Saliency for Fine-grained Object Recognition in Domains with Scarce Training Data

Carola Figueroa Flores\textsuperscript{a,b,∗}, Abel Gonzalez-Garcia\textsuperscript{a}, Joost van de Weijer\textsuperscript{a}, Bogdan Raducanu\textsuperscript{a}

\textsuperscript{a}Computer Vision Center
Edifici “O” - Campus UAB
08193 Bellaterra (Barcelona), Spain

\textsuperscript{b}Department of Computer Science and Information Technology
Universidad del Bio Bio, Chile

Abstract

This paper investigates the role of saliency to improve the classification accuracy of a Convolutional Neural Network (CNN) for the case when scarce training data is available. Our approach consists in adding a saliency branch to an existing CNN architecture which is used to modulate the standard bottom-up visual features from the original image input, acting as an attentional mechanism that guides the feature extraction process. The main aim of the proposed approach is to enable the effective training of a fine-grained recognition model with limited training samples and to improve the performance on the task, thereby alleviating the need to annotate large dataset. The vast majority of saliency methods are evaluated on their ability to generate saliency maps, and not on their functionality in a complete vision pipeline. Our proposed pipeline allows to evaluate saliency methods for the high-level task of object recognition. We perform extensive experiments on various fine-grained datasets (Flowers, Birds, Cars, and Dogs) under different conditions and show that saliency can considerably improve the network’s performance, especially for the case of scarce training data. Furthermore, our experiments show that saliency methods that obtain improved saliency maps (as measured by traditional saliency benchmarks) also translate

\textsuperscript{∗}Corresponding author

Email address: cafigueroa@cvc.uab.es (Carola Figueroa Flores)
to saliency methods that yield improved performance gains when applied in an object recognition pipeline.

*Keywords:* object recognition, fine-grained classification, saliency detection, scarce training data

## 1. Introduction

Fine-grained object recognition focuses on the classification of subclasses belonging to the same category. Examples of fine-grained datasets include natural categories such as flowers [1], birds [2], dogs and cats [3] and man-made categories such as airplanes [4] and cars [5, 6]. The problem of fine-grained object classification is difficult because the differences between subclasses are often subtle and correct classification requires exact localization of discriminating attributes [7], which typically requires expert labelers. Therefore the collection of large datasets is expensive and the development of algorithms that only require few labeled examples is of special interest to the field.

Computational saliency estimation aims to identify to what extent regions or objects stand out with respect to their surroundings to human observers. Saliency methods can be divided in methods that aim to identify the salient object (or objects) and methods that aim to produce a saliency map that is in accordance to measurements of human eye-movements on the same image [8, 9]. Itti et al. [10] proposed one of the first computational saliency methods based on combining the saliency cues for color, orientation and luminance. Many works followed proposing a large variety of hand-crafted features for saliency [11, 12, 13, 14]. Similar as other fields in computer vision, computational saliency estimation has moved in recent years from hand-designed features to end-to-end learned deep features [15, 16, 17, 18].

Saliency detection in human vision plays a role in the efficient extraction of information by placing the attention on those regions in the image that are most informative. However, the vast majority of saliency methods are not evaluated on their efficiency to improve object recognition but instead are evaluated on
the task of how accurate their generated saliency masks are. Given that saliency
is only an intermediate step of the visual pipeline, evaluating the efficiency of
saliency in terms of an improvement of the final task - here we consider fine-
grained recognition - could be considered a more valuable evaluation. Therefore,
in this paper we aim to evaluate the usefulness of saliency by directly evaluating
its improvement on image classification.

Previous works have found that the incorporation of attention mechanisms
in neural networks could be beneficial. This was first proposed in the context
of language translation networks where an attention model selects part of the
input sentence that is the current focus of translation of a recurrent network [19,
20]. This theory was subsequently extended to captioning methods where the
attention highlights the part of the image that is currently being described by
words, again within a recurrent model [21, 22]. Similar to these methods we
will incorporate a saliency model, which modulates the normal forward pipeline
similarly as an attention model would, but now within the context of fine-grained
image classification. Contrarily to these attention methods, we use a saliency
network that is pretrained on the task of saliency estimation. Especially, we
are interested in demonstrating its effectiveness in the case of scarce training
data, a scenario where attending to the relevant information from the image can
significantly reduce the danger of overfitting.

In this paper, we investigate to what extent saliency estimation can be ex-
plained to improve the training of an object recognition model when scarce
training data is available. For that purpose we design an image classification
deep neural network that incorporates saliency information as input. This net-
work processes the saliency map through a dedicated network branch and uses
the resulting features to modulate the standard bottom-up visual features from
the original image input. The main aim of the proposed methods is to enable
the effective training of a fine-grained recognition model with limited training
samples and to improve the performance on the task, thereby alleviating the
need to annotate large dataset. We evaluate our method on different datasets
and under different settings, achieving considerable performance improvements
when leveraging saliency data, especially when training data is scarce.

This paper is organized as follows. In section 2 we discuss the related work. Section 3 describes our method in detail, and we perform extensive experiments in section 4. Finally, section 5 presents the conclusions.

2. Related Work

Saliency estimation: The seminal work of Itti et al. [10] proposed one of the first biologically motivated computational models for saliency estimation. Their saliency map was inferred from multi-scale representations of color, orientation and intensity contrast. Saliency research was propelled further by the availability of large data sets for both object saliency [23, 24] and eye-tracking based saliency [25, 26]. These datasets allowed for direct comparison of methods and enabled the use of data-driven methods based on machine learning algorithms. Interestingly, a recent study that optimized the parameters of the original Itti et al. [10] method showed that this model still obtains competitive results [27].

Recent methods in saliency are mostly based on deep learning networks. Initially, pretrained deep convolutional networks were used directly to extract features for saliency estimation [28]. Afterwards, end-to-end networks that learn a mapping from the input image to the saliency map [29] were introduced. But like most previous work on saliency estimation, the main focus of these works is to estimate a saliency map, not how saliency could contribute in a object recognition pipeline. In this paper, we aim to investigate if saliency can improve the recognition of objects with deep neural networks.

