

# Interpretable and Fine-Grained Visual Explanations for Convolutional Neural Networks

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## Abstract

To verify and validate networks, it is essential to gain insight into their decisions, limitations as well as possible shortcomings of training data. In this work, we propose a post-hoc, optimization based visual explanation method, which highlights the evidence in the input image for a specific prediction. Our approach is based on a novel technique to defend against adversarial evidence (i.e. faulty evidence due to artefacts) by filtering gradients during optimization. The defense does not depend on human-tuned parameters. It enables explanations which are both fine-grained and preserve the characteristics of images, such as edges and colors. The explanations are interpretable, suited for visualizing detailed evidence and can be tested as they are valid model inputs. We qualitatively and quantitatively evaluate our approach on a multitude of models and datasets.

## 1. Introduction

Convolutional Neural Networks (CNNs) have proven to produce state-of-the-art results on a multitude of vision benchmarks, such as ImageNet [34], Caltech [12] or Cityscapes [9] which led to CNNs being used in numerous real-world systems (*e.g.* autonomous vehicles) and services (*e.g.* translation services). Though, the use of CNNs in safety-critical domains presents engineers with challenges resulting from their black-box character. A better understanding of the inner workings of a model provides hints for improving it, understanding failure cases and it may reveal shortcomings of the training data. Additionally, users generally trust a model more when they understand its decision process and are able to anticipate or verify outputs [30].

To overcome the interpretation and transparency disadvantage of black-box models, post-hoc explanation meth-

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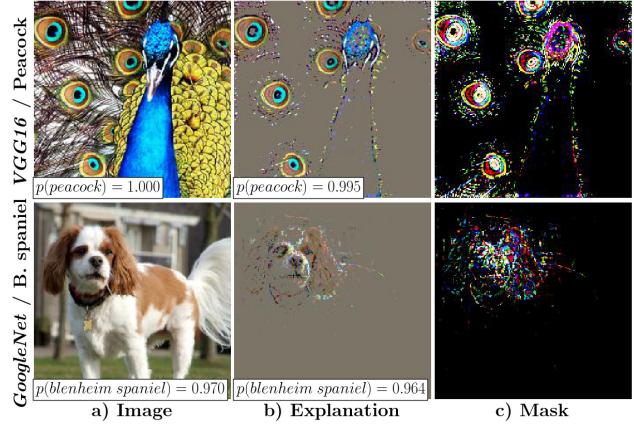


Figure 1: Fine-grained explanations computed by removing irrelevant pixels. a) Input image with softmax score  $p(c_{ml})$  of the most-likely class. Our method tries to find a sparse mask (c) with irrelevant pixels set to zero. The resulting explanation (b), *i.e.*: ‘image  $\times$  mask’, is optimized in the image space and, thus, can directly be used as model input. The parameter  $\lambda$  is optimized to produce an explanation with a softmax score comparable to the image.

ods have been introduced [53, 35, 42, 49, 32, 17, 11]. These methods provide explanations for individual predictions and thus help to understand on which evidence a model bases its decisions. The most common form of explanations are visual, image-like representations, which depict the important pixels or image regions in a human interpretable manner.

In general, an explanation should be easily interpretable (Sec. 4.1). Additionally, a visual explanation should be class discriminative and fine-grained [35] (Sec. 4.2). The latter property is particularly important for classification tasks in the medical [20, 18] domain, where fine structures (*e.g.* capillary hemorrhages) have a major influence on the classification result (Sec. 5.2). Besides, the importance of different color channels should be captured, *e.g.* to uncover

a color bias in the training data (Sec. 4.3).

Moreover, explanations should be faithful, meaning they accurately explain the function of the black-box model [35]. To evaluate the faithfulness (Sec. 5.1), recent work [35, 32, 7] introduce metrics which are based on model predictions of explanations. To be able to compute such metrics without having to rely on proxy measures [35], it is beneficial to employ explanation methods which directly generate valid model inputs (*e.g.* a perturbed version of the image).

A major concern of optimization based visual explanation methods is adversarial evidence, *i.e.* faulty evidence generated by artefacts introduced in the computation of the explanation. Therefore, additional constraints or regularizations are used to prevent such faulty evidence [17, 11, 14]. A drawback of these defenses are added hyperparameters and the necessity of either a reduced resolution of the explanation or a smoothed explanation (Sec. 3.2), thus, they are not well suited for displaying fine-grained evidence.

