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# Breaking Out of the Black Box in Automated Flower Recognition

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## Abstract

Currently, fully automated methods for plant recognition are being developed. These systems work based on images. But, they only give the name of the plants as a result and do not give an explanation (black box approach). On the contrary, giving the explanation (by describing the plants characteristics) formally is used by taxonomists before they can determine the plants name. Providing the explanation is very important since it fit in the standard practice and as a basis of plant identification for several decades.

This paper comes with the new perspective in automated image-based plant recognition. A system that acts not as a black box system has proposed. It can mimic the taxonomist in explaining the decision and giving useful alternatives. The research firstly focuses on the flower. In the first part of this paper, the background of the new perspective is presented. Then, some problems that we want to answer also will be shown. Finally, some solutions to achieve the goal are discussed. As the first attempts, we also conduct a little experiment using the decision tree to deal with the goal.

## 1 Introduction

In Indonesia, there is a need for automated plant recognition because the number of taxonomists is limited, while there is high biodiversity [1]. Not only in Indonesia, but also elsewhere in the world, botanists can benefit from an automated plant identification process. Plant identification provides useful input for the management of biodiversity, such as managing livestock systems, protecting threatened species from trading, understanding what will grow best in an area, etc.

To identify plants, taxonomists follow a systematic approach called the identification key. It is a list of characteristics that can lead taxonomists to the species name. They work according to this list, but because most identification keys are paper-based, the process requires access to literature, time, and skills [2, 3]. However, computer-based identification keys have already been developed, such as stand-alone applications like Delta Intkey, Lucid [4, 5] or interactive web applications like GoBotany, MEKA, FloraGator, NatureGate, etc [6, 7, 8, 9]. These systems are already easier to use but still require expert knowledge.

Nowadays, fully automated methods are also being developed [3]. These systems work based on images. They only give the name of the plants as a result and do not give an explanation (black box approach). Providing the explanation is important because

it can mimic the taxonomists work and fit in the standard practice. Actually, the explanation is not only useful for taxonomists/botanists, but also for non-specialists, for example for educational purposes. Another thing is about the decision. The decision provided by these systems are crisp. In fact, the decision come with uncertainty. Therefore, it will be good if there is a system that also provide alternatives. Both explanation and alternatives will improve the trustworthiness of the system.

Although there are some systems that give some explanations about the plant, but the explanation comes after the decision. They just picked the description of the plant from database after they know the decision. It is different with the real traditional plant identification.

So, the goal of this paper is to design an automated image-based system for plant identification that mimics the taxonomist in explaining the decision and giving useful alternatives. For that purpose, this paper will seek to answer some problems regarding to that goal, i.e. which types of architecture are useful/work, how to integrate taxonomist knowledge, and how to handle uncertainty?

To understand easily our proposed solution, we organized this paper into some sections. Section 1 is introduction (we have already been here). We explain the background and the goal of this research. Then, the remained of this paper are organized as follows. Section 2 describes the method that we proposed, with some sub sections to answer the problems. Section 3 contains a little experiment and result. Finally, the last section contains conclusion of this research.

## 2 Proposed Method

### 2.1 Types of possible architecture

To deal with the goal, we should make a bridge to accommodate the recent plant identification method in Computer Science and the method which taxonomists usually did in Taxonomy. For that purpose, we think that the most possible architecture to solve the problems decribed above are Decision Tree and Bayesian Network (BN). Both of them have the possibility of providing us with alternatives. They show steps that can explain the decision and also can handle uncertainty.

Decision tree is a method in machine learning to show a sequence of inter-related features/attributes and targets [10]. These relations represented by a tree where each node represents a feature/attribute. The tree has a root node in the top as the best predictor, branches in the middle as the possible choices and leafs node in the bottom as the decisions. From this representation, a set of rule can be used to classify/predict the decision. Thus, the simple way of Decision Tree which mimic the human thinking is making the decision process easy to understand (not like blackbox algorithm such as deep learning, SVM, etc.).