Attention: The method proposed in this paper is partially based on insights gained from some recent work on attention in neural networks. In [30] the authors propose a method that incorporates attention branches within a feed-forward network for object classification. The attention map, which is repeated for multiple layers in the network, learns to modulate the network features with an attention mechanism. Our saliency branch is similar to the proposed attention mechanism in [30]. In our work, however, we use a pretrained saliency
branch that is optimized to return a saliency map in accordance with human vision. The fact that the network is pretrained is important because that allows it to be used even for object classification problems with very few training examples. In this case, the proposed method in [30] would probably fail because it would have to train additional parameters for the attention branch, which would be extremely challenging in the scarce data domain.

Zagoruyko and Komodakis [31] propose a method to train a student network from a teacher network. Their novelty with respect to earlier work is the usage of attention to guide the teaching of the student network. They construct a spatial attention map by considering the activations of an image in a teacher network, and mapping these activations to a single spatial attention map which reflects on what locations the hidden neuron activations were most prominent. They consider that this information is important and can help guide the training process once it is also transferred to the student network. They show that their approach significantly improves the learning of the student network. Concretely, they show that guiding the backpropagation of gradients by telling to what spatial coordinates to 'attend' can assist in the training process. Our paper supports this claim by showing that spatial guidance can help training, although within a different context as in our case we use saliency as attention map and train the network for a new task.

**Fine-grained recognition:** Most of the state-of-the-art general object classification approaches [30, 32] have difficulties in the fine-grained recognition task, which is more challenging due to the fact that basic-level categories (e.g. different bird species or flowers) share similar shape and visual appearance. One reason for this could be attributed to the popular codebook-based image representation, often resulting in the loss of subtle image information that is critical for the fine-grained task. For this reason, most fine-grained approaches [7, 33, 34, 35, 36, 37] increase their discriminative power by leveraging part information, which enables capturing subtle appearance variations across classes.
Current fine-grained recognition approaches operate on a two-stage pipeline, first detecting some object parts and then categorizing the objects using this information. For example, Zhang et al. [33] detects two semantic parts of birds (head and torso) using the popular R-CNN detector [38] and includes them in a pose-normalized representation used for recognition. SPDA-CNN [34] integrates the part detection stage within the network, leveraging the top nearest-neighbors in the training images to transfer part annotations as proposals. Similarly, Deep LAC [7] localizes and aligns object parts with specialized sub-networks. The work of Huang et al. [35] first localizes a set of part keypoints, and then simultaneously processes part and object information to obtain highly descriptive representations. Mask-CNN [37] also aggregates descriptors for parts and objects simultaneously, but using pixel-level masks instead of keypoints.

The main drawback of these models is the need of human annotation for the semantic parts in terms of keypoints or bounding-boxes. Many fine-grained datasets, however, do not provide such annotations, and obtaining them is costly, tedious, and does not generalize well to new tasks [39]. For this reason, some approaches [40, 41] have attempted to detect parts without explicit annotations, for example using co-segmentation [40] or a bilinear model [41]. The method of [42] first performs unsupervised part candidate discovery and global object discovery, and then feeds this information into a two-stream CNN in order to jointly model both local and global features. In [43], object and part detections are extracted by interpreting the feature maps of the CNN. Alternatively, [44] uses Fisher vectors for image representation and show that larger codebooks are able to model subtle visual details without explicitly modeling parts, which leads to better classification accuracy compared to small codebooks. Regardless, most fine-grained approaches use the object ground-truth bounding-box at test time, achieving a significantly lower performance when this information is not available. Our approach is more general, as it only requires image level annotations at training time and could easily generalize to other recognition tasks.
Few-shot learning: Few-shot learning aims to create models for which very few labeled samples are available. Early work on this topic is attributed to Fei-Fei et al. [45], who showed that, taking advantage of previously learned categories, it is possible to learn new categories using one or very few samples per class. More recently, [46] proposed a conditional distance measure that takes into account how a particular appearance model varies with respect to every other model in a model database. The approach has been applied to one-shot gesture recognition. Nowadays, several deep learning-based approaches have emerged to address the problem of few-shot learning. We can identify two main strategies. One family is based on metric learning. In [47], they use a siamese network in order to learn pairwise similarities between two objects. A similar approach is followed in [48], but in this case they use a recurrent neural network to learn the similarities between object pairs. In [49], the authors propose a framework that trains a network to map a small labeled support set and an unlabeled example to its label. An extension of this idea is presented in Prototypical networks [50], but in this case each class in the support set has been substituted by a ‘prototype’ (computed as the mean of the samples in the corresponding class), to which each sample is compared. This idea is further exploited in [51], where their formulation follows an information retrieval-inspired approach. Each sample in the batch is seen as a query that ranks the remaining ones based on its predicted relevance to them.

The other family of approaches in based on meta-learning, i.e. learning a model that given a few training examples of a new task tries to quickly learn a learner model that solves this new task [52]. In [53], the authors propose an LSTM-based meta-learner that is trained to optimize a neural network classifier. The meta-learner captures both short-term knowledge within a task and long-term knowledge common among all the tasks. This idea is further improved in [54], where the authors use a model-agnostic meta-learner. The model parameters are rapidly learned in a few gradient steps from a small amount of training data from the new task. A different approach is followed in [55], where the authors address the problem of meta-learning using memory-augmented
neural networks (MANN), i.e. a class of networks equipped with external memory. They demonstrate that MANNs are capable of meta-learning in tasks that carry significant short- and long-term memory demands. The approach presented in [56] shows that a network can efficiently learn new tasks from only a few training samples while at the same time it will not forget the initial tasks on which it was trained. To achieve this goal, the authors propose a novel attention-based weight generator as well as a cosine-similarity based classifier.

3. Saliency Modulation for Scarce Data Object Classification

Image classification results have improved much since the advent of deep convolutional neural networks [32, 57] due to the excellent visual representations learned by these models. Given the great number of parameters of these networks, we require large datasets of labeled data to effectively train them. For example the popular ImageNet dataset has over 1M labeled images [58]. Once learned, these strong image representations can be transferred to other related tasks by a process called finetuning [59]. This process allows to use deep learning on tasks for which significantly less labeled data is available. In some cases, however, the available data for the target task is so scarce that is still insufficient to finetune large networks and obtain satisfactory results.

