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ARTICLE

A CONVOLUTIONAL NEURAL NETWORK WITH A NEW ARCHITECTURE APPLIED ON LEAF CLASSIFICATION

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ABSTRACT

In this research, an application of Convolutional Neural Networks (CNNs) on the task of leaf classification is presented. Nowadays, CNNs have become well known methods in object recognition to generate learned feature representations and classification, and gradually have been dominating on various image domains. There exists few works that applied CNNs on leaf recognition and classification which mostly used existing CNN architectures and pretrained models. In this paper, a new CNN architecture is proposed and applied on leaf classification task. The use of recently introduced Exponential Linear Unit (ELU) instead of Rectified Linear Unit (ReLU) as the non-linearity function of CNN is also experimented. The model is examined on Flavia and Swedish leaf datasets and the classification results show that the proposed CNN is effective for leaf classification and closely compete with the current state-of-the-art.

KEY WORDS
Leaf, Classification, Recognition, Convolutional Neural Network, Exponential Linear Unit

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INTRODUCTION

Plants play an important role in the life cycle of nature. With the rapid progress of information technologies, many works [2, 3], have been dedicated to applying the technologies of pattern recognition and image processing to plant identification. Rapid and accurate plant identification is essential for effective study and management of biodiversity, as well as contributing to biosecurity measures. Therefore, automated systems for plant identification are a very important although challenging task.

Leaf is an organ of plant which is the basic feature that can be used in identification of plants. Types of leaf can be described in terms of leaf shape, leaf margin, leaf venation, leaf texture, leaf vein, leaf color, leaf tip and leaf base. Leaves are available for longer duration and in abundance and happen to be a suitable choice for automatic classification of plants. Since leaves of the same specie tend to subtly differ in size and shape due to the phenotypic plasticity, identification of plant species or leaf groups within a population is a challenging task.

The traditional approach for image classification tasks has been based on hand-engineered features such as SIFT [6], HoG [7], SURF [9], etc., and then to use some form of learning algorithm in these feature spaces. This led to the performance of all these approaches depending heavily on the underlying predefined features. In the literature of plant identification, different leaf features are used for classification like aspect ratio, circularity, eccentricity, roundness and others. Fourier descriptors [10], wavelets [11], saw tooth pattern, vein structure, color, texture and shape of a leaf [12] and centroid contour distance [13] are also used for leaf identification. Feature engineering itself is a complex and tedious process which needed to be revisited every time the problem at hand or the associated dataset changed considerably.

The performance of Convolutional Neural Networks (CNNs) in object recognition and image classification has made tremendous progress in the past few years [14, 15]. CNNs have emerged as a powerful framework for feature representation and recognition for a variety of image domains. A CNN is able to learn basic filters automatically and combine them hierarchically to enable the description of latent concepts for pattern recognition. The absence of the labor-intensive phase of feature engineering and the generalizability of the solution makes them a very promising candidate for a practical and scalable approach for various vision problems.

In this paper, a CNN architecture is proposed to apply on the leaf classification task. It is tried to suggest a simple but powerful CNN that in addition to achieve a valuable classification accuracy, the learning time of the CNN remains affordable to train in the CPU mode without need for especial hardware like GPU. In the architecture, the usage of Exponential Linear Unit (ELU) [16] as the non-linearity function instead of commonly used Rectified Linear Unit (ReLU) [14] is examined to speeds up learning and achieve higher classification accuracies. Also the simple reflection augmentation is applied to both datasets to improve the final results compared to the results obtained from the original datasets. The experiments, applied on Flavia [17] and Swedish [18] leaf datasets, show the effectiveness of the proposed model in leaf identification in comparison with current state-of-the-art.

RELATED WORKS

In this section, some latest works on leaf recognition are reviewed. Started with some conventional methods, the recent deep models applied on leaf classification are summarized.

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Since shape of leaves vary between different species, provides valuable information for plant identification. The existing methods for shape representation and identification can be classified into contour-based and region-