Our main contribution is a new adversarial defense technique which selectively filters gradients in the optimization which would lead to adversarial evidence otherwise (Sec. 3.2). Using this defense, we extend the work of [17] and propose a new fine-grained visual explanation method (FGVis). The proposed defense is not dependend on hyperparameters and is the key to produce fine-grained explanations (Fig. 1) as no smoothing or regularizations are necessary. Like other optimization-based approaches, FGVis computes a perturbed version of the original image, in which either all irrelevant or the most relevant pixels are removed. The resulting explanations (Fig 1 b) are valid model inputs and their faithfulness can, thus, be directly verified (as in methods from [17, 14, 6, 11]). Moreover, they are additionally fine-grained (as in methods from [35, 38, 48, 42]). To the best of our knowledge, this is the first method to be able to produce fine-grained explanations directly in the image space. We evaluate our defense (Sec. 3.2) and FGVis (Sec. 4 and 5) qualitatively and quantitatively.

## 2. Related Work

Various methods to create explanations have been introduced. Thang *et al.* [50] and DU *et al.* [13] provide a survey of these. In this section, we give an overview of explanation methods which generate visual, image-like explanations.

**Backpropagation Based Methods (BBM).** These methods generate an importance measure for each pixel by backpropagating an error signal to the image. Simonyan *et al.* [38], which build on work of Baehrens *et al.* [5], use the derivative of a class score with respect to the image as an importance measure. Similar methods have been introduced in Zeiler *et al.* [48] and Springenberg *et al.* [42], which additionally manipulate the gradient when backpropagating through ReLU nonlinearities. Integrated Gradients [43] additionally accumulates gradients along a path

from a base image to the input image. SmoothGrad [40] and VarGrad [1] visually sharpen explanations by combining multiple explanations of noisy copies of the image. Other BBMs such as Layer-wise Relevance Propagation [4], DeepLift [37] or Excitation Backprop [49] utilize top-down relevancy propagation rules. BBMs are usually fast to compute and produce fine-grained importance/relevancy maps. However, these maps are generally of low quality [11, 14] and are less interpretable. To verify their faithfulness it is necessary to apply proxy measures or use pre-processing steps, which may falsify the result.

**Activation Based Methods (ABM).** These approaches use a linear combination of activations from convolutional layers to form an explanation. Prominent methods of this category are CAM (Class Activation Mapping) [53] and its generalizations Grad-CAM [35] and Grad-CAM++ [7]. These methods mainly differ in how they calculate the weights of the linear combination and what restrictions they impose on the CNN. Extensions of such approaches have been proposed in Selvaraju *et al.* [35] and Du *et al.* [14], which combine ABMs with backpropagation or perturbation based approaches. ABMs generate easy to interpret heat-maps which can be overlaid on the image. However, they are generally not well suited to visualize fine-grained evidence or color dependencies. Additionally, it is not guaranteed that the resulting explanations are faithful and reflect the decision making process of the model [14, 35].

**Perturbation Based Methods (PBM).** Such approaches perturb the input and monitor the prediction of the model. Zeiler *et al.* [48] slide a grey square over the image and use the change in class probability as a measure of importance. Several approaches are based on this idea, but use other importance measures or occlusion strategies. Pet- siuk *et al.* [32] use randomly sampled occlusion masks and define importance based on the expected model score over masks. LIME [33] uses a super-pixel based occlusion strategy and a surrogate model to compute importance scores. Further super-pixel or segment based methods are introduced in Seo *et al.* [36] and Zhou *et al.* [52]. The so far mentioned approaches do not need access to the internal state or structure of the model. Though, they are often quite time consuming and only generate coarse explanations.

Other PBMs generate an explanation by optimizing for a perturbed version of the image [11, 17, 14, 6]. The perturbed image  $\mathbf{e}$  is defined by  $\mathbf{e} = \mathbf{m} \cdot \mathbf{x} + (1 - \mathbf{m}) \cdot \mathbf{r}$ , where  $\mathbf{m}$  is a mask,  $\mathbf{x}$  the input image, and  $\mathbf{r}$  a reference image containing little information (Sec. 3.1). To avoid adversarial evidence, these approaches need additional regularizations [17], constrain the explanation (*e.g.* optimize for a coarse mask [6, 17, 14]), introduce stochasticity [17], or utilize regularizing surrogate models [11]. These approaches generate easy to interpret explanations in the image space, which are valid model inputs and faithful (*i.e.* a faithfulness

measure is incorporated in the optimization).

Our method also optimizes for a perturbed version of the input. Compared to existing approaches we propose a new adversarial defense technique which filters gradients during optimization. This defense does not need hyperparameters which have to be fine-tuned. Besides, we optimize each pixel individually, thus, the resulting explanations have no limitations on the resolution and are fine-grained.

