Research on insect pest image detection and recognition based on bio-inspired methods

Loris Nanni\textsuperscript{a}, Gianluca Maguolo\textsuperscript{a}, Fabio Pancino\textsuperscript{a}

\textsuperscript{a}University of Padova, via Gradenigo 6, Padova 35131, Italy

Emails:
loris.nanni@unipd.it
gianluca.maguolo@phd.unipd.it
fabio.pancino@studenti.unipd.it

\begin{abstract}
Insect pest recognition is necessary for crop protection in many areas of the world. In this paper we propose an automatic classifier based on the fusion between saliency methods and convolutional neural networks. Saliency methods are famous image processing algorithms that highlight the most relevant pixels of an image. In this paper, we use three different saliency methods as image preprocessing to train 4 different convolutional neural networks for every saliency method. We obtain several trained networks. We evaluate the performance of every preprocessing/network couple and we also evaluate the performance of their ensemble. The best stand-alone network is ShuffleNet with no preprocessing. However, our ensemble reaches the state of the art accuracy in a publicly available insect pest dataset, approaching the performance of human experts. Besides, we share our MATLAB code at: https://github.com/LorisNanni/.
\end{abstract}

\section{Introduction}

The economy of many countries depends on their agricultural sector, which is often at the mercy of climate change and the damage caused by the surrounding fauna and micro fauna. One of the most serious problems concerning agriculture is pest. Pest ruins the harvest of thousands of plantations every year in large areas of the planet. Pests include rodents, birds and insects; we shall focus on insects in our research. Insects are a serious problem, not only because of the potential loss of income related to the growth of crops, but, if untreated, they can also cause significant damage to machinery, equipment, and property. Besides, they can have negative and harmful effects on the natural environment. As a result, crop protection is a global necessity, requiring a variety of tools and practices \cite{1}.

The best chance of finding a solution starts with identifying the problem. To specifically recognize the insects and to know how to act correctly, farmers should have adequate knowledge of pests, but the correct identification of the type of pests often requires a human expert. Since this task requires continuous monitoring of the crops there is a growing interest in the automatic classification of pest species \cite{2}.

The development of image classification \cite{3,4} is offering new opportunities for researchers to develop increasingly automated systems capable of recognizing any type of object with a high degree of accuracy. Limiao Deng et al. \cite{5} proposed a novel insect pest dataset containing 563 images divided in 10 different classes. They trained a Support Vector Machine (SVM) on hand-crafted features to classify their dataset. The growing interest in pest recognition led Sandler et al. \cite{6} to collect a new large-scale dataset containing 75000 labelled images divided in 102 classes. However, in recent years, convolutional neural networks outperformed every previous technique in tasks like image classification, image segmentation and object recognition, especially on large datasets. This lead to first attempts to automatically classify pests using convolutional neural networks \cite{7}. The authors use a pretrained version of AlexNet \cite{8} to classify a portion of the dataset used in \cite{5} using transfer learning. In order to have a baseline comparison, they tested the accuracy rate of six human expert on the same dataset. The result is that they managed to reach an accuracy higher than four of the six human experts.

In this paper we propose a new deep learning-based method for the classification of pests. Our approach consisted in combining saliency methods and convolutional neural networks (CNNs). Saliency methods are image processing algorithms that highlight the most relevant part of an image \cite{9}. The idea behind these methods comes from the observation that the human eye does not focus on all its field of view, but accurately discriminates between its relevant and not relevant parts. Hence, we used saliency methods as a preprocessing to modify the images in the dataset and use them for data augmentation. To be more precise, we created two different datasets for every saliency method. The saliency methods cut the foreground of the images out and let the CNNs focus on the relevant part of the picture. We trained four different CNNs on those datasets. Our experiments prove that the ensemble of those networks can classify pest images with very high accuracy. We use three different saliency methods and for each saliency method two images are created: in this way, our best ensemble is built by $3 \times 2 + 1$ (also add the original image) deep networks for each.
network topology. The different CNNs are combined by sum rule.