Saliency is an attentional mechanism which allows humans to focus their limited resources to the most relevant information in the image. Since processing resources are limited, the data is processed in a serial manner, prioritizing those parts that are expected to have high information content [8]. In this paper, we investigate another potential application of saliency, namely its function to facilitate the fast learning of new objects in the context of deep neural networks. Especially when only a few training examples are available, focusing on the relevant parts of the image could significantly improve the speed of learning, understanding speed as the number of example images required to learn a new class. Therefore, we seek to incorporate saliency estimation into an image classification pipeline, with the aim to decrease the data requirements for learning.
Fig. 1 provides an overview of the proposed network architecture. Our network contains two branches: one to process the RGB images and one to process their corresponding saliency images, which are pre-computed and given as input. They are combined with a modulation layer (× symbol) and further processed by several shared layers of the joint branch to finally end on a classification layer. Note how the RGB branch followed by the joint branch correspond to a standard image classification network. The novelty of our architecture is the introduction of the saliency branch, which transforms the saliency image to the modulation image. This modulation image is then used to modulate the features of the RGB branch, putting more emphasis on those features that are considered important for the fine-grained recognition task. In the following sections we provide the details of the network architecture, the functioning of the modulation layer, and the saliency methods used. We explain our model using AlexNet [32] as base classification network, but the theory could be applied to most convolutional neural network architectures. We also consider ResNet-50 [57] as base network in our experiments (sec. 4.2).
3.1. Combining RGB with Saliency for Image Classification

Consider a saliency map \( s(x, y) \) where \( x \) and \( y \) are the spatial coordinates. We will assume that saliency maps are of the same size as the original image \( I(x, y, z) \), where \( z = \{1, 2, 3\} \) indicate the three color channels of the image. A straightforward way to incorporate the saliency into the image classification network is by concatenating the image and the saliency map into an image with four channels such that \( I(x, y, 4) = s(x, y) \). This strategy has been previously used by Murabito et al. [60] in a classification pipeline that combines two CNN networks: one to compute top-down saliency maps from an RGB image, and a second network that appends the generated saliency map to the RGB image channels to perform image classification. In this case, the classification network only needs to train from scratch the weights of the first layer, the following layers can be initialized with a pretrained network. We call this approach \textit{early fusion} of saliency and image content.

In this article we propose \textit{delayed fusion} of saliency and image content, where we use the saliency map to modulate the features of an intermediate network layer. Consider the output of the \( i^{th} \) layer of the network, \( l^i \), with dimension \( w_i \times h_i \times z^i \). Then we define the modulation with a function \( \hat{s}(x, y) \) as

\[
\hat{l}^i(x, y, z) = l^i(x, y, z) \cdot \hat{s}(x, y),
\]

yielding the saliency-modulated layer \( \hat{l}^i \). Here the modulation image \( \hat{s} \) is the output of the saliency branch, which takes \( s \) as input (as depicted in Fig. 1).

Note that we consider a single saliency map \( \hat{s} \) that is independent of the number of feature maps. To ensure that \( \hat{s} \) has the same spatial dimensions as \( l^i \), we use a similar architecture for both the saliency branch and the RGB branch. Concretely, the main difference resides in the size of the channel dimension: the saliency branch takes an intensity image as input (instead of a 3-channel RGB image) and outputs a scalar modulation image of \( w_i \times h_i \times 1 \) (instead of a \( w_i \times h_i \times c_i \) feature map). Moreover, we use a sigmoid activation function at the end of the saliency branch, as opposed to the ReLU non-linearity of the RGB
branch. This ensures that $0 \leq \hat{s}(x, y) \leq 1$ and thus provides a suitable range for feature modulation.

In the original architecture, max pooling is performed right after the second convolutional layer. In our model, we postpone this max pooling to after the features from both branches are fused, i.e. we perform max pooling on the salience-modulated layer $\hat{l}$. The reasoning behind this choice is to leverage the greater modulation potential of higher resolution saliency features. We experimentally show (sec. 4.2) that this results in a small performance boost.

In addition to the formulation in Eq. (1) we also introduce a skip connection from the RGB branch to the beginning of the joint branch, defined as

$$\hat{l}^i(x, y, z) = l^i(x, y, z) \cdot (\hat{s}(x, y) + 1).$$

This skip connection is depicted in Fig. 1 (+ symbol). It prevents the modulation layer from completely ignoring the features from the RGB branch. This is inspired by a previous work [31] that found this approach beneficial when using attention for network compression. We confirm the usefulness of the skip connection in the experiments section, sec. 4.2.

We train our architecture in an end-to-end manner. The backpropagated gradient from the modulation layer into the image classification branch is equal to

$$\frac{\partial L}{\partial \hat{l}} = \frac{\partial L}{\partial l} \cdot (s + 1),$$

where $L$ is the loss function of the network. This shows that the saliency map not only modulates the forward pass (see Eq. (2)), but it also modulates the backward pass in exactly the same manner; in both cases putting more weight on the features that are on locations with high saliency, and putting less weight on the irrelevant features in the background on which the network could potentially overfit.

3.2. Training the Saliency Branch

The aim of the saliency branch is to process the saliency map $s(x, y)$ into effective modulation features $\hat{s}(x, y)$ that increase the classification performance
when training with scarce data. The main intuition is that the saliency features \( \hat{s} \) will focus the backpropagated gradient to the relevant image features, thereby reducing the required data necessary to train the network. The additional saliency branch necessary to compute \( \hat{s}(x, y) \) has its own set of parameters and could, in principle, increase the possibility of overfitting. We therefore consider two different scenarios to initialize this branch. In both cases, we start with an equivalent architecture to the one depicted in Fig. 1 but without the saliency branch. We pretrain this network for image classification on ImageNet [61]. Then, we add the saliency branch and apply either of the following options:

- **Initialization from scratch**: the weights of the saliency branch are randomly initialized using the Xavier method [62].

- **Initialization from pretrained**: the weights of the saliency branch are pre-trained in an image classification network as follows. We continue pre-training the initial network for classification using the ImageNet validation dataset, which consists of 50K images (40K were used for training and 10K for validation). We then used this further pretrained network (including the saliency branch) to initialize all the weights of our network except the top classification layer.

