithm, in more detail, in the next section.

5. Mass distribution estimation

As shown in Fig. 5, the proposed EkNN takes three inputs which are the bark characteristics of the unknown tree, the N most likely species associated with a probability distribution (output of the first step) and the filtered bark dataset. Let us consider $\Gamma=\{S_1,S_2,...,S_N\}$ and $\Pr=\{p_1,p_2,...,p_N\}$ the output of the first step of our system where Γ is the set of N species and Pr is their associated probabilities, i.e. p_i is the probability that S_i is the right species $\Pr(S_i)=p_i$. Let us, also, consider B to be the unknown bark and $\Lambda=\{b_1,b_2,...,b_M\}$ be the sampled bark dataset that contains M labeled bark sample belonging to the N species. Then each $b_i\in\Lambda$ is associated with label $\theta_i\in\Gamma$ such that $\Pr(\theta_i)\in\Pr$. The EkNN starts by estimating the distance, $\delta(B,b_i)$, between B and the set of labeled bark $b_i\in\Lambda$. The distance $\delta(B,b_i)$ can be estimated using the Euclidian Distance. Next, we adjust the distances $\delta(B,b_i)$ using the probability $\Pr(\theta_i)\in\Pr$ as follows:

$$d(B,b_i)=\frac{\delta(B,b_i)}{\Pr(\theta_i)} \tag{4}$$

Next, the algorithm selects the k nearest neighbors to the unknown object (the bark in the case of our application), B, according to their updated distances d.

From the selected nearest neighbors and their distance with the unknown bark, a set of mass functions is estimated. The existing EkNN (Denoeux, 1995) estimates a mass distribution for each nearest neighbor. In fact, it calculates a mass value, x, on the class of the nearest neighbor and it puts the rest of the mass, 1-x, on the frame of discernment. However, this estimation method does not consider the partial ignorance between neighbors. The partial ignorance is important as it models the ignorance about a subset of the frame of discernment. It is essential to consider partial ignorance in the tree's recognition problem. In fact, this problem presents the main issue which is the interspecies similarity. This issue is the origin of many confusions the system can have between several species which makes their differentiation harder. Consequently, partial ignorance allows us to model these confusions and to put an amount of belief on the union of confusing species. In this case, the system is abler to model such confusion.

In this paper, we introduce a new mass distribution estimation algorithm for the evidential kNN. The novelty of this solution is that it models the confusions that may appear between similar neighbors through partial ignorance. In fact, when the distance between two or more neighbors is almost the same, we consider that we are not able to distinguish these neighbors and we define a focal

element with their union. Algorithm 1 details the proposed method to estimate mass distributions from the selected nearest neighbors set on subsets of the frame of discernment. The algorithm takes four inputs which are: Neighbors: an ordered table of nearest neighbors according to their distance with the unknown object (bark). Distances: list of the nearest neighbor's distances values with the unknown object. T: Maximum allowed value of distance difference between neighbors, and Γ: the set of N species. The result of the algorithm is the set of estimated mass distributions, BbaSet.

The algorithm starts by looping over the Neighbors in order to detect all sets of neighbors having almost the same distance value, i.e. the absolute difference between their distances is less than or equals to T. Next, for each obtained set of neighbors it estimates a simple mass distribution having as main focal element the union of classes of these neighbors which allows the system to model the confusion between these neighbors to process it in the next steps.

Algorithm 1: Mass distributions estimation

Input:
Neighbors: Selected nearest neighbors sorted in ascending order according to their distance to the unknown object
Distances: Table of nearest neighbors distances values (sorted in ascending order) with the unknown object
T: Maximum allowed value of distance difference between neighbors to put them in the same focal element
$\Gamma=\{S_1,S_2,...,S_N\}$: the set of N species
Output:
BbaSet: Set of mass distributions
Algorithm:
Begin
  For each neighbor i in Neighbors **Do**
    j ← i+1 /*next neighbor*/
    A←{ } /*the focal element*/
    Add the neighbor i to A
    While (abs(Distances[i] – Distances[j]) ≤ T **&&** j ∉ A) **Do**
      Add the neighbor j to the focal element A
      j←j+1 /*next neighbor*/
    End While
    Estimate the mean distance D of the neighbors in A
    Estimate a BBA distribution having two focal elements A and Γ and add it to BbaSet
  End For
End

Let us consider Ω to be the set of all possible species that our system can recognize, $\Gamma\subseteq\Omega$, $\Gamma=\{S_1,S_2,...,S_N\}$ the set of N species selected by the first step of our system, let $A\subseteq\Gamma$ be a focal element obtained using Algorithm 1 and let D be the mean distance value of the neighbors in A. Next, we estimate a mass distribution as follows:

$$\begin{cases} m(A)=\alpha*\Phi(D) \\ m(\Gamma)=1-m(A) \end{cases} \tag{5}$$

where $\alpha\in[0,1]$ is a discounting parameter and $\Phi(D)$ is a decreasing function that can be defined as follows:

$$\Phi(D)=e^{-\gamma D^{\beta}} \tag{6}$$

where $\gamma > 0$ and $\beta \in [0,1]$. The result of the Algorithm 1 is the set of mass distribution BbaSet.