2. Materials and methods

2.1. Dataset

We use the same dataset proposed in [5]. It is composed of ten different classes of pests that are mainly found in tea plants and in other plants scattered between Europe and Central Asia. The division of the dataset can be found in Table 1. This collection of images comes from various online sources, one of which is Mendeley Data, which contains photos taken with a Single Lens Reflex (SLR), while the others were taken from Insert Images, IPM images, Dave’s Garden and others. Some images samples can be found in Figure 1.

Table 1 – Composition of the dataset

| Species                  | Number of Samples |
|--------------------------|-------------------|
| Locusta migratoria       | 72                |
| Parasa lepida            | 59                |
| Gypsy moth larva         | 40                |
| Empoasca flavescens      | 41                |
| Spodoptera exigua        | 68                |
| Chrysocus chinensis      | 50                |
| Laspeyresia pomonella larva | 50          |
| Spodoptera exigua larva  | 56                |
| Atractomorpha sinensis   | 62                |
| Laspeyresia pomonella    | 65                |

2.2. Saliency Methods

Saliency maps [9] are functions that take an image as an input and output those locations where the image has its most relevant features. It is usually made of three different steps: linear feature extraction, the application of a non linearity (activation) to the extracted features, and, at last, their fusion. In our paper, we extract several saliency maps from the images in our dataset using three different algorithms, namely, Graph-Based Visual Saliency (GBVS), Cluster-based Saliency Detection (COS) and Spectral Residual (SPE). In Figures 2-4 one can see which pixels of the original images are highlighted by the saliency methods. SPE is the method that changes the image the most. It only highlights very few pixels. GVBS seems to return a blurred version of the original images. The COS transformation apparently returns a gray-scale version of the insect. Every saliency method can be used to create a binary mask by setting to 1 all the pixels whose value is above a threshold and setting to 0 all the others. For every image in the dataset, we use a saliency method to create two different images: foreground (FG) and region of interest (ROI). The FG image consists in the multiplication of the original image and its binary mask. This operation sets the foreground of the image to black. The ROI image is a smaller image that only contains the insect. It discards the part of the image where the binary mask has a large number of zeros.

2.2.1. GVBS

Graph-Based Visual Saliency [10] is an algorithm to combine different feature maps. The idea is to use the feature maps to create a dissimilarity measure on the pixels of the image. This measure is used to create a Markov chain on the fully-connected graph made by the pixels of the image. The transition probability \( p(i,j,\mathbf{k},l) \) from \( (i,j) \) to \( (k,l) \) on this graph is proportional to the multiplication of the dissimilarity of the two pixels and a decreasing function of their distance.

\[
p(i,j,\mathbf{k},l) = d((i,j)\| (k,l)) \cdot F(i - k, j - l)
\]

where

\[
d((i,j)\| (k,l)) = \log \left( \frac{M(i,j)}{M(k,l)} \right)
\]

\[
F(a,b) = \exp \left( - \frac{a^2 + b^2}{2\sigma^2} \right)
\]

and \( M \) is a feature map. The transition probability must also be normalized in order to sum to 1. The saliency map is given by the stationary probability distribution associated to the Markov chain. The most relevant pixels found by this method are close pixels that have a large dissimilarity. To give an example of how the algorithm works, let \( I \) be a small image with 9 pixels and suppose that \( M(i,j) \) is constant for every pixel except \( M(x,y) \) and that \( M(x,y) \) is very different. Then, the transition probability towards \( (x,y) \) will be very large, hence the stationary distribution will have a large value.
2.2.2. Cluster-based Saliency Detection (COS)

The co-saliency map can be used in various vision applications. It is used to discover the common saliency on multiple images. Co-saliency detection is defined as utilizes the repetitiveness property as additional constraint, and discovers the common salient object in the images.

