Dynamic CNN Combination for Morocco Aromatic and Medicinal Plant Classification

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Abstract: In few last years, deep learning has itself set up as the new strategy for plant classification. Deep learning has a best performance for object recognition. In this paper, we have focused on the case of Morocco aromatic and medicinal plant (AMP) classification. Leaf is an important organ of plant, it has shown satisfying performances for plant classification and recognition In addition to leaves, we have used an others organs of AMP.ie. leaf veins and branches. We have proposed a new model combining dynamically the CNN classification result using the entropy impurity method. In the experiments, we have used VGG16, ResNet50 and Inception V3 CNN models. We have used Keras with Tensorflow backend to build and compile all neural network models. The experiments present that our model shown the higher classification accuracy.

Keywords: Deep learning, classification, combination, CNN, plants

1. INTRODUCTION

Aromatic and medicinal plants (AMPs) compose an essential part of our daily lives. Their presence is mainly in the environment, medicine, agronomy, botany as well as industry in general. However, Morocco, due to its geographical location, constitutes a completely original natural setting offering a complete range of the Mediterranean favoring a rich and varied flora with very marked endemism. Moreover, Morocco has around 7000 species and subspecies of aromatic and medicinal plants [1]. Furthermore, Morocco occupies first place among the countries of the South of the Mediterranean for its richness in endemic plants [1]. Due to this big number of AMPs in Morocco, Classifying these AMPs ought to be essential, and is included in any work that adopts their use. However, this process of manual recognition or classification is often laborious and time-consuming.

Hence many studies have based on the physical characteristics of plants to classify and identify them automatically [2][3]. Leaf is an important organ of plant, for this reason, the most works in computer vision have used leaves as a comparative tool to classify plants [4][5].

Computer based methods have been designed to support botanists [6]. Most existing literature based on leaf characters for automatic identification and classification of plants. Although the structural features of a leaf are important in the plant identification task. However, for certain plants, such as deciduous or semi-evergreen plants, leaves are not visible or available over different periods of the years. In these cases, multiple organs are required to identify the correct species. In 2015, the Life Clef challenge [7] provided the first multi-organ plant dataset. This was the first multi-organ plant classification benchmark in computer vision. In our work,

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in addition of leaves, we have used also other organs such us the leaf veins and the branches to classify the AMPs.

Plant classification and recognition became easy by technologies equipped with deep learning methods. In recent years, deep learning, achieve high quality in pattern recognition and classification [8]. The most celebrate deep learning method for object recognition and classification is CNN (Convolutional neural network) [9]. Furthermore, CNN is considered one of the competent classifiers, especially in terms of its accuracy. For that, we have considered in our work. Moreover, classification is the most common application in CNNs, such as GoogLeNet [10], VGG-Net [11], AlexNet[12], ResNet[13], Inception v3[14], Xception[15], etc. where the output represents a class label for the image.

However, training a CNN using small datasets leads to over fitting and reducing their ability to generalize unseen invariant data [16]. Deep learning methods often require a lot of training data as they have to train millions of parameters. In reality, many real-world problems typically do not have a lot of data. Therefore, to solve this problem, a commonly used technique is transfer learning [17]. The advantages of transfer learning (feature extraction and complete fine-tuning) are that it allows to reduce the training time and often obtain better performance. In this paper, we used a pre-trained CNN. The models of CNN based in this work are InceptionV3, ResNet50 and VGG16. In this paper we proposed a dynamic CNN combination Morocco AMPs classification.

The rest of the paper is organized around the following sections. Section 2 describes related work. Section 3 presents botanic information and our contribution. Section 4 evaluates experimentally and discusses the classification result of AMPs. Finally, Section 5 concludes the paper.

2. RELATED WORK

Faced on the large number of AMPS in Morocco, it sometimes becomes extremely difficult to classify or identify them. It is necessary to provide a new solution to identify and classify AMPs. Several solutions are proposed in the literature based on different machine learning algorithms brought an encouraging results.

As before cited, convolutional neural networks (CNN) is one the best deep learning method that have been introduced to learn automatically features of the input data through multiple layers of transforms. CNNs have proved effective in detecting and classifying objects [18]-[20]. Some networks [10]-[12] have used with success for plant identification and have obtained an encouraging results compared to other traditional methods [21].