6. Mass fusion & decision making

In the previous two sections, a two-step classification approach for tree species recognition was introduced. The proposed approach recognizes the tree species from two modalities which are the leaf and the bark. The first step recognizes the leaf characteristics and determines a set of N most probable species for the characterized leaf. This step uses a random forest classifier. The second step identifies the bark characteristics from the N species selected in the first step. In fact, it applies an adapted evidential nearest neighbor algorithm introduced in the previous section. At the end of the second step, we obtain set mass distributions. In this section, we detail the fusion of the masses and the decision-making.

The theory of belief functions provides a wide variety of combination rules like Dubois and Prade's rule (Dubois Prade, 1988), Dempster's rule, CRC, etc. The choice of an adapted rule depends on the information to fuse and to its source. For example, if the sources are dependent, we can use the cautious combination rule (Denoeux, 2006). If we have conflicting information coming from sources unreliability, we can use an adapted rule that distributes the conflict on the union of conflictual elements like Dubois and Prade's rule for example.

In the case of the proposed tree species recognition approach, the mass distributions have independent sources. However, they have a special particularity in that, they are defined on a subset of the frame of discernment $\Gamma \subseteq \Omega, \Gamma = \{S_1, S_2, ..., S_N\}$, such that Γ is obtained from the output of the first step. It is the set of the selected N species returned by the random forest classifier. The set Γ might be non-exhaustive. This particularity has some influence on the obtained set of mass distributions. In fact, it can be the origin of some conflict, $m(\varnothing)$, that may appear between the mass distributions while combining them. Then, the conflict in this case is considered as an indicator on the exhaustiveness on the referential set Γ. Indeed, the higher $m(\varnothing)$ is, the less exhaustive Γ is. Consequently, we need a combination rule that does not distribute the conflict. Hence, the most adapted combination rule in such cases is the conjunctive combination rule, CRC. The CRC combines the pieces of evidence coming from independent sources and puts the total conflict amount on $m(\varnothing)$. Besides this rule reduces partial ignorance as it puts the combined mass value on the intersection of focal elements. Thus, the resulting mass distribution is refined and more reliable.

After the mass fusion, we obtain a mass distribution, m, defined on Γ that summarizes the information we have about the species. Then, we need to decide on the species. In fact, the main purpose of the proposed approach is to give the user a prediction about the species of the tree that he wants to identify. For that purpose, we use the maximum pignistic criteria (Smets, 1990) for decision-making. Then, we transform the mass distribution, m, to a pignistic probability using the following equation:

$$BetP(S_i) = \frac{1}{1 - m(\varnothing)} \sum_{S_i \in A} \frac{m(A)}{|A|} \tag{8}$$

Where $A \subseteq \Gamma$. As a result we obtain $BetP(S_i)$ which is a probability distribution defined on Γ those attributes to each species, S_i, the probability that it is the good species.

7. Experiments & performance analysis

In this section, we evaluate the proposed solution. Besides, we study the parameters and their impact on the results of the recognition rate.

The system in our experiments returns the set of ten most likely species and estimates the accuracy that the good species is one of these species. In fact, many existing solutions in the literature have the same kind of output that allows the system to handle the problem of interspecies similarity which allows the user to have a set of possible species and their descriptions. The reader can find the executable version of the system and the data on the following link: https://projects.listic.univ-smb.fr/reveries/RF_EkNN.zip

This section is organized as follows: first we detail the used dataset and its characteristics, next, we introduce an example to illustrate the proposed approach and finally we present a set of experiments to compare the proposed approach to existing solutions.

7.1. Dataset description

In this paper, we use a dataset from the challenge ImageClef 2015[4]. Indeed, the dataset is a part of the PlantClef task data in which we have photos of leaves and bark of 72 different tree species from mainland France. Besides, it is a collaborative dataset where photos are taken in nature by non-professional users using their own camera or smartphone camera. Then, this dataset is adapted to evaluate the proposed tree species recognizer. In fact, the quality of the photos is similar to the photos taken by the users of our system. We remind that in this paper, we seek to develop a tree species identification approach to be used through a mobile application by a novice or a lover of the trees universe.