3.3. Saliency input

The input to the saliency branch is a saliency map. Among the many saliency methods that provide satisfactory results [63], we perform most of our experiments using two of the top performing methods:

- iSEEL [64] leverages the inter-image similarities to train an ensemble of extreme learners. The predicted saliency of the input image is then calculated as the ensemble’s mean saliency value. Their approach is based on two aspects: (i) the contextual information of the scene and (ii) the influence of scene memorability (in terms of eye movement patterns by resemblance with past experiences). We use MATLAB code released by the authors.
• SALICON [65] exploits the power of high-level semantics encoded in a CNN pretrained on ImageNet. Their approach represents a breakthrough in saliency prediction, by reducing the semantic gap between the computational model and the human perception. Their method has key elements: (i) an objective function based on saliency evaluation metrics and (ii) integration of information at different image scales. We use the open source implementation provided by [66].

Besides these two methods, we also perform experiments with three other approaches for a more comprehensive comparison.

• Itti and Koch [10]: First, we consider the classical saliency model of Itti et al. Several activation maps, corresponding to multiscale image features (color, intensity and orientations) are generated from the visual input and combined into a single topographical saliency map. A neural network is used to select the most salient locations in order of decreasing magnitude, which could be subsequently analyzed by more complex, higher cognitive level processes.

• GBVS [67]: The Graph-based Visual Saliency (GBVS) is also a biologically-plausible bottom-up model following the approach proposed earlier by Itti et al., but improving the performance of the generation of activation maps and the normalization/combination step. They used the Markovian formalism to describe the dissimilarity and concentration of salient locations of the image seen as a graph.

• BMS [68]: Boolean Map based Saliency (BMS) approach computes saliency by analyzing the topological structure of the Boolean maps. These maps are generated by randomly thresholding the color channels. As topological element they choose ‘surroundedness’ because it better characterizes the image/background segregation.

Figure 2 depicts the estimated saliency maps for an example image using the five different saliency methods presented above. In addition to these methods,
Figure 2: Saliency images generated with the different saliency estimation approaches considered, as well as the two baseline saliency maps evaluated, White and Center. We also include the original RGB image for reference.

we consider two additional saliency map baselines. White regards all image pixels as equally salient, and thus the saliency maps are uniformly white. On the other hand, Center emulates a center prior by representing saliency as a centered 2-dimensional Gaussian distribution. These two baselines allow us to determine whether our model is actually leveraging the saliency information contained in the maps, or it is simply adding a general image bias that is beneficial for recognition (e.g. center bias). We are especially interested in assessing whether saliency methods that obtain higher performance on saliency benchmarks also yield better performance when incorporated into our saliency pipeline.

4. Experiments

4.1. Experimental Setup

Datasets. We have performed the evaluation of our approach on four standard datasets used for fine-grained classification

- **Flowers**: Oxford Flower 102 dataset [1] consists of 8189 images of flowers grouped in 102 classes. Each class contains between 40 and 258 images.

- **Birds**: is a dataset consisting of 11,788 images of bird species divided into 200 categories. Each image is annotated with its bounding box and the
image coordinates of 15 keypoints. However, in our experiments we used the whole image.

- **Cars**: the dataset in [69] contains 16,185 images of 196 classes of cars. The data is split into 8,144 training images and 8,041 testing images, where each class has been separated roughly in a 50-50 split.

- **Dogs**: Stanford Dogs [70] consists of 20,580 images of different breeds of dogs from around the world grouped in 120 categories. Since some of these images appear also in Imagenet, in our experiments we have discarded the repeated ones.

**Networks.** Our base network is AlexNet [32], which consists of five convolutional layers followed by three fully connected layers. We used the pretrained network on ImageNet [61] and fine-tuned it for fine-grained recognition on each dataset for 70 epochs with a learning rate of 0.01 and a weight decay of 0.003. The top classification layer is randomly initialized using Xavier [62]. We have attached a saliency branch to this network as shown in figure 1.

For some experiments we have also used the ResNet-50 network [57], consisting of 50 convolutional layers organized in 4 residual blocks. The structure of the saliency branch has been kept the same as in figure 1, i.e. consisting of two convolutional layers and having a ReLu activation function after the first one and a sigmoid function after the second.

**Evaluation protocol.** For all the above datasets, we randomly select and fix 5 images for test, 5 for validation, and keep the rest for training. We train each model with subsets of k training images for $k \in \{1, 2, 3, 5, 10, 15, 20, 25, 30, K\}$, where $K$ is the total number of training images for the class. Contrarily to current few-shot approaches, this settings grants us a more complete disclosure of the results of our model under multiple limited-data scenarios. We use accuracy in terms of percentage of correctly classified samples as evaluation measure. We train and test each model five times with different random initializations, and show the average performance for the five runs.

15
Method | 1 | 2 | 3 | 5 | 10 | 15 | 20 | 25 | 30 | AVG  
--- | --- | --- | --- | --- | --- | --- | --- | --- | --- | ---  
Baseline-RGB | 31.8 | 45.8 | 53.1 | 63.6 | 72.4 | 76.9 | 81.2 | 85.1 | 87.2 | 88.0 | 68.5  
Early Fusion | 19.3 | 25.7 | 30.1 | 40.8 | 60.9 | 69.2 | 75.3 | 79.9 | 82.4 | 83.7 | 56.7  
Fusion L1 | 33.3 | 47.9 | 54.3 | 65.1 | 71.9 | 76.3 | 82.1 | 85.9 | 87.9 | 90.7 | 69.5  
Fusion L2 | 34.7 | 49.3 | 55.2 | 65.2 | **72.7** | 76.7 | **83.9** | **86.5** | **89.1** | **91.3** | **70.5**  
Fusion L3 | 32.9 | 46.7 | 54.1 | 64.9 | 71.7 | 74.4 | 82.3 | 85.1 | 87.3 | 89.1 | 68.9  
Fusion L2 + After pool | 34.3 | 49.1 | **55.5** | **66.0** | 72.1 | **77.5** | 83.6 | 85.6 | 88.9 | 90.2 | 70.2  
Fusion L2 + No SC | 33.9 | 48.1 | 55.1 | 65.1 | 71.1 | 77.6 | 82.4 | 86.3 | 88.1 | 90.9 | 69.9  

Table 1: Results for the baseline model and different variations of our architecture incorporating saliency information. The results correspond to the classification accuracy on the Flowers dataset [1] with AlexNet [32]. Each column indicates the number of training images used, and the rightmost column shows the average.