The idea of this method is presented in [11]. Given a set of images, the authors use a two layer clustering; initially, one layer groups the pixels on each image (single image), and the other layer associates the pixels on all the images (multi-image). Then the saliency cues (Contrast cue, Spatial cue, Corresponding cue) are computed for each cluster, and the cluster-level saliency is measured. The measured features include:

- Contrast cue: the advantage of the contrast cue is the ability of identify the rarest pixel clusters within the image, is very efficient in cases where there is a single subject, loses efficiency with the increase of similar subjects within the image.
- Distance from the image center (on single/multi-image). Spatial cue limits the low performance of the contrast cue when more subjects appear in the background. This indicator is based on the spatial distribution of the pixels clusters and is able to highlight the most 'salient' cluster of the image through the calculation of the Euclidean distance between the centroid of the cluster and the center of the image.
- the repetitiveness is computed by measuring how the distribution of clusters varies, giving a higher score to those that appear more frequently, in order to be able to identify with better approximation the most salient clusters.

At last, based on these cluster-level cues, our method computes the saliency value for each pixel, which is used to generate the final saliency map.
The content of the residual spectrum can be interpreted as the unexpected portion of the image. In different log spectra what deserves attention is the information that jumps out of the smooth curves.

3. Convolutional Neural Network

Convolutional Neural Networks (CNNs) [8] are a class of multi-layer neural networks, designed to recognize visual patterns directly from pixel images with minimal pre-processing.

The architecture of such networks can be summarized in a feature extractor and a classifier that are trained end-to-end. The feature extractor is made by many convolutional and pooling layers. Convolutional layers performs weighted convolutions between their inputs and their learnable weights. Thus, they find local patterns in the input. Pooling layers are non-trainable layers that reduce the dimensionality of their input by locally mapping a little square in the input into a single number. The classifier is usually made by one or more fully connected layers and a softmax function. However, light networks designed for mobile applications do not use fully connected layers because they contain the largest number of parameters of the network.

The CNNs used in this paper are: AlexNet, GoogLeNet, ShuffleNet, MobileNetv2.

3.1.1. AlexNet (AN)

AlexNet [8] was designed in 2012 and it managed to outperform every previous algorithm in ImageNet image classification. It contains eight learnable layers: the first five are convolutional and the remaining three are fully-connected. Every learnable layer is followed by a Rectified Linear Unit (ReLU) as activation function. Among the convolutional layers, max-pooling layers are used to reduce the dimensionality of the hidden layers. The output of the last fully-connected layer is fed into a softmax function that produces a probability distribution over the possible output classes.

3.1.2. GoogLeNet (GL)

GoogleNet [13] architecture consists of a 22 layer CNN. It only has 4 million parameters, which is a very low number compared with the 60 million parameters of AlexNet. The main feature of GoogleNet is the use of inception layers. They are made of different convolutional layers with different size, whose outputs are combined at the end of the module. The idea is that filters of different size can spot different patterns of the input.

3.1.3. ShuffleNet (SN)

ShuffleNet [14] is a very light network that uses grouped convolutions and channel shuffle to have a very low complexity. Grouped convolution are \(1 \times 1\) convolutions that only consider a subset of the channels of the hidden layer. In this way the number of multiplications is strongly reduced. Then, in order to increase the communication between the neurons, the channels of the output are shuffled. The result is that the network is 13 times faster than AlexNet, maintaining similar accuracy.

3.1.4. MobileNetv2 (MN)

MobileNetv2 [15] is a light convolutional network for mobile applications. It contains several depthwise separable convolutions, which can be thought as convolutional layers where the 3D weights tensor is factorized in one 2D tensor and a 1D tensor, requiring much less memory. This kind of layers is often used in light convolutional networks. With respect to other networks, MobileNetv2 has fewer nonlinearity. The authors give an interpretation on why this should give better results in their network and state that the same network performed worse when they tried to add more nonlinearities. Besides, this network has inverted skip connections. This means that the hidden layers connected through skip connections are low dimensional, reducing the number of operations made by the network.