In the data set, there is 5104 leaves photos and 1938 bark photos unequally distributed on 72 species. In fact, we have some species that are well presented in the dataset. However, we have some other species that are less presented and some species that have only two exemplary. We used 2572 leaves photos and 971 bark photos for training and the rest for testing. In our experiments, we need couples of leaf and bark from the same species to evaluate the proposed tree species recognition approach. Then, we generate a set of couples from our testing data using the following steps: 1) for each species, we take its leaves and bark photos, 2) we associate each leaf photo with the bark photo having the same order, i.e. we associate the first leaf to the first bark and the second leaf to the second bark, etc. 3) If we have more leaves than bark of more bark than leaves, we loop again on the fewest sample until associating each photo at least once. Using these steps, we obtained 2792 couples of leaves and bark for testing.

From each photo we extract a feature vector that describes the leaf or the bark morphological characteristics. Indeed, to describe the leaf photo we have a characteristic vector composed of:

- Nine parameters to describe the polygonal model
- Ten parameters to describe the apex and the base
- Ten parameters to describe the margin of the leaf

To describe the bark photo, we have a characteristic vector composed of:

- Two hundred and fifty-five parameters to describe the color hue H of the HSV space
- Three parameters to describe the texture (Gabor) space
- Sixty-nine parameters to describe the vertical orientation of the bark texture
- Forty-nine parameters to describe the horizontal orientation of the bark texture

These morphological characteristics are used by botanists to identify tree species. These feature vectors were described in more detail in some previous works (Bertrand et al. 2018; Cerutti et al., 2011; 2013). Then using them allows us to identify the tree and to explain the results as a botanist do.

7.2. Illustrative example

In this section, we present an example to illustrate the proposed approach.

Step 1: Fig. 6 illustrates the impact of the confusion on the output of the random forest classifier. We note that it selects four species having similar leaves to the unknown one. Besides, the

[4] https://www.imageclef.org/lifeclef/2015/plant

selected species have almost the same probability to be the good species. Furthermore, we notice that the good species Viburnum tinus L. (S_4 in this case) appears in the second position. Then, if the system chooses the most probable species (Rhamnus cathartica L., S_3), its response will be wrong. Consequently, the second step of the proposed approach is used to reduce the impact of such cases of confusion and to refine the results.

Step 2: The first step of the system selected four tree species that have similar leaves to the Viburnum tinus L. species. In this second step, we consider the bark of these selected species. Fig. 7 presents the bark of the four species selected in the first step. The photos of the bark of trees are positioned according to their distance to the unknown bark X (in the middle). In this example, we consider k = 4, then the system selects the four nearest neighbors as shown in the Fig. 7.

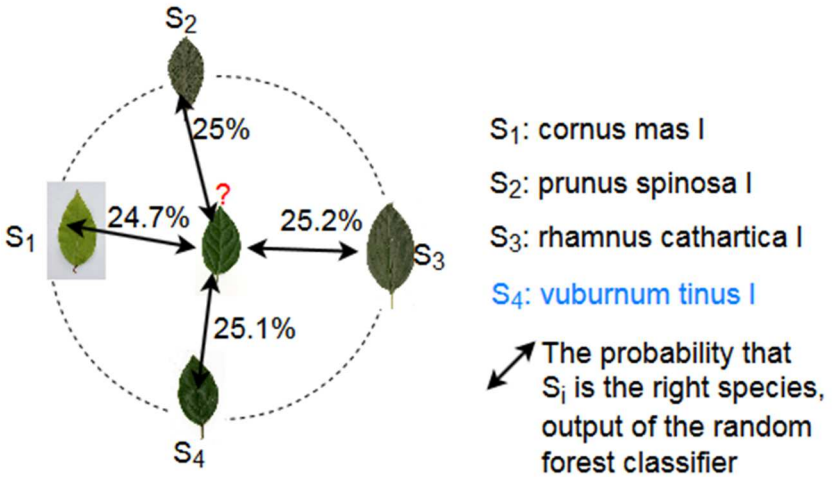


Fig. 6 : Impact of the species similarities on the output of the random forest classifier