In the context of our work, CNN is one of the deep learning methods that has been successfully applied to various fields such as plants (flowering species), plant organs. In the last few years, deep learning approaches

have been widely used to realize plant classification. Recently, several researchers have studied plant classification used CNN method. Wang, G et al. [22] used VGG16, 19, Inception-V3, ResNet50 in Automatic image-based plant disease severity estimation. In [23], Sue Han Lee et al. proposed the way where the leaf features are extracted and classified using deep learning. They use different orders of venation of leaf for feature extraction. They showed in experimental results, that their proposed model further improve the plant classification systems. Another work based on the deep learning, Jing Wei Tan et al.[24] have exploited the Leaf vein morphometric for plant species classification. Authors proposed a new CNN-based method named D-Leaf. This study showed that the proposed model achieved an average accuracy of 94.88% as compared to AlexNet (93.26%) and fine-tuned AlexNet (95.54%) models.

In the multi-organ plant identification task, many of the existing methods [25] employ deep learning to train an N-class species classifier, irrespective of the organ or organ structure. In [26], authors propose a HGO-CNN method, abbreviation of hybrid generic-organ CNN. HGO-CNN information for the multi integrates both generic and organ plant classification task. Furthermore, Voncarlos M. et al.[27] have used a fusion of deep models for plant leaf classification. The authors have combined at each hierarchical level (genus and species) the global leaf features and patch-based leaf features by pre-trained and fine-tuned CNNs. In [28], authors proposed which organ of a plant that is the most suitable for plant identification: flowers, leaves or both. They show that the top-1 accuracy reached 97% for fusion of all perspectives when averaged across species.

The fusion and the combination strategies of several plant features are considered closely related to our work;

In this paper, we propose a dynamic CNN combination for Morocco Aromatic and Medicinal Plant classification. We summarize the main contributions of this paper in two points: in the first point we use the entropy impurity [30] method to calculate the weight of each feature type. In the second point, we propose a linear combination of the result classes obtained for multiples features to find the best result class.

Details of our contribution are presented in the next section.

3. METHODS

A. Botanic information

The most research works for plant classification have based on their botanical characteristics. Among the botanical characteristics used in the classification, there is: leaf types, leaf arrangements or branches, flowers, fruits, etc. in our work we focused our classification on three types of botanical information: leaf types, leaf veins and leaf arrangements.

1)   Leaf dispositions

Leaf arrangement is an important characteristic of a plant. Depending on the number of leaves inserted at a node, we can distinguish between single, opposite or whorled leaves.
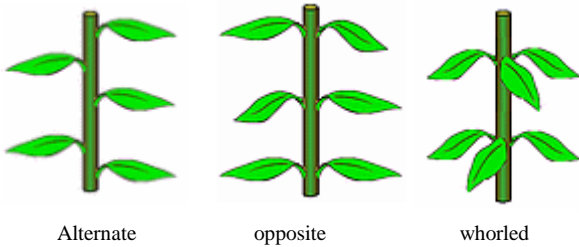

Alternate   opposite   whorled

Figure 1.   Leaf arrangements

2)   Leaf types

We can distinguish three main types of leaves:

Simple   Pinnately Compound   Palmately Compound
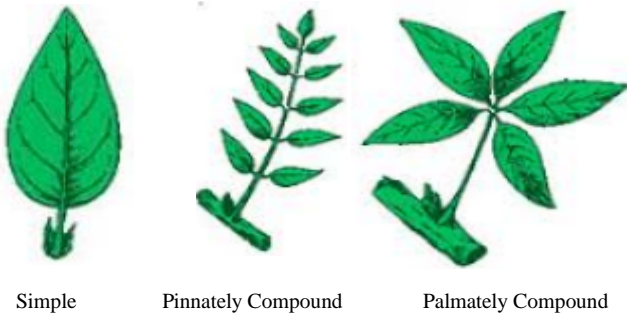
Figure 2.   Leaf types

3)   Leaf vein types

The arrangement of the veins in the leaves then gives a very specific shape to the leaves. This morphology and the arrangement of the leaves can be very useful in the identification of a species. You will find below a partial list of leaf vein types:

(1) Net veins: veins arranged in the form of a network.

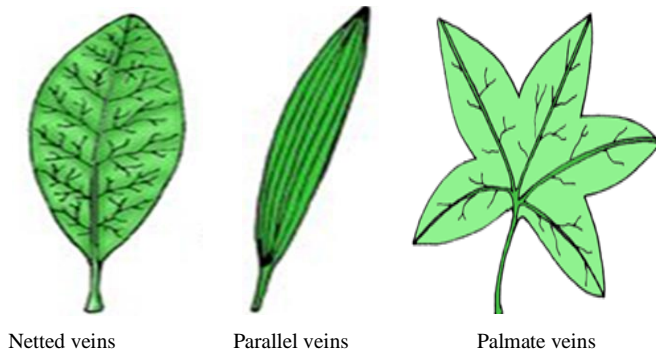(2) Parallel veins: Leaf veins originate from the base, run parallel. Monocot leaves.