Table 1: The proposed CNN architecture

Attributes	L1		L2		L3	L4	L5
Type	Conv	Pool	Conv	Pool	Conv	Conv	SoftMax
Filter Size	5×5	5×5	5×5	5×5	5×5	1×1	
Stride	2	5	2	2	2	1	
Number of Filters	100	100	250	250	100	100	
Output Size	78×78	37×37	17×17	7×7	1×1	1×1	

based methods [19]. In the former one, the shape features are extracted only from the contour, while in the latter one, the shape features are extracted from the whole shape region. Up to now, many contour-based descriptors and region-based descriptors have been proposed for leaf shape recognition. Recently, [13] presented a contour-based approach to describe shape of leaves called Centroid Contour Distance (CCD). CCD calculates the distance between the midpoint and the points on the edge corresponding to interval angle. These features was used to feed a Probabilistic Neural Network to classify the leaf shapes. In another work [5], the method, termed multi-scale arch height (MARCH), was proposed to use hierarchical arch height features at different chord spans extracted from each contour point to provide a compact, multi-scale shape descriptor. This algorithm was aimed to effectively capture the global and detailed features and provide a coarse-to-fine shape description of the leaf. The classification rate was calculated using the 1-nearest-neighbor classification rule and a prototype system for online plant leaf identification was developed for use on a mobile platform. In [4], an evolutionary optimization methodology was proposed to support parameter adjustment of a multi-scale shape descriptor for feature extraction and representation of leaf shapes in a high dimensional space.

The most recent works, have extensively analyzed the various features of leaf images. For example in [8], the invariant recognition of 2D binary images of tree leaves was considered. Two methods for invariant pattern recognition based on 2D Fourier power spectrum with guaranteed translation invariance were proposed. The first method introduced the features invariant to translation, scaling, rotation and mirroring (TSO invariance) and the second, presented the features invariant to general affine transform (A invariance). Harmonic analysis of power fluctuations around paths generated Fourier coefficients and their square absolute values were used as TSO/A invariant descriptors. After TSO/A invariant processing of thresholded digital images, kernel Support Vector Machine or self-organizing neural network was used for leaf categorization. In another work [1], an approach for the classification of leaf, based on the characterization of texture, shape, and color properties was proposed. An original plant leaf was preprocessed initially using the cellular automata (CA) filter to minimize the noise. For enhancing the contrast and quality of the image, the histogram equalization and ROI segmentation were applied respectively. The proposed feature extraction techniques overcome the difficulties faced by the existing GLCM and LBP methods. The descriptor comprised of Haralick texture based features, Gabor features, shape features, and color features. Subsequently, the kernel-based PSO was presented to overwhelm the issue of time complexity of selecting the optimum features. Finally, the Fuzzy Relevance Vector Machine (FRVM) was employed to recognize the type of leaves.

Convolutional Neural Networks (CNNs) are multi-layer supervised networks which can learn features automatically from datasets. For the last few years, CNNs have achieved state-of-the-art performance in almost all important classification tasks. It can perform both feature extraction and classification under the same architecture. However, latest studies have shown that state of the art performance can be achieved with networks trained using generic data.

A few papers have suggested the use of CNNs on the leaf identification task in recent years. [20] developed an application which classifies the type of a tree, based on a picture of one of its leaves. The system, utilized a CNN in an android mobile application to classify natural images of leaves, trained on the ImageCLEF 2012 plant identification task training set. The proposed architecture was consisted of one convolutional layer followed by a pooling layer and two fully connected layers applied on input images of size 60×80 pixels. AlexNet [14] is a deep convolutional neural network model poposed to detection of objects in large-scale datasets. [3] suggested a reduced version of AlexNet for leaf identification. They used Parametric Rectified Linear Units (PReLUs) instead of ReLUs and gray-scale images as input in their model. In [21], a one-to-one connection layer, named as single connected layer (SCL), was added into the proposed CNN architecture to make some improvements. This method was experimented on ICL leaf database, and the results reflected the rise of the precision.

Plant disease recognition is another field of research that mostly include the leaf identification process. [22], was concerned with a new approach to the development of plant disease recognition model, based on leaf image classification, by the use of deep CNNs. The developed model was able to recognize 13 different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. The dataset used in this paper, gathered by authors and assessed by agricultural experts.

CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Network (CNN) is an effective identification method, developed in recent years, that caused widespread attention. Now, CNN has become one of the most efficient methods in the field of pattern classification and recently, has been used more widely in the field of image processing [14, 23], and it can reach a better performance than traditional methods [24] through wide verification.

CNN consists of one or more pairs of convolutional and max pooling layers. A convolutional layer applies a set of filters that process small local parts of the input where these filters are replicated along the whole input space. A max-pooling layer generates a lower resolution version of the convolutional layer activations by taking the maximum filter activation from different positions within a specified window. This adds translation invariance and tolerance to minor differences of positions of objects parts. Higher layers use more broad filters that work on lower resolution inputs to process more complex parts of the input. Top fully connected layers finally combine inputs from all positions to do the classification of the overall inputs. This hierarchical organization generates good results in image processing tasks.