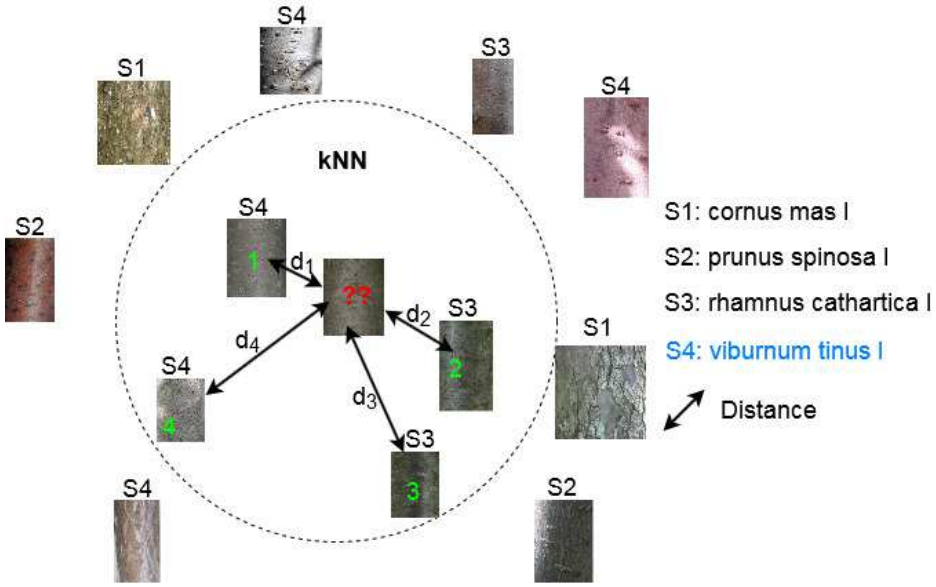


Fig. 7: Illustrative example of the selected 4-nearest neighbors using the Euclidean Distance.

We have four selected bark from two species were two among them belong to Rhamnus cathartica L species (S_3) and the two others belong to Viburnum tinus L. species (S_4). At this stage, we reduced the search space to the half (we have two possible species instead of four). The selected bark are ordered according to their similarity according to (Eq. 4) with the unknown bark X from 1 to 4 and their distances with X are respectively: $d_1 > d_2 > d_3 > d_4$ where $Abs(d_1 - d_2) > T$,

$Abs(d_2 - d_3) > T$ and $Abs(d_3 - d_4) \leq T$, where T is the maximum allowed value of distance difference between neighbors to put them in the same focal element. Next, we obtain the following three mass distributions:

$$\begin{cases} m_1(S_4) = 0.6 \\ m_1(\Gamma) = 0.4 \end{cases} \quad \begin{cases} m_2(S_3) = 0.4 \\ m_2(\Gamma) = 0.6 \end{cases} \quad \begin{cases} m_3(\{S_3, S_4\}) = 0,15 \\ m_3(\Gamma) = 0.85 \end{cases} \tag{9}$$

Where $\Gamma = \{S_1, S_2, S_3, S_4\}$. The first mass distribution m_1 models the information coming from the nearest bark (referenced with « 1 » in Fig. 7). Besides, we have $Abs(d_1 - d_2) > T$, then the proposed system considers that there is no ignorance between the first two bark. We notice that m_3 was defined on the union of $\{S_3, S_4\}$. In fact, the distance difference between the third and the fourth bark is smaller than or equals to T, $Abs(d_3 - d_4) \leq T$. Then, their distances are near to each other which makes their differentiation harder. In this case, we consider that there is a partial ignorance between the third and the fourth bark as we cannot differentiate them. Then, we define a mass distribution on the union of $\{S_3, S_4\}$ to model this ignorance.

Next, we use the conjunctive combination rule to fuse these masses and we obtain as a result the following mass distribution:

$$\begin{cases} m(\varnothing) = 0.264 \\ m(S_3) = 0.136 \\ m(S_4) = 0.396 \\ m(\Gamma) = 0.204 \end{cases} \tag{10}$$

We notice that $m(\varnothing) = 0.264$ which means that the amount of belief that the good species is in $\Omega \setminus \Gamma$ is 26.4%. Besides, the partial ignorance we have on m_3 was resolved on the combined distribution m. Thus, the confusion between the two species S_3 and S_4 eliminated. Next, to make a decision about the species we apply the pignistic transformation operator and we obtain the following result:

$$\begin{cases} m(S_4) = 0.6073 \\ m(S_3) = 0.2541 \\ m(S_1) = 0.0693 \\ m(S_2) = 0.0693 \end{cases} \tag{11}$$

As a result, we have an ordered list of the possible species. We note that the good species, S_4, is now in the first position with a confidence of 60.73%. At this stage, we can provide the user with the list of most probable species which are in this example S_4 and S_3 associated with their confidence.

7.3. Results & discussion

In a first experiment, we study the impact of the parameter K, i.e. the number of selected nearest neighbors, on the accuracy of the system. We fixed the parameter N to 15, i.e. N is the number of species returned by the first step of our system. We fixed the parameter T to 0.04, i.e. T is the maximum allowed value of distance between neighbors to put them in the same focal element. Then, we examine the accuracy of the system with different K values. The results are presented in Fig. 8. According to Fig. 8, the parameter K does not have an important effect on the first detected species. However, when K increases, we notice an important improvement in the accuracy of the system especially starting from the second detected species.

In a second experiment, we study the impact of the parameter N on the accuracy of the proposed tree species recognizer. In this experiment, we fixed K to 20 and T to 0.04. Fig. 9 shows the obtained results with different values of N. According to Fig. 9, we notice that the impact of the parameter N starts from the fourth detected species. Then we notice that the system accuracy decreases when the parameter N increases.