Netted veins   Parallel veins   Palmate veins

Figure 3.   Leaf vein types

(3) Palmate veins: Main veins begin from the base of the leaf like fingers of a hand.

B. Proposed method

The goal of our work is to improve the problem of classification of AMPs. To achieve our goal we have used CNN method and different organs of AMPs such as: leaves, leaves arrangements (branches) and leaves venation. The proposed formulation is described as follow:

Suppose the predictive output of the classifier for an image is a vector $C = \left(c_1, c_2, \ldots, c_n \right)$, where n represents the number of classes and each dimension $i \in \left[1, n \right]$ corresponds to the probability of a specific class (i^{th} class). $c_i \in \left[0,1 \right]$ and $\sum_{i=1}^{n} c_i = 1$.

The output label of the classification model is represented by the $Max(c_i)$ for $i \in \left[1, n \right]$

The learning problem is then defined by the function G :

Let Q be an AMP to classify. Q is represented by its leaf (Q_L), their vein (Q_{LV}), and its branch (Q_B).

The output label C_Q of the classification model of Q is defined as follow:

$$C_Q = G \left(Q_L, Q_{LV}, Q_B \right).$$

G is a function, which calculates statistics on leaves, leaf veins, and branches of AMPs and returns a class indicator according to these statistics, where the predictions on leaves, leaf veins and branches are independent. For example, G can return C_1 the majority class for leaves, C_2 for leaf veins, C_3 for branches and combine them to deduce the final class C. Several methods are proposed in the literature to combine several characteristics in order to have a better classification, we cite the method proposed in [28] where the authors have concatenated the CNN of all the organs. This concatenation means that the importance (the weights) of each organ are equal.

However, the dominance and importance of each organ differs from one AMP to another, this is why we have proposed a method allowing to determine a better combination of the organs of AMP according to their dominance (their importance) in the classification. For that, we have adopted in our approach the method "Entropy impurity" which is proposed in [39] for improving the effectiveness in a retrieval system that implements

multiple feature extraction algorithms to choose from. The Entropy impurity method show their effectiveness for multi-metrics combination. For that, we considered it in our model. In our model, the combination is dynamic: it is depend of each organ for each AMP.

The goal of Entropy impurity (EI) method in our architecture is to determine the importance of each organ features such as features of leaf, features of leaf veins and features of branch. Furthermore, for each organ, we apply the « EI » to calculate it weight when training and testing our classifier for the end three epochs. This technique is proved by : more the classification result is stable for a type of features, more it weight is important.

In definition 1, we describe the redefinition of the "EI" for an organ feature type.

Definition1 : *weight calculation using entropy impurity method*

Let C be the set of classes. Let T c C be a finite set of training classes.

Let $I_q \in T$ be a plant to classify that is described by three features vectors: features vector for leaf (FL), features vector for leaf vein (FLV) and features vector for branch (FB).

Let $P \in \{0,1\}^K$ is a binary vector (with the value 0 of ith index denotes the wrong class and the value 1 denote the best class), where K is the number of last K results epoch for CNN.

For the K_i^{th} epoch $P_i\{I_q, K_i\} = 1$ if the result class is the same for I_q and 0 otherwise.

Then, the entropy impurity for the feature vector I to classify is computed looking at the k classification results that we obtained for the last k epochs of our training model, i.e., it is equal to zero if all the k retrieved classes are the same of the class of I and it has a maximum value if each of the k classes is different to the class of I.

The mathematical formulation of the Entropy Impurity [30] for the feature vector I is define as follow:

$$Entropy\,impurety\,(I) \; = $$

$$- \sum_{j=1}^{K(number\ of\ last\ epochs)} \begin{cases} P_i \log_2(P_i) & if\ P_i = 1, \\ \\ 0 & otherwise \end{cases} \quad (1)$$

The weight value for feature vector I (i.e., the weight for the ith organ of an AMP classes) is computed as the inverse of the entropy impurity plus one (to avoid dividing by zero):

$$\omega_I = \frac{1}{1 + Entropy\,impurety\,(I)} \quad (2)$$

Definition 2. *linear combination*

Let I_q an AMP to classify by using their three organs: Leaf, leaf veins and branch.