There are many types of decision trees like ID3 [11] and C4.5, CART, the probabilistic decision tree [12], the fuzzy decision tree [13] and the random forest [14]. ID3 (Interactive Dichotomizer 3) is an algorithm to build a decision tree using entropy. Entropy is used to select the best attribute in each step of the growth tree. C4.5 is extended algorithm of ID3. The difference between them is only on the number of split in the tree. If ID3 uses binary split, C4.5 uses multiple split. CART (Classification and Regression Tree) is another algorithm for decision tree. It uses Gini coefficient to determine which attribute will be splitted [15]. The decisions usually come with uncertainty. Thus, Probabilistic Decision Tree and Fuzzy Decision Tree are coming up to handle the crisp decisions. Random forest is a kind of decision tree which build many trees using CART algorithm, and it classifies new instance by using majority vote. Further study should be conducted to find out which one is better for flower's recognition problem.

BN is another approach that seems also have a possibility to solve these problems. Since it represented by a structure which have directed arch, it can be easy to explain the decision process. BN is different with the tree. If the tree only has a root, BN can have multiple roots. The tree reflects how the attributes can affect the target, without care about the dependency. Meanwhile, BN is very concern to the direction of arch. It refers to conditional independency that has a big impact in the decision. In BN, it is not permitted to get a cyclic graph. Thus, there is a specific method and pattern to get BN structure. Not like Decision Tree which only built from data, BN structure provides an alternative by combining data and expert knowledge when there is not sufficient data [16]. By using BN, we can know the conditional dependencies between the variables, compute the joint probability table, and determine the probability of the non-evidence variables given the evidence.

## 2.2 Integrating taxonomist knowledge to the automated image-based system

In this research, we will first focus on images of flowers because an identification based on the complete plant would be too complex. To find a bridge between what taxonomists do in traditional identification and what computer scientists do in image processing, we will acquire the characteristics of flowers that are usually used by taxonomists. When taxonomists identify a flower, they will start by checking, for example, the types of flower arrangement (inflorescence). Then, they also check the symmetry, shape, color, texture and other characteristics of the flower. Figure 1 is an illustration of how this could work. This tree is not static because the taxonomist can proceed in a different way.

From those information, we can adopt taxonomists work by making the structure that can explain and find the decision using the architecture explained in Section 2.1. By using the proposed architectures, we can integrate taxonomist knowledge into the system.

Moreover, one of the basic characteristics of the proposed architecture is feature/attribute by node. We note that we need a classifier to deal with properties of the plant at that level. So, part of the research is how to design this classifier. Every node in this tree is a classifier that we have to design, and the information is to be extracted from the images. For example, nodes 1-6 in Figure 1 are the classifiers for checking: 1) the type of inflorescence, 2) the type of cluster, 3) the symmetry of the flower, 4) the labellum, 5) the shape of the flower, 6) color and texture.

## 2.3 Handling Uncertainty

Even though the proposed architectures have mechanism to compute the probability of a final result, but the uncertainty does not only come from the result. For example, to check the type of inflorescence in Figure 1. If after read the image, the system does not sure whether the flower is single or cluster, then the system can give us the probability 0.5 for single and 0.5 for cluster. Another example is determine the colour. Sometimes we say if the flower has blue colour. But, another person will say if it has purple colour.

To handle this uncertainty, we need a classifier that can handle the probability of each attribute. It will not be easy because we directly extract the flower characteristic from the image and determine its probability. This mechanism will apply to our proposed architecture and the trustworthiness of the system will improve.