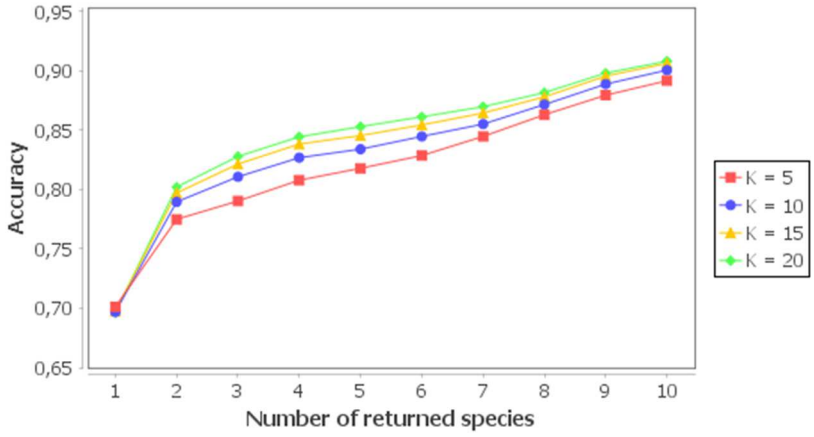


Fig. 8: System accuracy with different K values and N=15

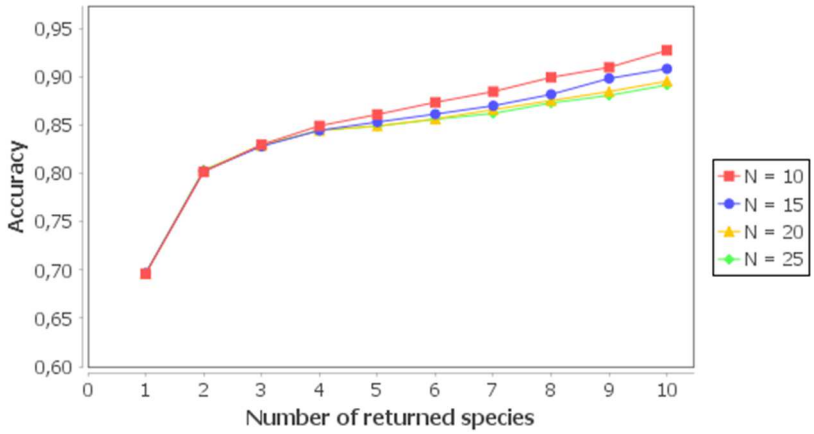


Fig. 9: System accuracy with different N values and K=20

In Fig. 10, we study the impact of the distance adjustment on the result of the system. Indeed, the distance adjustment allows the proposed evidential kNN to consider the information coming from the first step of the system, i.e. the output of the random forest, as explained in section 4. Then Fig. 10 shows the importance of this adjustment. In fact, without distance adjustment, we have only 25% accuracy on the first detected species. However, when we adjust the distance this accuracy increases to about 70%.

In the experiment of Fig. 11, we study the impact of the second step of our system presented in Fig. 5. Then, we compare the system accuracy at the output of the random forest (the first step), the blue curve, with the accuracy of the system called RF EkNN, red curve. In this experiment, we fixed N to 10, K to 20 and T to 0.04. Fig. 11 shows that adding the bark information at the second step improves the system accuracy for the first three detected species. In fact, the accuracy increases from 63.59% using the random forest (output of step 1) to 69.11% when we consider the bark information (output of the system RF EkNN).