Let $C(FL)$, $C(FLV)$ and $C(FB)$ are a list of classes (i.e., list of vectors) of I_q obtained by using CNN method for feature vector of a leaf (FL), feature vector of a leaf veins (FLV) and feature vector of branch (FB) respectively. And let ω_{FL}, ω_{FLV} and ω_{FB} are a list of weights of each organ cited before of I_q, that are calculate by the formula (2) such as $|C(FL)| = |C(FLV)| = |C(FB)| = m$

The linear multi-classes combination is defined as:

$$C\begin{pmatrix} I_q \end{pmatrix} = \omega_{FL} . C(FL) + \omega_{FLV} . C(FLV) + \omega_{FB} . C(FB) \quad (3)$$

Then, the result class of I_q is the maximum value of $C(I_q)$. Figure 4 present the architecture of our proposed model.
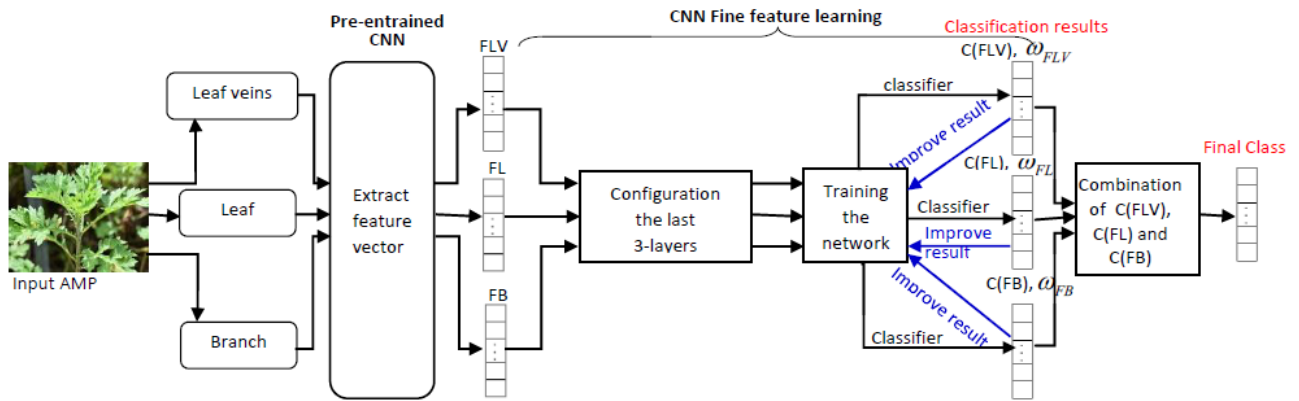
Figure 4. Schema representing our proposed architecture using transfer learning while adopting a fine-tuning strategy for some of the last three layers. Such as ω_{FL}, ω_{FLV} and ω_{FB} are a list of weights for Leaf, leaf veins and branch organs respectively that are calculated by the formula (2).

According to the literature, the authors [31] show that the amount of training data is a crucial point for estimating and improving network performance. Usually increasing the data involves increasing the size of the training database by adding new examples created from deformations of the initial examples.

We note that, the complexity of our method depend to the complexity of the CNN method that we have used. Therefore, the complexity of our method equal that of CNN method multiplied by p, where p is the number of organs that we have used.

C. Datasets

1) Description

Three datasets of leaves (DL), leaf veins (DLV) and branches (DB) of AMPs are built in our work. The DLV dataset was obtained by using morphological feature extraction to segment the leaf venation. We have used the Sobel edge detection method [32].

We have created our three datasets based on the Morocco AMPs. Each dataset contain 1000 images separated into 50 classes, where each class contains 20 sample images. These three datasets contain images from different position, varies with lighting condition and different background color. We performed data augmentation for images by distorting, shifting, zooming and applying geometric distortions: horizontal, vertical symmetry, and rotations of 15°, 30°, 45°, 60°, 75°, 105°, 120°, 135°, 150°, 165°, 180°, 195°, 210°, 215°, 240°, 255°, 270°, 285°, 300°, 315°, 340°, 355. Figure 5 and figure 6 show respectively the way where we have create our datasets and an example of augmented images.
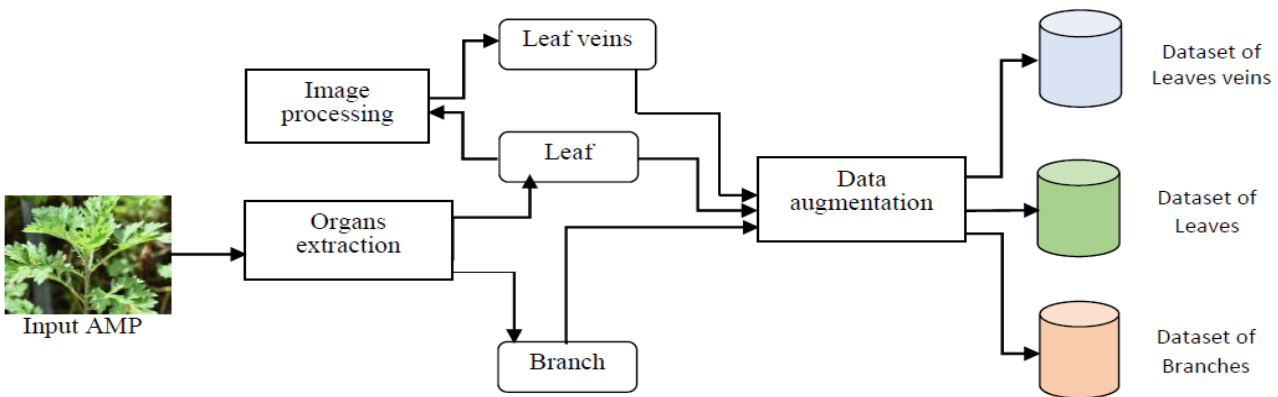