4. Training

For each CNN, we used Stochastic Gradient Descent (SGD) with the following training parameters: 30 training epochs, mini-batch size of 30 and learning rate of 0.0001. In addition, at the beginning of each epoch, we use data augmentation. Data augmentation is a way of creating new samples by modifying the original ones without changing their classes. In our case, we randomly reflect the images along both axis. Besides, we rotate the image by an angle between \([-10, 10]\), and translate it along both axes, by a number of pixels between \([0, 5]\). Finally we randomly scale the image independently in both axis with a value that varies between \([1, 2]\).

We fine-tuned the pre-trained networks the we presented in Section 3. We performed it by replacing the last 2 layers of the various networks with a fully connected layer, used to classify the data into the classes and a softmax layer. In order to learn faster in the new layers than in the transferred layers, we increased the relative learning rate of the last fully connected layer by a factor of 20.

The training set consisted in 20 images randomly extracted for every class, while the rest were used in the test set. This protocol is the same used in [5]. This splitting is performed five times, then the average results are reported.

Apt from the original dataset, we created two more different datasets: a Foreground (FG) dataset where the background of every insect is turned to black; a Region Of Interest (ROI) dataset made by the portions of the original images that contain the insects.

We trained every network on seven different datasets: the original one and the six other datasets obtained by using the saliency maps of Section 2 as image preprocessing on the FG and the ROI datasets. We summarize our method in Figure 5. We report the performance of every protocol and we also create some ensemble of these networks using the sum rule on the softmax output.
5. Experimental Results

The results reported in Table 1 include the training of the single CNNs on the different datasets. The row 'OriginalImage' shows the results obtained by the CNNs on the original dataset. The rows named after saliency methods contain the performance of the networks after the saliency method has been applied. ‘FusionSum’ is the performance of the ensemble created by the same network trained on the seven datasets, while ‘AllSum’ is the ensemble created with all the networks trained.

The networks trained on the original images are the ones that reach the best performances. Among the preprocessed datasets, GVBS is the best one and COS comes right after. As expected, SPE is the worst performing method. The motivation of this result can be found in Figures 2-4, where it can be seen that SPE highlights very few pixels and does not consider important parts of the insect. The best performing stand-alone method is ShuffleNet applied to the original image. In general, the saliency methods reduce the performance of the networks with respect of the original image. This could be because of a correlation between the insect and its foreground, which is cut by the saliency method. However, the ensemble of a specific network trained on the four datasets outperforms the one of the single networks. Besides, the ensemble of all the networks outperforms the four smaller ensembles. The row ‘AllSum\Spectral’ contains the performance of the ensemble of all the networks but the ones trained on the SPE datasets, which are the worst performing. This shows that even those networks are useful when included in the ensemble, probably because the information brought by those networks is somehow independent from the information brought by the others.

As a comparison, in [5], the authors train a SVM classifier and reach an accuracy of 85.5%, which is clearly outperformed by our best ensemble.

To the best of our knowledge, the only other paper where the same dataset is used is [7]. However, they only use a partial and unbalanced version of the dataset because they...
We managed to improve our methods, we share all our MATLAB code at order to encourage the replication and the in-put of human experts. 

Our results are nearly as good as the ones obtained by human experts.

| Table 3: Human expert performance |
|----------------------------------|
| Expert | 1 | 2 | 3 | 4 | 5 | 6 |
| Performance | 0.96 | 0.96 | 0.92 | 0.91 | 0.90 | 0.82 |

6. Conclusions

The purpose of this paper was to create an automatic classifier of pest species. We explored the possibility to combine CNNs and saliency methods to create an ensemble of 28 classifiers combined by sum rule. We managed to outperform the performance of the previous literature on the same dataset. [7] achieves better performances than we do, but with a simpler testing protocol. Their method trained and tested with our testing protocol performs worse than ours. As future work we plan to test our method on a much larger pest dataset proposed in [6]. We proved that our method is very competitive on small datasets, we shall test its results on a larger dataset. Besides, we plan to create a similar ensemble using larger and better performing CNNs which are more suitable to be used on a large dataset due to their potential overfitting.

Finally, in order to encourage the replication and the improvement of our methods, we share all our MATLAB code at https://github.com/LorisNanni/.

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