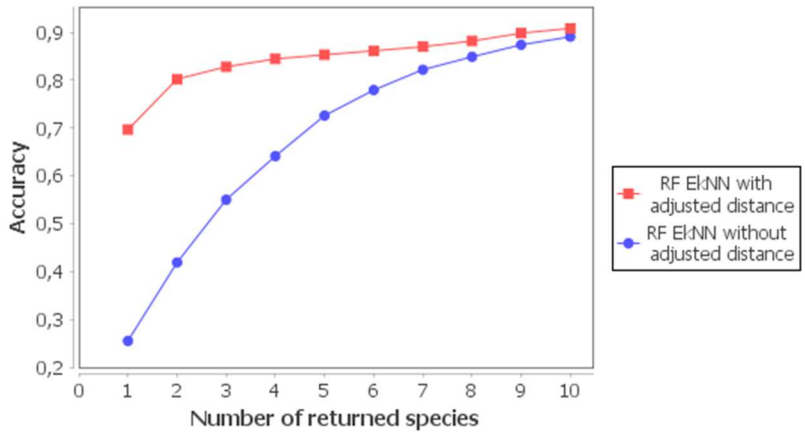


Fig. 10: Impact of the distance adjustment on the system accuracy

Fig. 12 presents a radar chart that compares the proportion of correctly recognized trees of each species (recognition rate per species) at the output of the first step to the output of the second one of the proposed system. We considered the first returned species. According to Fig. 12, the second step of the system improved the recognition rates of several species compared to the first step. Then, the consideration of the bark in the second step was useful to reduce the impact of the conflict between species. For example, the fifth species, called Acer pseudoplatanus L., has a null recognition rate at the output of the first step, this rate is increased to 33%. We analyzed the first step recognition results of the Acer pseudoplatanus L. and we find that it was confused especially with the Acer Campestre L. species and the Acer Opalus Mill species. Fig. 13 presents the leaves of the Acer pseudoplatanus L., the Acer Campestre L. and the Acer Opalus Mill species respectively. According to Fig. 13 we can see that these three species have a similar base, apex and polygonal models which explain the confusion of the first step of the proposed approach. Some of these confusions are removed using the bark of these species and the second step of the proposed approach.

According to Fig. 12, we have some species that are not recognized either by the first step or by the second one like the species 11 and 23. In fact, these species have few exemplary in our dataset. For example, the species 11 which is Betula pendula Roth has only two leaves in our leaves dataset, also, the species 23 which is Crataegus laevigata (Poir.) DC. has three leaves. Besides, these two species have many similarities with other species which makes their identification conflictual. Another important observation is that the accuracy of some few species has been decreased with the second step. In such cases, the bark brings some confusion to the system. Let take the species 60 for example. It is Quercus rubra L. species. When we analyze the output of the second step for this species, we notice that there is a confusion between Quercus cerris L. and Quercus pubescens Willd. that have similar bark to Quercus rubra L. as shown in Fig. 14.

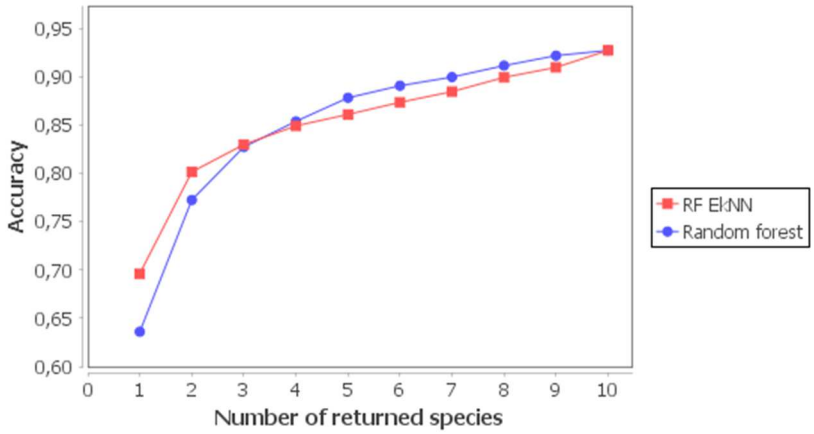


Fig. 11: Comparison between the accuracy of the random forest on leaves and the output of RF EkNN