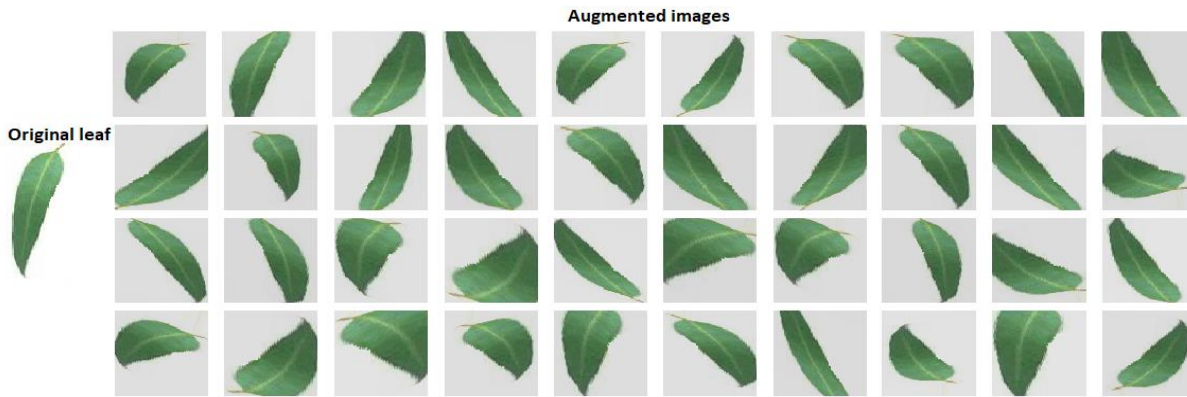Figure 5. Diagram of organ datasets construction

Figure 6.   Example of data augmentation for a leaf

The data augmentation technique allows models to distinguish better the invariant features and increase the number of images with the same concepts and captions. Figure 5 shows our diagram organ datasets construction.

Table 1 shows the number of classes and the number of samples for each dataset after they are split in training and test sets. Number of images in our each dataset.

TABLE I.   NUMBER OF IMAGES IN OUR EACH DATASET.

Category	Non-augmented data		Augmented data	
	Number of classes	*Number of images*	*Number of classes*	*Number of images*
Leaf	50	1000	50	40000
Leaf Vein	50	1000	50	40000
Branch	50	1000	50	40000

2) Data pre-processing

Image preprocessing is an important operation of its application in different areas. Because it makes to standardize the images to be processed and so to avoid specific processing for a few images and apply it for another. Indeed, initially, images are in different sizes, different resolutions, images in RGB, and others in grayscale.

In this paper, before classifying images all images of our datasets are transformed in their equivalent in RGB form. In the learning step and to avoid the learning to include the scale factor in the weights to be estimated and to remove the effects of the illumination conditions, we have normalized [33] AMPs so that each descriptor value varies within the same range. We normalized the descriptor values to have data of mean zero and variance one. We respect the standard sizes of data for each network, i.e., we set 224×224 for ResNet50, VGG16, and 299×299 for Inception V3.

For performance evaluation, each dataset was separated into a ratio of 0.8: 0.2 for the training and testing set for measuring classification accuracy.

4.   EXPERIMENTS AND RESULTS

In this section, evaluation metrics are first introduced, next choice of hyper-parameters are provided, next Convolutional neural network training. Finally, detailed accuracy and discussion are analyzed and discussed.