### 4.2. Experimental Results

**Architectural changes.** In order to justify the design choices in our model, we present here multiple architectural variations to integrate saliency information into a neural network. We call Baseline-RGB to the original network model, which only contains the RGB branch and thus does not use any saliency information. We test an Early fusion model in which the saliency image is directly concatenated to the RGB input.

We consider several variants of our model in which delayed fusion is performed at different network levels, indicated as Fusion L1 for fusion after layer 1 (similarly for Fusion L2 and L3). Moreover, we evaluate whether performing the fusion after the pooling layer is a better option than doing it before. Finally, we include a model without the skip connection from the RGB branch to the joint branch.

We evaluate all models on Flowers [1] with AlexNet [32] and using iSEEL [64] as the saliency method of choice. Table 1 shows the results for different numbers of training images. First, we observe how the performance of all methods steadily grows when increasing the number of training images. In general, incorporating saliency information helps when fused within the network, but damages the accuracy if concatenated to the input image. We attribute this to the need to learn a low-level filter from scratch, which in turn affects the feature repre-
Figure 3: Experiments on four datasets using iSEEL method to generate the saliency maps. Baseline-RGB is compared against two different ways to initialize the saliency branch of our model: from scratch (Xavier) and pretrained on ImageNet [61].

sentation at higher levels. Performing the fusion immediately after the second convolutional layer seems to be the best option. Fusing before or after the pooling layer leads to similar results, the advantage of fusing higher resolution saliency features gives only a marginal boost. Finally, the skip connection from the RGB branch to the joint branch is also beneficial.

Pre-training saliency branch on ImageNet. As described in section 3, we consider two alternative ways of initializing the saliency branch: from scratch and pretrained on ImageNet [61]. In this section, we compare these two approaches with respect to the Baseline-RGB. The experiments are performed on
Flowers dataset (see figure 3a) and represent the classification accuracy versus the number of training samples. Adding a saliency branch initialized from scratch already outperforms the baseline using only RGB (see also Tab. 1), and pre-training this branch with ImageNet further increases the performance in a systematic and substantial manner. Our method with pretraining is especially advantageous in the scarce-data domain (i.e. < 20 images per class). For example, we obtain a better performance than the baseline using half the data, 10 images/class vs. 20 images/class, respectively. Furthermore, in the very low-range of number of samples we obtain similar performance with only one third of the samples (3 images/class vs. 10 images/class). Finally, our saliency branch is still beneficial even when using all available training samples. In fact, our method trained with a limited number of samples (around 25 per class) already surpasses the final performance of baseline using all samples.

Figure 4 shows some qualitative results for the case when the pretrained version of our approach predicts the correct label, meanwhile the Baseline-RGB fails. Alternatively, figure 5 depicts the opposite case: the Baseline-RGB predicts the correct label of the test images, meanwhile the pretrained version of our approach fails. In both cases, the saliency images have been generated using the iSEEL method. A possible explanation for the failures in this latter case could be that the saliency images are not able to capture the relevant region of the image for fine-grained discrimination. Thus, the salience-modulated layer focuses on the wrong features for the task.

Different datasets Besides Flowers dataset, we validate our approach on three other datasets: Birds, Cars and Dogs (see figures 3b, c, and d, respectively). We follow the same experimental protocol as in the Flowers case. We can see how most trends observed in Flowers also apply to these datasets. For example, incorporating saliency information improves the classification accuracy, especially when data is scarce. Moreover, pretraining the saliency branch is beneficial for our method and leads to a further performance boost. Even when using all available samples, our method outperforms the baseline model.
Therefore, we can claim that our approach successfully generalizes to other fine-grained datasets.

**Different saliency methods.** Table 2 presents results on the *Flowers* using our full AlexNet model combined with the different input saliency maps. We can observe how, instead of helping, the two saliency baselines are actually hurting the method performance with respect to the Baseline-RGB. We hypothesize that this is due to the noise introduced in the network’s internal representation when the input saliency map is independent of the input image. On the other hand,
all the saliency estimation methods increase the method performance, especially in the scarce-data range (i.e. < 10 images). Moreover, better saliency methods (e.g. iSEEL and SALICON) result in higher accuracies. In order to experimentally confirm this observation, we show in Fig. 6 the accuracy of our image classification model as a function of the saliency estimation performance of the corresponding method. We measure saliency estimation performance in terms of Normalized Scanpath Saliency (NSS), which is the official measure currently used by the popular MIT saliency benchmark [63] to sort all the participating methods. There is indeed a clear linear correlation, supported quantitatively by a Pearson product-moment correlation coefficient [71] of 0.95. Therefore, we conclude that our model is agnostic to the saliency method employed and correlates well with the method performance.

**Different base networks** In order to evaluate the generality of our approach across different base networks, we have considered ResNet-50 as an alternative to AlexNet. We have tested several possible fusion architectures, but the optimal
Figure 6: Correlation between the performance of the saliency method in terms of NSS and the fine-grained recognition accuracy of our method using the corresponding saliency model. Results with AlexNet [32] on Flowers [1].

Performance has been obtained when the fusion between the RGB and saliency branches takes place after the 4th residual block. Results in table 3 show the classification accuracy achieved on Flowers when using ResNet-50 and SALICON saliency maps. We compared our two initialization methods for the saliency branch (from scratch and pretrained on ImageNet) against the Baseline-RGB. Although under both initializations we obtained higher accuracy, the one that performs the best is the pretrained. These results confirm the trend already observed for AlexNet regarding the benefits of pretraining the saliency branch.