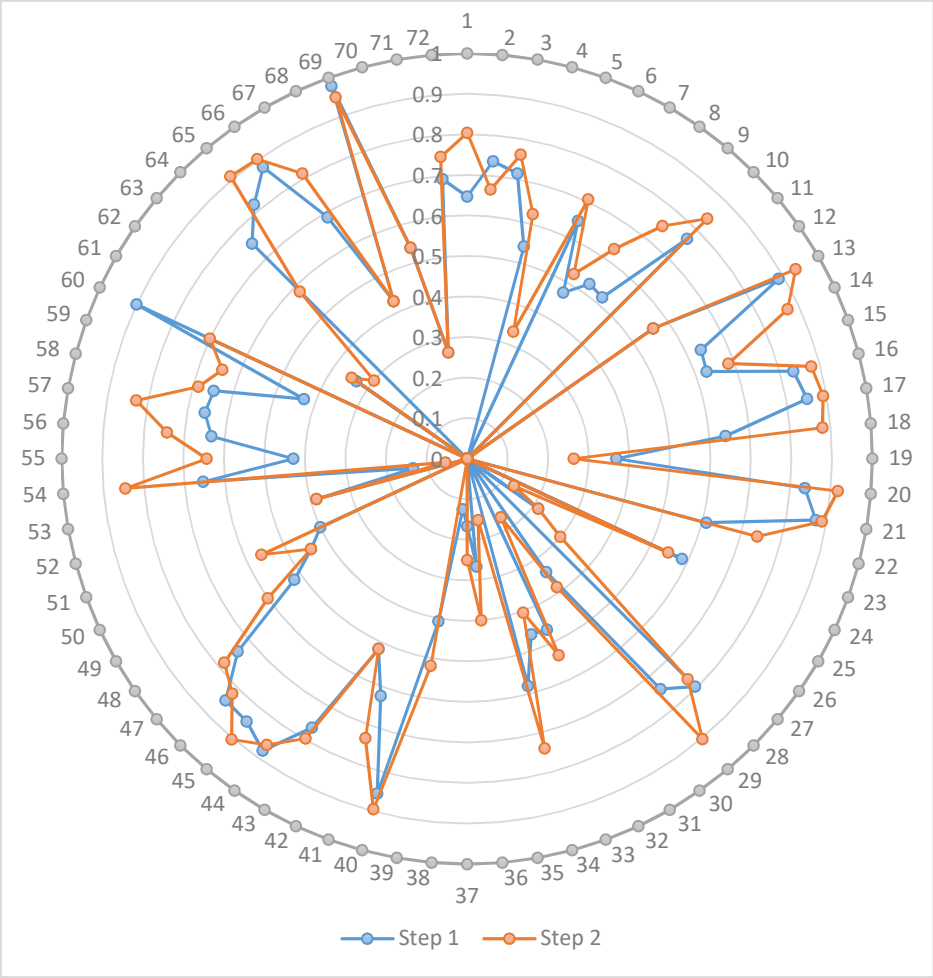


Fig. 12: Comparison of the proportion of correctly recognized trees of each species at the output of the first step (first returned species) to the output of the second one (first returned species) of the proposed system.

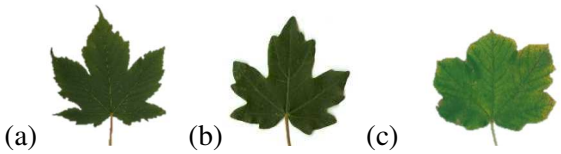


Fig. 13: Example of confused species: (a) Acer Pseudoplatanus L. (b) Acer Campestre L. (c) Acer Opalus Mill

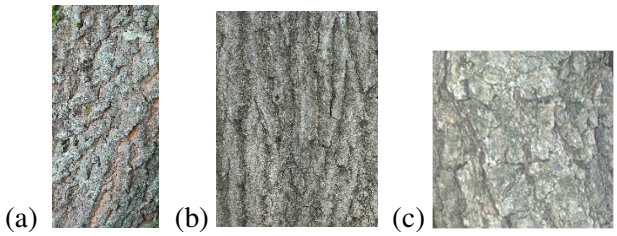


Fig. 14 : Example of confused bark: (a) Quercus cerris L., (b) Quercus rubra L. (c) Quercus pubescens Willd.

Table 3: Accuracy comparison between the proposed solution RF EkNN, LNS-EkNN, RF based fusion system, EkNN, SVM and Folia classifier for recognizing the tree species from leaf and bark photo

	Folia classifier (Cerutti et al., 2013)	SVM	EkNN	LNS EkNN	RF based fusion system (Ben Ameur et al. 2017)	RF EkNN
1	53.78	60.13	42.56	50.05	55.96	**69.11**
2	67.32	72.14	56.10	62.48	68.86	**79.64**
3	74.13	76.77	62.88	69.50	75.49	**81.72**
4	78.69	80.26	67.39	74.63	79.50	**83.33**
5	81.67	82.44	71.26	78.28	82.22	**84.09**
6	83.97	84.31	74.27	81.40	83.87	**85.05**
7	85.96	85.88	76.42	83.76	85.23	**86.16**
8	87.33	87.03	78.28	85.05	86.52	**87.60**
9	88.40	87.87	80.83	86.59	87.74	**89.43**
10	89.17	88.59	81.97	87.78	88.67	**90.32**

Table 4: Processing time to recognize a species in milliseconds

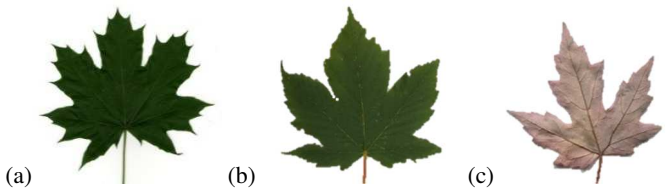
LNS EkNN	RF EkNN	Random Forest based fusion system
127.8	**44.6**	275.4

In Table 3, we compare the accuracy of the proposed RF EkNN with the accuracy of some existing solutions which are LNS EkNN (Jendoubi et al., 2010), RF-based fusion system (Ben Ameur et al. 2017), EkNN, SVM and Folia classifier (Cerutti et al., 2013) respectively. Then, we compare the accuracy of these solutions to recognize the tree using its leaf and bark photo. According to Table 3, we notice that RF-based fusion system, SVM and Folia classifier has close results. Besides, the best accuracy is given by the proposed solution RF EkNN that gives 69.11% for the first detected species and 90.32% for the tenth one.