A. Evaluation metrics

To measure the classification performance, we use the accuracy measure. This metric is represented in Equation (4) and it is calculated by using four different measures, true positives (TP), true negatives (TN), false positives (FP) and false-negatives (FN), where:

-TN (True negative) is the number of plants that are classified as negative,

-FP (False positives) is the number cases that are incorrectly classified.

-TP(true positives), is the number of plants that are correctly classified and identified.

-FN (false negatives), which is the number of plants that are mis-classified and identified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (4)$$

B. Choice of hyper-parameters

In order to be able to test several architectures, the parameterization has an important influence on the performance and on the weight distribution of the network used.

We employ fine-tuned pre-trained CNN architectures for AMP classification. The pre-trained architectures used in our study for classification are: VGG16, ResNet50 and Inception V3. For each of these architectures, we set the number of neurons of the last fully connected (FC) layer to 50.

For the parameter setting, when training the fully connected model we used the adaptive ADAM optimizer [34].

In the fine-tune step, stochastic gradient descent (SGD) [35]. Furthermore, thanks to its efficiency, SGD has become the most famous optimization algorithm. We chose 0.0001 for the learning rate. Experiments ran in 10 epochs for each step, such as, each epoch represents the number of the training iteration.

Furthermore, we use L2 and dropout regularization. Dropout used to avoid over-learning and it's using had a great importance in the optimization and estimation result. Finally, we note that training a network takes a lot of time to produce the best models, for that we run the experiments using GPU with 6GB of RAM on a machine with an Intel i5 CPU and 16 GB of RAM.

C. Convolutional neural network training

To accomplish our method, we chose to use a neural network trained on images from a different domain and to adjust it to the AMPs.

The classification process consists of three step (figure 4): first, we will use a pre-learned neural network to perform the feature extraction for the three dataset. In the second step, we train a fully connected network and calculate the weight using the formula (2) for the last 3 epochs for each class in the dataset. In the last step, we use the formula (3) to deduce the final class. The objective of the first part is to obtain for each AMP organ a feature vector describing its content, which can later be used to accomplish the AMP classification. The second step, allows classifying AMP for each organ and calculating their weight using the formula (3).

We perform fine-tuning for each the three last dataset. We use the VGG16, Inception v3, and Restnet50 models and we adapt them to our method and our data case. We fine-tune the network cited before by replacing their final fully connected layer with 50 neurons corresponding to 50 classes.

The models have been trained in Python (version 3.8) environment; we have used Keras with TensorFlow backend.

D. Detailed accuracy and discussion

In this section, we analyze the classification performance of our proposed method compared to other models. For three dataset cited before, all experiments were evaluated for top-5 accuracy, averaged across all images of test dataset. The top-5 accuracy was computed as the fraction of test images where the ground-truth class label shows in the list of first 5 predicted class labels when predictions are sorted by decreasing classification score.

TABLE II.   AVERAGE CLASSIFICATION PERFORMANCE ACCORDING THE ACHIEVED TOP-5 ACCURACY FOR 50 EPOCHS USING VGG16 USING AUGMENTED AND NON-AUGMENTED DATASETS.

CNN Architecture	Organ type	Average test accuracy(%)	
		Non-augmented database	*augmented database*
VGG16	Leaf	61,3	87.2
	Leaf vein	63.1	90.8
	Branch	44,3	69
Our method	Leaf, Leaf vein, Branch	**68,9**	**96.8**
Our method	Leaf, Leaf vein	67.1	94.1
Our Method	Leaf, branch	64,1	92.8
Our Method	Leaf vein, Branch	65.5	93.9
Voncarlos M. et al [27]	Fusion of global and patch based features	64,3	92.6

TABLE III.   AVERAGE CLASSIFICATION PERFORMANCE ACCORDING THE ACHIEVED TOP-5 ACCURACY FOR 50 EPOCHS USING INCEPTION V3 USING AUGMENTED AND NON-AUGMENTED DATASETS.

CNN Architecture	Organ type	Average test accuracy(%)	
		Non-augmented database	*augmented database*
Inception V3	Leaf	60.2	87.5
	Leaf vein	61.4	91.8
	Branch	40.3	66.3
Our method	Leaf, Leaf vein, Branch	**66.2**	**96.1**
Our method	Leaf, Leaf vein	65.6	93.9
Our Method	Leaf, branch	62.1	91.8
Our Method	Leaf vein, Branch	64.7	92.7
Voncarlos M. et al [27]	Fusion of global and patch based features	62.3	92.1

TABLE IV.   AVERAGE CLASSIFICATION PERFORMANCE ACCORDING THE ACHIEVED TOP-5 ACCURACY FOR 50 EPOCHS USING RESNET50 USING AUGMENTED AND NON-AUGMENTED DATASETS.