Comparison with few-shot method. Our scarce-data approach is similar in spirit to the few-shot learning methods [47, 49, 50, 52]. For this reason, we propose here a comparison with the state of the art method for few-shot classification, Prototypical networks [50]. In the standard few-shot protocol, the task is framed as $N$-way $k$-shot, i.e. provide each time a set of $k$ labeled
| Method           | 1    | 2    | 3    | 5    | 10   | 15   | 20   | 25   | 30   | K  | AVG |
|------------------|------|------|------|------|------|------|------|------|------|----|-----|
| Baseline-RGB     | 31.8 | 45.8 | 53.1 | 63.6 | 72.4 | 76.9 | 81.2 | 85.1 | 87.2 | 88.0| 68.5|
| Baseline-White   | 23.1 | 29.7 | 37.2 | 55.1 | 66.9 | 73   | 82.5 | 84.8 | 86.6 | 87.9| 62.7|
| Baseline-Center  | 24.3 | 30.3 | 39.2 | 55.7 | 68.3 | 74.1 | 82.7 | 84.5 | 86.8 | 87.8| 63.4|
| Itti-Koch [10]   | 32.8 | 46.8 | 53.9 | 64.0 | 72.9 | 77.1 | 82.9 | 85.4 | 87.1 | 88.3| 69.1|
| GBVS [67]        | 33.3 | 46.9 | 54.0 | 64.1 | 73.0 | 77.3 | 83.1 | 85.7 | 87.5 | 88.8| 69.4|
| BMS [68]         | 34.2 | 47.3 | 54.9 | 64.8 | 73.3 | 77.8 | 83.4 | 86.1 | 88.1 | 90.1| 70.0|
| iSEEL [64]       | 34.7 | 49.3 | 55.2 | 65.2 | 72.7 | 76.7 | 83.9 | 86.5 | 89.1 | 91.3| 70.5|
| SALICON [72]     | **37.6** | **51.9** | **57.1** | **68.5** | **75.2** | **79.7** | **84.9** | **88.2** | **91.2** | **92.4** | **72.7** |

Table 2: Comparison of different saliency methods regarding the effect on our model. The results correspond to the classification accuracy on the Flowers dataset [1] when using our full model with AlexNet [32] as base network. Each column indicates the number of training images used, and the rightmost column shows the average.

| Method          | 1    | 2    | 3    | 5    | 10   | 15   | 20   | 25   | 30   | K  | AVG |
|-----------------|------|------|------|------|------|------|------|------|------|----|-----|
| Baseline-RGB    | 39.1 | 59.6 | 67.8 | 81.6 | 89.3 | 91.7 | 92.7 | 93.0 | 93.0 | 95.4| 80.3|
| Ours Xavier     | 45.8 | 64.1 | 71.8 | 83.0 | 90.5 | 93.0 | 93.9 | 94.6 | 93.7 | 96.7| 82.7|
| Ours Pretrained | **47.1** | **65.2** | **72.9** | **83.8** | **91.3** | **93.9** | **94.6** | **95.4** | **94.7** | **97.4** | **83.6** |

Table 3: Results for Flowers using ResNet-50 as base network and SALICON as saliency method.

samples from each of \( N \) classes that have not previously been trained upon. The goal is then to classify a disjoint batch of unlabeled samples, known as ’queries’, into one of these \( N \) classes. Therefore, some classes are used to train the few-shot method, while others are only used at test time. In our case, we do not require such split, as we can train and test the model in all classes simultaneously. Moreover, their test episodes are composed of only \( N \) classes at a time, where

| Method                      | 20-way 5-shot | 102-way 5-shot |
|-----------------------------|---------------|----------------|
| Prototypical networks [50]  | 53.8          | 26.2           |
| Ours                        | 81.0          | 73.8           |

Table 4: The results correspond to the classification accuracy on the Flowers dataset [1] when using our full model with AlexNet [32] as base network.
$N$ is generally a small number (e.g. below 20). Contrarily, we follow a more general classification approach and test on all classes simultaneously, which is inherently more challenging as the misclassification probability increases.

We propose two different scenarios to compare our method to Prototypical networks on the task of Flower [1] classification. The first, 20-way 5-shot, closely resembles the setting introduced by [49] and usually employed by few-shot approaches. We split the set of classes in train and test, selecting 20 random classes for the testing phase. Then, we run Prototypical networks for the 20-way 5-shot classification task, following similar settings to those used in the mini-ImageNet experiment of [50]. We train until convergence using 100 training episodes and test using 5 episodes, with 5 queries per episode both during training and testing. The second scenario, 102-way 5-shot, is more similar to the conventional classification task, in which all classes are used for training and testing. We maintain the training settings for this case, but remove from the ‘shot’ set those queries used at test time. Table 4 presents the results of these experiments. Our method leads to substantially superior performance in both cases, but the difference is especially remarkable for the 102-way setting. This demonstrates the limitations of this type of few-shot approaches when scaling to many classes, even when they are trained with the same set of classes used for test.

5. Conclusions

In this paper, we investigated the role of saliency in improving the classification accuracy of a CNN when the available training data is scarce. For that purpose we have considered adding a saliency branch to an existing CNN architecture, which was used to modulate the standard bottom-up visual features from the original input image. We have shown that the proposed approach led to an improvement of the recognition accuracy with limited number of training data, when applied to the task of fine-grained object recognition.

Extensive evaluation has been performed on several datasets and under different settings, demonstrating the usefulness of saliency for fine-grained object
recognition, especially for the case of scarce training data. In addition, our approach allows to compare saliency methods on the high-level task of fine-grained object recognition. Traditionally, saliency methods are evaluated on their ability to generate saliency maps that indicate the relative relevance of regions for the human visual system. However, it remained unclear if these saliency methods would actually translate into improved high-level vision results for tasks such as object recognition. Our experiments show that there exists a clear correlation (Pearson product-moment correlation coefficient of 0.95) between the performance of saliency methods on standard saliency benchmarks and the performance gain that is obtained when incorporating them in a object recognition pipeline. Future work will be devoted to extend the current framework by proposing an end-to-end deep architecture that estimates automatically the saliency map, thus eliminating the need for pre-computing it off-line.

Acknowledgements

This work is partially funded by MINECO grant TIN2016-79717-R, Spain. Carola Figueroa is supported by a Ph.D. scholarship from CONICYT, Chile. We acknowledge the CERCA Programme of Generalitat de Catalunya. We also acknowledge the generous GPU support from NVIDIA.

References

[1] M.-E. Nilsback, A. Zisserman, Automated flower classification over a large number of classes, in: Sixth Indian Conference on Computer Vision, Graphics & Image Processing, 2008, pp. 722–729.

[2] P. Welinder, S. Branson, T. Mita, C. Wah, F. Schroff, S. Belongie, P. Perona, Caltech-UCSD Birds 200 (2010) [Last accessed: July 10th, 2018]. URL http://www.vision.caltech.edu/visipedia/CUB-200.html
[3] O. M. Parkhi, A. Vedaldi, A. Zisserman, C. Jawahar, Cats and dogs, in: IEEE Conference on Computer Vision and Pattern Recognition, 2012, pp. 3498–3505.