In another experiment, we study the performance of the proposed RF EkNN against an existing solution that uses a deep network and a huge dataset for training, which is Pl@ntNet. Besides, our dataset is part of Pl@ntNet learning data. We note that it is not possible to run Pl@ntNet on our testing data using one running and such access was not performed by the authors of this application. Consequently, we were obliged to do these tests manually through the running of Pl@ntNet on each photo separately. To simplify the task, we run Pl@ntNet on ten photos per species for which we have more than ten photos, and we run the tests on all the species photos if we have less than ten. For this experiment, we used our testing leaves dataset. We note that our dataset is a part of the training data of Pl@ntNet. Then to compare the proposed approach to Pl@ntNet, we learned and tested the RF EkNN approach on the testing dataset.

Pl@ntNet has good results for almost considered species. However, we notice that for some species the proposed RF EkNN performs better results than Pl@ntNet. Let us take the case of the species 4 (Acer platanoides L.). Pl@ntNet recognized only 50% of the photos of this species and RF EkNN was more efficient in this case and recognized 62.5% (for this result we used only the leaves dataset for the two steps of RF EkNN). In fact, Pl@ntNet has some confusions generally between the Acer platanoides L., Acer pseudoplatanus L. and Acer saccharinum L. Fig. 15 presents leaves photos of these species, we can visibly notice that they are similar. On the other hand, RF EkNN was more robust to such confusions in the recognition of the Acer platanoides L.

We noticed that the dataset we are using in our experiments is a part of Pl@ntNet learning data which explains its high performance in recognizing many species. Then, to put the proposed system in a similar condition, we learned and evaluated the RF EkNN using the testing dataset. In this case, the proposed RF EkNN was perfect in recognizing all the species and we obtained 100% of system accuracy.



(a) (b) (c)

Fig. 15 : Leaves examples of (a) Acer platanoides L., (b) Acer pseudoplatanus L. and (c) Acer saccharinum L.

In the last experiment, we compare the processing time to recognize a species between RF EkNN, LNS EkNN, and Random Forest-based fusion system. Table 4 presents the recognition time in milliseconds. We notice that the proposed RF EkNN gives the best recognition time, 44.6 milliseconds. Next, we have LNS EkNN that takes 127.8 ms to recognize a species and the Random Forest-based fusion system that takes 275.4 ms. The recognition time reduction is an important advance in this paper. In fact, the proposed approach will be run on a smartphone and should give a result to the user as fast as possible.

To sum up, the proposed RF EkNN is efficient, in terms of accuracy, to identify the tree species compared to LNS-EkNN, RF-based fusion system, EkNN, SVM and Folia classifier. This is a result of the proposed mass distribution estimation process that detects confusing species and defines a mass distribution on their union. In fact, modeling these confusions as a partial ignorance allows the system to reduce them later in the information fusion step through an adapted combination rule. Thus, the proposed solution is able to make more accurate recognition.

8. Conclusion & Perspectives

This paper proposes an evidential recognition approach for tree species identification. The performance of the proposed solution is studied through a set of experiments on a dataset from the ImageClef 2015 challenge. Compared to the experimented solutions, the proposed approach is the most accurate one in recognizing tree species.

In an uncertain environment which is characterized by several conflict situations between tree species, if the proposed approach can take advantage of the ability and the flexibility of the belief functions theory in elaborating a powerful decision system, it can be sometimes criticized for its limitations and disadvantages. Therefore, the used method can be confronted with problems of robustness, especially in the presence of very weak information and its homogeneity. Moreover, the proposed method is not equipped to handle cases of total conflict between species. In this situation, the decision system is not able to give a decision and the tree species is not recognized. Our method may also suffer from the inherent drawbacks of kNN algorithms (feature scaling, sensitivity to noisy data, outliers, …).

Additional research will focus on the following three aspects. 1) Method optimization: considering the weaknesses mentioned in the kNN algorithm, we could first propose another distance (Eq. 4) for the EkNN algorithm and then consider other types of more efficient classifiers. 2) Method expanding, by bridging fuzzy logic and probabilistic reasoning, the theory of belief functions can become a primary tool for knowledge representation and uncertain reasoning in expert systems. A methodological reflection about this problem and its robustness will be conducted in our future works. 3) Application system: based on the two-step recognition system, another research is underway to establish a knowledge element system for an expert and intelligent system in the field of mushroom recognition. We adapted our two-step recognition system, by recognizing from a photo of the mushroom as a whole (the cap with the stem) the type of mushroom (gills, tubes, pores, etc.) then in a second stage refine the search thanks to additional characteristics extracted from a second image.

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