CNN Architecture	Organ type	Average test accuracy(%)	
		Non-augmented database	*augmented database*
ResNet50	Leaf	63.1	89
	Leaf vein	64.2	90.1
	Branch	46.3	68,3
Our method	Leaf, Leaf vein, Branch	**70.2**	**97.4**
Our method	Leaf, Leaf vein	67.7	95.8
Our Method	Leaf, branch	64.8	91.3
Our Method	Leaf vein, Branch	65.3	92,8
Voncarlos M. et al [27]	Fusion of global and patch based features	66.3	93.6

Table II, III and IV illustrate the comparison results using VGG16, Inception V3 and ResNet50 respectively for 50 epochs. We observe that our proposed model is the most effective model compared to others for AMP classification. In addition, for our method, using more than one organ is very performance than using single organ. Furthermore, our method shows a major improvement using three organs Leaf, Branch and leaf Vein compared to use two organs. In overall, our method achieve the highest accuracy compared to the approach proposed by [27] for the multi-organ plant classification that concatenate global and patch based features.

Table II, III and IV show also the performances of different classification methods according to two types of image databases augmented or not augmented that we have used. They allow us to conclude that increasing training databases dramatically improves classification performance. Increasing the amount of data in a class helps to avoid over-learning. In reality, the classes must be large enough for the learned classifiers to be efficient. So, data augmentation plays a fundamental role in data learning. Indeed, the behaviors of descriptors learned by deep learning methods are not known upstream. In particular, we do not know their invariances such as rotation, translation, etc. In deep learning, these invariances are built by analyzing a sufficient amount of data or by adding dedicated transforms through data augmentation. The data augmentation used in this paper is satisfactory but could be improved by adding other additional operations.

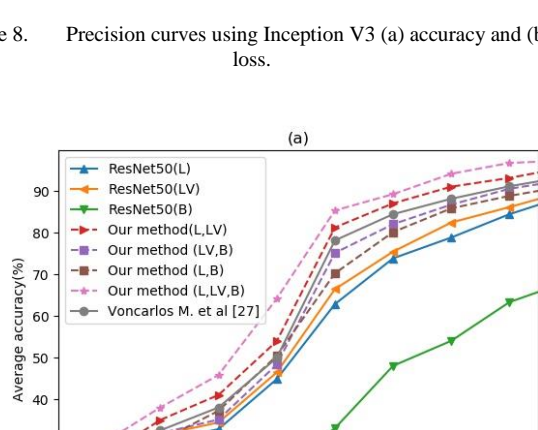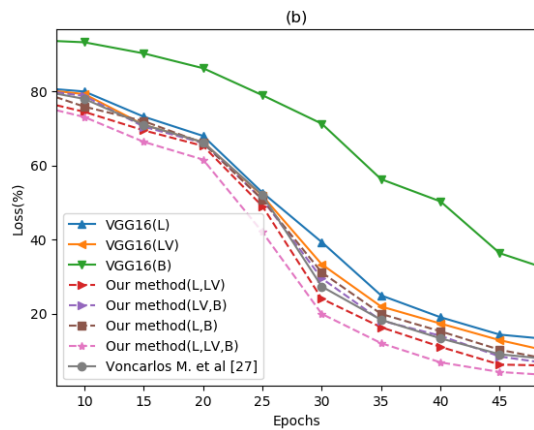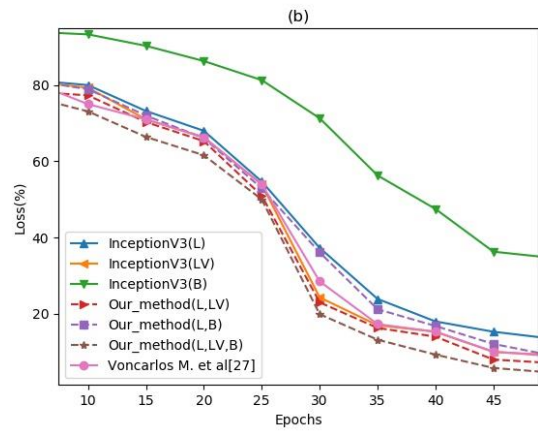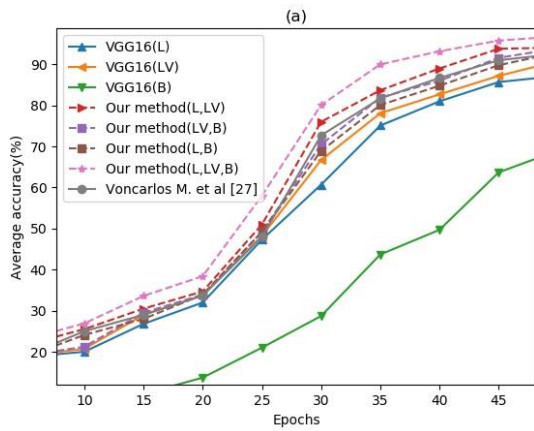Figure 8.   Precision curves using Inception V3 (a) accuracy and (b) loss.