[4] S. Maji, G. Shakhnarovich, Part and attribute discovery from relative annotations, International Journal of Computer Vision 108 (1) (2014) 82–96.

[5] M. Stark, J. Krause, B. Pepik, D. Meger, J. J. Little, B. Schiele, D. Koller, Fine-grained categorization for 3d scene understanding, in: British Machine Vision Conference, 2012, pp. 36.1–36.12.

[6] J. Krause, M. Stark, J. Deng, L. Fei-Fei, 3d object representations for fine-grained categorization, in: 4th IEEE Workshop on 3D Representation and Recognition, at ICCV, 2013, pp. 1–8.

[7] D. Lin, X. Shen, C. Lu, J. Jia, Deep lac: Deep localization, alignment and classification for fine-grained recognition, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 1666–1674.

[8] L. Itti, C. Koch, A saliency-based search mechanism for overt and covert shifts of visual attention, Vision Research 40 (10) (2000) 1489–1506.

[9] X. Sun, H. Yao, R. Ji, X. M. Liu, Toward statistical modeling of saccadic eye-movement and visual saliency, IEEE Transactions on Image Processing 23 (11) (2014) 4649–4662.

[10] L. Itti, C. Koch, E. Niebur, A model of saliency-based visual attention for rapid scene analysis, IEEE Transactions on Pattern Analysis and Machine Intelligence 20 (11) (1998) 1254–1259.

[11] S. Ramanathan, H. Katti, N. Sebe, M. Kankanhalli, T.-S. Chua, An Eye Fixation Database for Saliency Detection in Images, Springer Berlin Heidelberg, Berlin, Heidelberg, 2010, pp. 30–43.

[12] T. Judd, K. Ehinger, F. Durand, A. Torralba, Learning to predict where humans look, in: IEEE International Conference on Computer Vision, 2009, pp. 2106–2113.
[13] A. Borji, D. N. Sihite, L. Itti, What/where to look next? modeling top-down visual attention in complex interactive environments, IEEE Transactions on Systems, Man, and Cybernetics: Systems 44 (5) (2014) 523–538.

[14] T. Deng, K. Yang, Y. Li, H. Yan, Where does the driver look? top-down-based saliency detection in a traffic driving environment, IEEE Transactions on Intelligent Transportation Systems 17 (7) (2016) 2051–2062.

[15] W. Yang, W. Ouyang, H. Li, X. Wang, End-to-end learning of deformable mixture of parts and deep convolutional neural networks for human pose estimation, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3073–3082.

[16] J. Pan, E. Sayrol, X. Giro-i Nieto, K. McGuinness, N. E. O’Connor, Shallow and deep convolutional networks for saliency prediction, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 598–606.

[17] X. Li, L. Zhao, L. Wei, M. H. Yang, F. Wu, Y. Zhuang, H. Ling, J. Wang, Deepsaliency: Multi-task deep neural network model for salient object detection, IEEE Transactions on Image Processing 25 (8) (2016) 3919–3930.

[18] W. Wang, J. Shen, Deep visual attention prediction, IEEE Transactions on Image Processing 27 (5) (2018) 2368–2378.

[19] D. Bahdanau, K. Cho, Y. Bengio, Neural machine translation by jointly learning to align and translate, in: International Conference on Learning Representations, 2015.

[20] O. Firat, K. Cho, B. Sankaran, F. T. Y. Vural, Y. Bengio, Multi-way, multilingual neural machine translation, Computer Speech & Language 45 (2017) 236–252.

[21] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, Y. Bengio, Show, attend and tell: Neural image caption generation with visual attention, in: International Conference on Machine Learning, 2015, pp. 2048–2057.
[22] M. Cornia, L. Baraldi, G. Serra, R. Cucchiara, Paying more attention to saliency: Image captioning with saliency and context attention, ACM Transactions on Multimedia Computing, Communications, and Applications 14 (2) (2018) 48:1–48:21.

[23] T. Liu, Z. Yuan, J. Sun, J. Wang, N. Zheng, X. Tang, H.-Y. Shum, Learning to detect a salient object, IEEE Transactions on Pattern Analysis and Machine Intelligence 33 (2) (2011) 353–367.

[24] Y. Li, X. Hou, C. Koch, J. M. Rehg, A. L. Yuille, The secrets of salient object segmentation, in: IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 280–287.

[25] T. Judd, F. Durand, A. Torralba, A benchmark of computational models of saliency to predict human fixations, in: MIT Technical Report, 2012.

[26] A. Borji, L. Itti, Cat2000: A large scale fixation dataset for boosting saliency research, in: Workshop on “Future of Datasets” at CVPR, 2015.

[27] S. Frintrop, T. Werner, G. Martin Garcia, Traditional saliency reloaded: A good old model in new shape, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 82–90.

[28] G. Li, Y. Yu, Visual saliency based on multiscale deep features, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 5455–5463.

[29] G. Li, Y. Yu, Deep contrast learning for salient object detection, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 478–487.

[30] F. Wang, M. Jiang, C. Qian, S. Yang, C. Li, H. Zhang, X. Wang, X. Tang, Residual attention network for image classification, in: IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 3156–3164.
[31] S. Zagoruyko, N. Komodakis, Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer, in: International Conference on Learning Representations, 2017.

[32] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, in: Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.

[33] N. Zhang, J. Donahue, R. Girshick, T. Darrell, Part-based r-cnns for fine-grained category detection, in: European Conference on Computer Vision, 2014, pp. 834–849.

[34] H. Zhang, T. Xu, M. Elhoseiny, X. Huang, S. Zhang, A. Elgammal, D. Metaxas, Spda-cnn: Unifying semantic part detection and abstraction for fine-grained recognition, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1143–1152.

[35] S. Huang, Z. Xu, D. Tao, Y. Zhang, Part-stacked cnn for fine-grained visual categorization, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1173–1182.

[36] J. Deng, J. Krause, M. Stark, L. Fei-Fei, Leveraging the wisdom of the crowd for fine-grained recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence 38 (4) (2016) 666–676.

[37] X.-S. Wei, C.-W. Xie, J. Wu, C. Shen, Mask-cnn: Localizing parts and selecting descriptors for fine-grained bird species categorization, Pattern Recognition 76 (2018) 704 – 714.