EXPONENTIAL LINEAR UNIT

All neurons in a neural network usually have nonlinear activation units associated with them that convert input space to a linearly separable space. The most common nonlinear activation in shallow neural networks is sigmoid function but in deep neural networks, ReLU is the favorite one because of the practically better results. Recently [16] have introduced Exponential Linear Unit (ELU) which have improved learning characteristics in deep neural networks compared to the units with other activation functions. Like ReLUs, ELUs alleviate the vanishing gradient problem via the identity for positive values but in contrast to ReLUs, they have negative values which allows them to push mean unit activations closer to zero with lower computational complexity. The formulation of ELU with $\alpha > 0$ is as follows.

$$f(x)=\begin{cases} x & if\ x>0 \\ \alpha\left(\exp(x)-1\right) & if\ x\le 0 \end{cases},\quad f'(x)=\begin{cases} 1 & if\ x>0 \\ f(x)+\alpha & if\ x\le 0 \end{cases}, \tag{1}$$

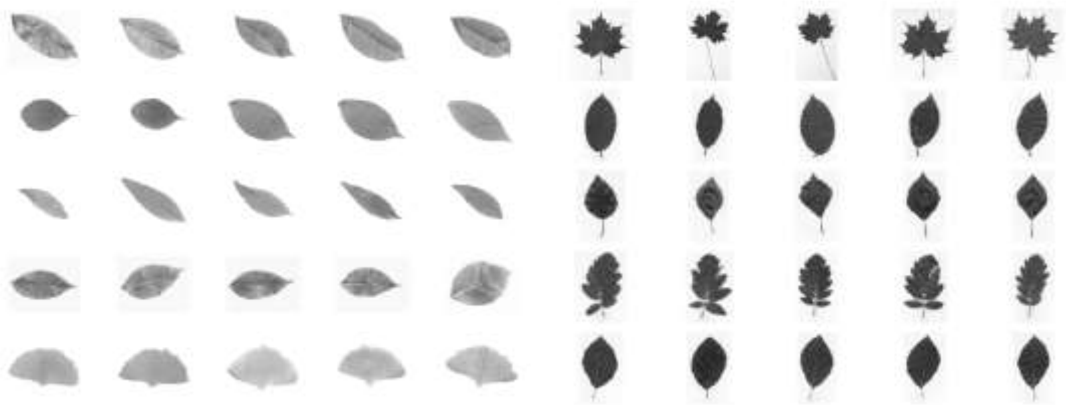
The ELU hyper-parameter α controls the value to which an ELU saturates for negative net inputs.

THE PROPOSED CNN MODEL

CNN architectures vary with type of images and especially when input image sizes are different. In this paper, the size of input images is considered to be 160×160 pixels. The proposed architecture is described in [Table 1]. After each Conv layer a ReLU or ELU activation function is used and for each pooling layer, MaxPooling approach is applied. The fully connected layers are defined as convolutional layers with the filter size of 1×1 as it is conventional in MatConvNet [25]. The final layer has 32 or 15 output units corresponding to 32 and 15 category of leaves in Flavia and Swedish leaf datasets. After all layers, a SoftMax loss is placed.

EXPERIMENTS AND RESULTS

The proposed method is applied on Flavia [17] and Swedish [18] leaf datasets . Flavia dataset contains leaves of 32 plant species with 1907 samples. All the input leaf images are 1600×1200 which are resized to the later dimension. Swedish dataset contains 15 species of Swedish tree leaves with 75 samples in each. Some



(a) (b)

Fig. 1: Sample of datasets prepared for the experiments: (a) Flavia Dataset (b) Swedish Leaf Dataset.

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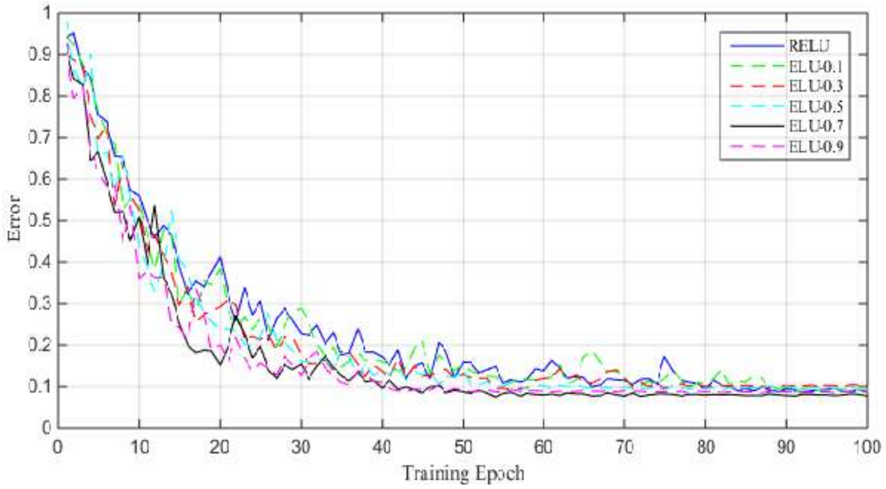
samples of these datasets are showed in [Fig. 1].