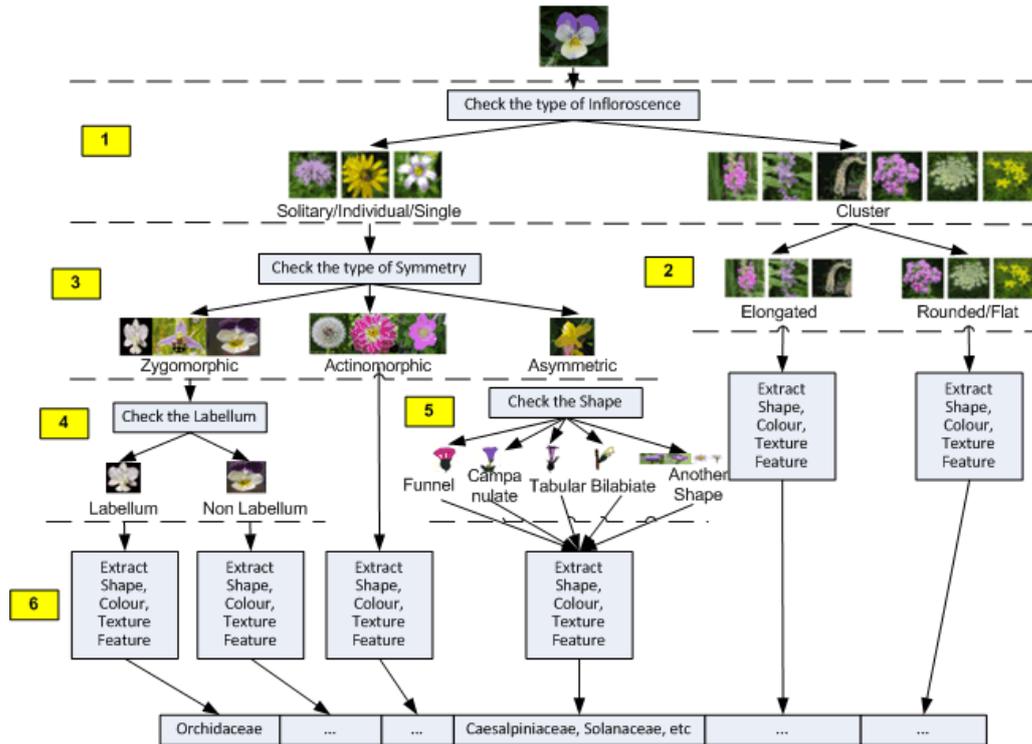


Figure 1: Flower Properties

### 3 Experiment and Preliminary Result

The starting point of our approach is the decision tree. So, in this paper we conducted a little experiment to implement the new perspective in plant recognition using that approach. This experiment does not cover all of our proposed method. We just make a simulation with a small data to know whether the decision tree can be used in our case. Firstly, we collect the information about the flower characteristics from the online flower identification software (GoBotany [6]). This step is used temporarily to substitute reading characteristics from the image. After our design classifier is ready to use, for the next, the characteristic should be read directly from the image and become the input of the decision tree.

We used 3 attributes and 5 species of orchid flower. The attributes are colour of flower, colour of labellum and also texture, while the species are *Arethusa bulbosa*, *Calopogon tuberosus*, *Corallorhiza maculata*, *Corallorhiza trifida*, and *Cypripedium acaule*. For the simplicity, we symbolize the species by A, B, C, D, and E sequentially. From the information that we got, then we generate the synthetic data. The number of samples that we generated are 125. Some of the samples can be looked at Figure 2. As the first attempt, we used CART algorithm to build the tree from those data. The decision tree yielded by the algorithm can be shown in Figure 3.

Based on the decision tree in Figure 3, we can predict the species of the new data. For example, if we have the flower with these caharacteristics: colour of flower is white, colour of labellum is yellow, and it has spot, then the decision tree will decide D for the species. To test the performance of the decision tree and avoid overfitting, we used cross validation with k-fold=5. The overall performance of the decision tree in this case is still low. The accuracy of the system is 64 %. It can show by the confusion matrix in Figure 4 where species C is the most difficult species to identify. The accuracy itself is affected by some components like the number of samples, the features that we used,

	1 CF	2 CL	3 Class	4 T
1	'Purple'	'Pinktored'	'C'	'Spot'
2	'Pink'	'White'	'C'	'Spot'
3	'Purple'	'Pinktored'	'A'	'Spot'
4	'Green'	'Pinktored'	'B'	'NoSpot'
5	'Blue'	'Pinktored'	'A'	'Spot'
6	'Yellow'	'White'	'C'	'Spot'
7	'White'	'Pinktored'	'B'	'NoSpot'
8	'Brown'	'Pinktored'	'A'	'Spot'
9	'Pink'	'Pinktored'	'A'	'Spot'
10	'Blue'	'White'	'B'	'NoSpot'
11	'White'	'White'	'B'	'NoSpot'
12	'Purple'	'Pinktored'	'E'	'NoSpot'
13	'Green'	'Pinktored'	'A'	'Spot'