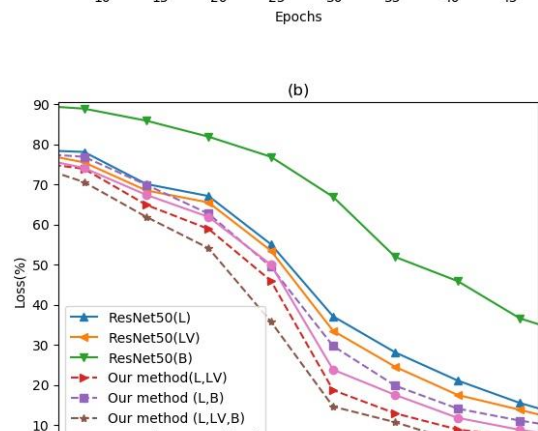Figure 7.   Precision curves using VGG16: (a) accuracy and (b) loss.
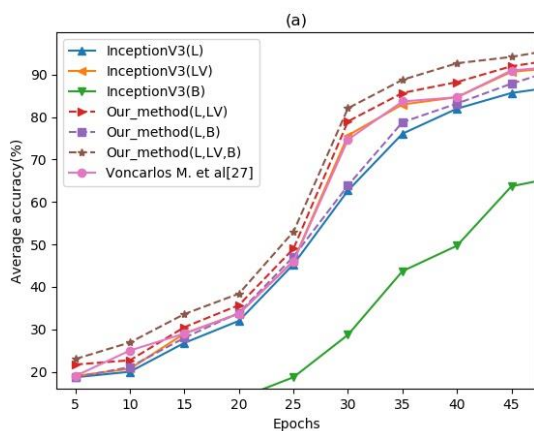

Figure 9.   Precision curves using Resnet50 (a) accuracy and (b) loss.

In addition to the results of the three previous tables, the results presented in Figures 7, 8 and 9 are the

classification scores of different networks according to the number of epochs and types of organs used. The performance of our model is the best compared to the one of other networks for all numbers of epochs. On the other hand, we also noticed that the quality of VGG16, InceptionV3 and Resnet50 models that we have tested is affected to our model, i.e., it is therefore obviously, because they are exploited in our method. However, the type of organs also has an impact on the quality of the scores. On the other hand, we have noticed that the "leaf veins" are more efficient than other organs for all the models. However, the branches have shown a poor performance compared to other organs for all the models under the same conditions. In fact, several AMPs have almost similar branches. However, the use of branches with other organs improves classification performance. We also noted that the quality of our model did not deteriorate in the case where an organ exhibited poor performance. Indeed, the score of each organ is affected in the final result, i.e. if an organ presented a strong performance it will have a strong score and vice versa. This result is due to the efficiency of the way of combining several classes in our method. We concluded that the score values of each organ have a great influence on the result. Indeed, the wrong combination degrade the quality of the result. It is important to cite, that our method is influenced by the performance of the basic model used. The choice of parameters for the basic optimization algorithm changes the final performance, but the structure of our method remains unchanged.

5. CONCLUSION

We elaborated a dynamic class combination for Morocco AMPs. We used pre-trained convolutional neural networks with transfer learning. Our contribution is applying and fine-tuning pre-trained VGG16, Inception V3 and Resnet50 CNN models for AMP classification purposes.

The experiments show also that increasing number of training dataset size improves significantly accuracy of AMPs classification for all the models without the risk of overfitting. In addition, experiments show also that our method achieves high accuracy for all architectures that we have used, i.e. for example, our method achieves 97.4% of accuracy using Resnet50. However, the method proposed in [27] achieved 91.5% for the same conditions. Indeed, the effectiveness of our method related to the way that we have achieved the dynamic class combination. Furthermore, using entropy impurity for calculating weight of each organ has a major effect of the performance of our method.

In conclusion, all results in this paper are specific to Moroccan AMPs classification. We can also apply our method for other use cases. This research can obviously be further extended by adding others specific organs and semantic features.

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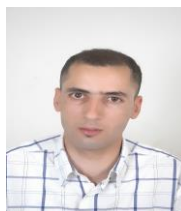
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