curves of validation errors of experiments of the different values of the parameter of ELU applied on Flavia dataset without augmentation

In the first step, leaf color images are converted to grayscale by extracting the green channel of colors because this channel is better represent the pattern of leaves. Then the values of pixels are mapped from [0, 255] to [0, 1]. To resize images to the desired size of 160×160 pixels, first images are resized such that the larger dimension of them are equal to 160, then the smaller one are padded with pixels having the value of 1. In the next step, the data augmentation methods are applied to dataset. Data augmentation, is a method to generate extra samples from a given image which is commonly used in CNNs. The proposed model is compared in the cases of datasets without augmentation and datasets with simple horizontal reflection augmentation. After augmentation, datasets are separated to 70%, 10% and 20% as training, validation and test sets, respectively.

CNNs have hyper-parameters which are the parameters that will not be learned, thus commonly are specified intuitively. Aside from the model itself, hyper-parameters include the learning rate, momentum (if used), weight decay, Initial weights, mini-batch size and the maximum number of epochs. In this work those hyper-parameters are set as, fixed to 0.001, 0.9, 0.0005, randomly selected from standard normal distribution multiplied by 0.01, 100 and 100, respectively. The model is trained by stochastic gradient descent with momentum. For the parameter of ELU, some values including 0 (which equals to ReLU), 0.1, 0.3, 0.5 and 0.8 are experimented and it is observed that the value of 0.7 results better convergence and classification accuracy among them. [Fig. 2] illustrates the curves of validation errors of experiments of the different values of the parameter of ELU applied on Flavia dataset without augmentation.

The leaf classification accuracies (the mean average precisions) of the proposed CNN on Flavia and Swedish leaf datasets, are reported in [Table 2]. For each experiments on a dataset with specific augmentation, top 1 and top 5 accuracies in the cases of original and augmented (with reflection augmentation) datasets are presented. The classification accuracies of conventional methods, experimented on both datasets are represented in [Table 3]. Among the recent methods, applied on these datasets, none of them have used CNNs for feature representation and classification; existing few works [3, 20, 21], applied their methods only on ICL dataset which it was not accessible during the experiments of this work.

In [Table 2], it is observed that ELU-based CNNs slightly outperforms ReLU-based ones but it must be noted that the use of ELUs, slows down the process of training in comparison to ReLUs because of the relative complexity of the function of ELU. [Table 3] shows that CNN-based feature learning and classification is easily compete with the current results of conventional approaches. Regardless of very extensive methods such as [1] that almost approached to 100% accuracy on these datasets, the proposed method outperforms current state-of-the-art, without need to devise multiple feature types and descriptors that may not work well on different inputs. Also this method is a learner which its learned model can be matured by feeding new inputs.

Table 2: The classification accuracies of the different experiments of the proposed CNN

Dataset	Augmentation	Type of function	Top1	Top5
Flavia	No	ReLU	96.33	99.74
		ELU	96.85	99.74
	Yes	ReLU	96.46	100
		ELU	**97.24**	100
Swedish	No	ReLU	96.00	100
		ELU	96.89	100
	Yes	ReLU	98.00	100
		ELU	**99.11**	100

Table 3: Comparison of classification accuracies on Flavia and Swedish leaf datasets

Flavia leaf dataset		Swedish leaf dataset	
Method	Accuracy	Method	Accuracy
[1]	99.87	[1]	99.50
The proposed CNN	**97.24**	**The proposed CNN**	**99.11**
[4]	95	[5]	97.33
[2]	91	[8]	96.53

CONCLUSIONS

In this paper a novel CNN architecture was designed for leaf classification task. The model is based on 160×160 grayscale input images that obtained from Flavia and Swedish leaf datasets. The green channel of colorful leaf images was selected as grayscale version of them. The effect of horizontal reflection augmentation of datasets were presented but further augmentations such as shift and rotation was not applied because of the already good performance of the model but in object recognition literature the use of multiple augmentation (including shift and rotation) is also common to further improve the results. The substitution of well-known ReLU activation functions with newly suggested ELUs was also experimented that showed that although ELUs, slightly improved the quality of classification, but increased the learning time thus the use of ReLU in deep architectures seems more effective than ELUs. The results showed that the proposed architecture for CNN-based leaf classification is closely compete with the latest extensive approaches on devising leaf features and classifiers.

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None

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