Figure 2: The Samples

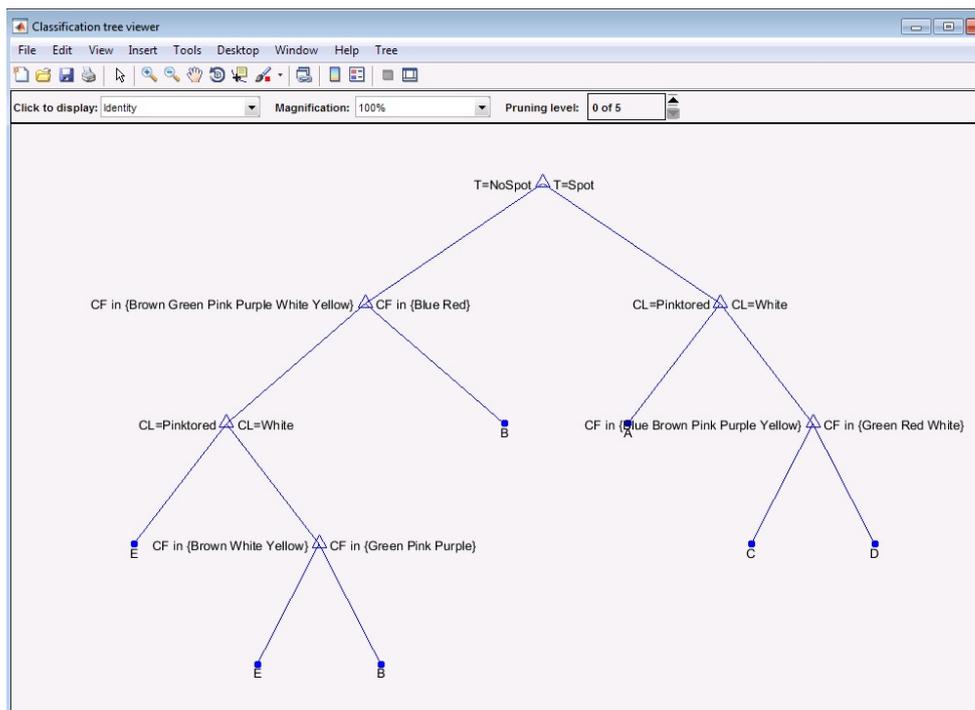


Figure 3: The Decision Tree

and also the algorithm that we choose. It needs more experiments about that.

Currently, our focus is not only in the accuracy of the system, but also on how to assign the probability in the decision tree. How if the color of the labellum is between yellow and orange, and the color of flower is not fully white, maybe like white greyish or white yellowish? The experiment about this issue have not implemented yet. Once more homework, in the next research this issue should be handled.

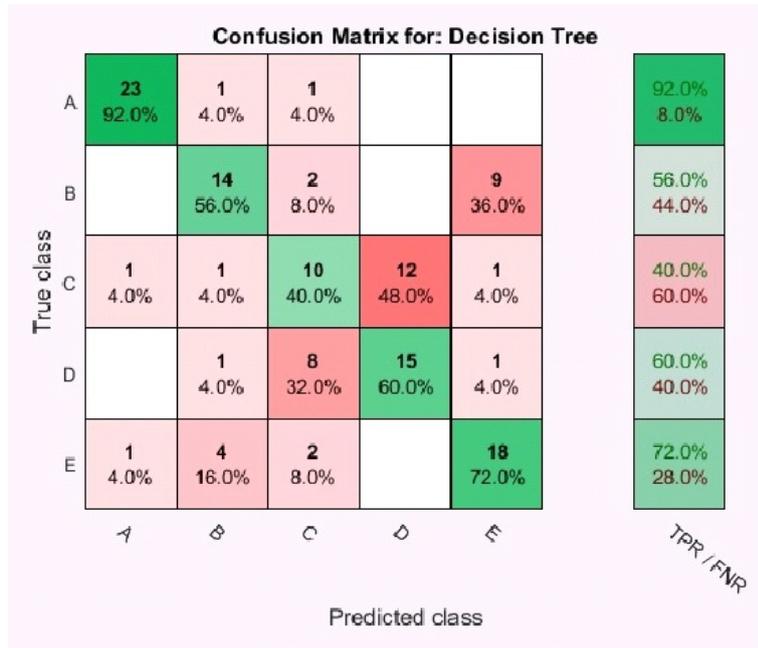


Figure 4: Confusion Matrix

## 4 Conclusion

We have proposed a new perspective in automated image-based flower recognition by designing a system that acts not as a blackbox system. From the experiment we have conducted, the decision yielded by the decision tree is quite low, with 64 % accuracy. Further research about implementation using the decision tree is still needed. Besides that this proposed method needs to be implemented as a whole and compares to another architecture in order to get the best performance.

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