[38] R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich feature hierarchies for accurate object detection and semantic segmentation, in: IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 580–587.

[39] C. Zhang, W. Xiong, J. Liu, Y. Zhang, C. Liang, Q. Huang, Fine-Grained Image Classification Using Color Exemplar Classifiers, Springer International Publishing, Cham, 2013, pp. 327–336.
[40] J. Krause, H. Jin, J. Yang, L. Fei-Fei, Fine-grained recognition without part annotations, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 5546–5555.

[41] T.-Y. Lin, A. Roy Chowdhury, S. Maji, Bilinear cnn models for fine-grained visual recognition, in: IEEE International Conference on Computer Vision, 2015, pp. 1449–1457.

[42] G.-S. Xie, X.-Y. Zhang, W. Yang, M. Xu, S. Yan, C.-L. Liu, Lg-cnn: From local parts to global discrimination for fine-grained recognition, Pattern Recognition 71 (2017) 118–131.

[43] T. Sun, L. Sun, D.-Y. Yeung, Fine-grained categorization via cnn-based automatic extraction and integration of object-level and part-level features, Image and Vision Computing 64 (2017) 47 – 66.

[44] P.-H. Gosselin, N. Murray, H. Jégou, F. Perronnin, Revisiting the fisher vector for fine-grained classification, Pattern Recognition Letters 49 (2014) 92–98.

[45] L. Fei-Fei, R. Fergus, P. Perona, One-shot learning of object categories, IEEE Transactions on Pattern Analysis Machine Intelligence 28 (4) (2006) 594–611.

[46] R. Krishnan, S. Sarkar, Conditional distance based matching for one-shot gesture recognition, Pattern Recognition 48 (4) (2015) 1302 – 1314.

[47] G. Koch, R. Zemel, R. Salakhutdinov, Siamese neural networks for one-shot image recognition, in: International Conference on Machine Learning, 2015.

[48] P. Shyam, S. Gupta, A. Dukkipati, Attentive recurrent comparators, in: International Conference on Machine Learning, 2017.

[49] O. Vinyals, C. Blundell, T. Lillicrap, K. Kavukcuoglu, D. Wierstra, Matching networks for one shot learning, in: Advances in Neural Information Processing Systems, 2017.
[50] J. Snell, K. Swersky, R. Zemel, Prototypical networks for few-shot learning, in: Advances in Neural Information Processing Systems, 2017, pp. 4077–4087.

[51] E. Triantafillou, R. Zemel, R. Urtasun, Few-shot learning through an information retrieval lens, in: Advances in Neural Information Processing Systems, 2017.

[52] T. Munkhdalai, H. Yu, Meta networks, in: International Conference on Machine Learning, 2017, pp. 2554–2563.

[53] S. Ravi, H. Larochelle, Optimization as a model for few-shot learning, in: International Conference on Learning Representations, 2017.

[54] C. Finn, P. Abbeel, S. Levine, Model-agnostic meta-learning for fast adaptation of deep networks, in: International Conference on Machine Learning, pp. 1126–1135.

[55] A. Santoro, S. Bartunov, M. Botvinick, D. Wierstra, T. Lillicrap, Meta-learning with memory-augmented neural networks, in: International Conference on Machine Learning, 2016, pp. 1842–1850.

[56] S. Gidaris, N. Komodakis, Dynamic few-shot visual learning without forgetting, in: IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 4367–4375.

[57] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770–778.

[58] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, Imagenet: A large-scale hierarchical image database, in: IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 248–255.

[59] M. Oquab, L. Bottou, I. Laptev, J. Sivic, Learning and transferring mid-level image representations using convolutional neural networks, in: IEEE
Conference on Computer Vision and Pattern Recognition, 2014, pp. 1717–1724.

[60] F. Murabito, C. Spampinato, S. Palazzo, D. Giordano, K. Pogorelov, M. Riegler, Top-down saliency detection driven by visual classification (2018) [Last accessed: July 10th, 2018].
URL https://doi.org/10.1016/j.cviu.2018.03.005

[61] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al., Imagenet large scale visual recognition challenge, International Journal of Computer Vision 115 (3) (2015) 211–252.

[62] X. Glorot, Y. Bengio, Understanding the difficulty of training deep feedforward neural networks, in: International Conference on Artificial Intelligence and Statistics, 2010, pp. 249–256.

[63] Z. Bylinskii, T. Judd, A. Borji, L. Itti, F. Durand, A. Oliva, A. Torralba, Mit saliency benchmark [Last accessed: July 10th, 2018].
URL http://saliency.mit.edu/

[64] H. R. Tavakoli, A. Borji, J. Laaksonen, E. Rahtu, Exploiting inter-image similarity and ensemble of extreme learners for fixation prediction using deep features, Neurocomputing 244 (2017) 10–18.

[65] X. Huang, C. Shen, X. Boix, Q. Zhao, Salicon: Reducing the semantic gap in saliency prediction by adapting deep neural networks, in: IEEE International Conference on Computer Vision, 2015, pp. 262–270.

[66] C. L. Thomas, Opensalicon: An open source implementation of the salicon saliency model, Tech. Rep. TR-2016-02, University of Pittsburgh (2016) [Last accessed: July 10th, 2018].
URL https://arxiv.org/pdf/1606.00110.pdf

[67] J. Harel, C. Koch, P. Perona, Graph-based visual saliency, in: Advances in Neural Information Processing Systems, 2006.
[68] J. Zhang, S. Sclaroff, Saliency detection: A boolean map approach, in: IEEE International Conference on Computer Vision, 2013, pp. 153–160.

[69] J. Krause, M. Stark, J. Deng, L. Fei-Fei, 3d object representations for fine-grained categorization, in: 4th International IEEE Workshop on 3D Representation and Recognition (3dRR-13), at ICCV, 2013.

[70] A. Khosla, N. Jayadevaprakash, B. Yao, L. Fei-Fei, Novel dataset for fine-grained image categorization, in: First Workshop on Fine-Grained Visual Categorization at CVPR, 2011.

[71] K. Pearson, Note on regression and inheritance in the case of two parents, Proceedings of the Royal Society of London 58 (1895) 240–242.

[72] M. Jiang, S. Huang, J. Duan, Q. Zhao, Salicon: Saliency in context, in: Conference on Computer Vision and Pattern Recognition, 2015, pp. 1072–1080.