### 3. Explaining Model Predictions

Explanations provide insights into the decision-making process of a model. The most universal form of explanations are *global* ones which characterize the overall model behavior. *Global* explanations specify for all possible model inputs the corresponding output in an intuitive manner. A decision boundary plot of a classifier in a low-dimensional vector space, for example, represents a *global* explanation. For high-dimensional data and complex models, it is practically impossible to generate such explanations. Current approaches therefore utilize *local* explanations<sup>1</sup>, which focus on individual inputs. Given one data point, these methods highlight the evidence on which a model bases its decisions. As outlined in Sec. 2, the definition of highlighting depends on the used explanation method. In this work, we follow the paradigm introduced in [17] and directly optimize for a perturbed version of the input image. Such an approach has several advantages: 1) The resulting explanations are interpretable due to their image-like nature; 2) Explanations represent valid model inputs and are thus testable; 3) Explanations are optimized to be faithful. In Sec. 3.1 we briefly review the general paradigm of optimization based explanation methods before we introduce our novel adversarial defense technique in Sec. 3.2.

#### 3.1. Perturbation based Visual Explanations

Following the paradigm of optimization based explanation methods, which compute a perturbed version of the image [17, 14, 6, 11], an explanation can be defined as:

**Explanation by Preservation:** The smallest region of the image which must be retained to preserve the original model output (*i.e.* minimal sufficient evidence).

**Explanation by Deletion:** The smallest region of the image which must be deleted to change the model output.

To formally derive an explanation method based on this paradigm, we assume that a CNN  $f_{cnn}$  is given which maps an input image  $\mathbf{x} \in \mathbb{R}^{3 \times H \times W}$  to an output  $\mathbf{y}_x = f_{cnn}(\mathbf{x}; \theta_{cnn})$ . The output  $\mathbf{y}_x \in \mathbb{R}^C$  is a vector representing the softmax scores  $y_x^c$  of the different classes  $c$ . Given an input image  $\mathbf{x}$ , an explanation  $\mathbf{e}_{c_T}^*$  of a target class  $c_T$  (*e.g.* the most-likely class  $c_T = c_{ml}$ ) is computed by removing either relevant (*deletion*) or irrelevant, not supporting

<sup>1</sup>For the sake of brevity, we will use the term explanations as a synonym for *local* explanations throughout this work.

$c_T$ , information (*preservation*) from the image. Since it is not possible to remove information without replacing it, and we do not have access to the image generating process, we have to use an approximate removal operator [17]. A common approach is to use a mask based operator  $\Phi$ , which computes a weighted average between the image  $\mathbf{x}$  and a reference image  $\mathbf{r}$ , using a mask  $\mathbf{m}_{c_T} \in [0, 1]^{3 \times H \times W}$ :

$$\mathbf{e}_{c_T} = \Phi(\mathbf{x}, \mathbf{m}_{c_T}) = \mathbf{x} \cdot \mathbf{m}_{c_T} + (1 - \mathbf{m}_{c_T}) \cdot \mathbf{r}. \quad (1)$$

Common choices for the reference image are constant values (*e.g.* zero), a blurred version of the original image, Gaussian noise, or sampled references of a generative model [17, 14, 6, 11]. In this work, we take a zero image as reference. In our opinion, this reference produces the most pleasing visual explanations, since irrelevant image areas are set to zero<sup>2</sup> (Fig. 1) and not replaced by other structures. In addition, the zero image (and random image) carry comparatively little information and lead to a model prediction with a high entropy. Other references, such as a blurred version of the image, usually result in lower prediction entropies, as shown in Sec. A3.1. Due to the additional computational effort, we have not considered model-based references as proposed in Chang *et al.* [6].

In addition, a similarity metric  $\varphi(y_x^{c_T}, y_e^{c_T})$  is needed, which measures the consistency of the model output generated by the explanation  $y_e^{c_T}$  and the output of the image  $y_x^{c_T}$  with respect to a target class  $c_T$ . This similarity metric should be small if the explanation preserves the output of the target class and large if the explanation manages to significantly drop the probability of the target class [17]. Typical choices for the metric are the cross-entropy with the class  $c_T$  as a hard target [24] or the negative softmax score of the target class  $c_T$ . The similarity metric ensures that the explanation remains faithful to the model and thus accurately explains the function of the model, this property is a major advantage of PBMs.

Using the mask based definition of an explanation with a zero image as reference ( $\mathbf{r} = \mathbf{0}$ ) as well as the similarity metric, a *preserving explanation* can be computed by:

$$\begin{aligned} \mathbf{e}_{c_T}^* &= \mathbf{m}_{c_T}^* \cdot \mathbf{x}, \\ \mathbf{m}_{c_T}^* &= \arg \min_{\mathbf{m}_{c_T}} \{\varphi(y_x^{c_T}, y_e^{c_T}) + \lambda \cdot \|\mathbf{m}_{c_T}\|_1\}. \end{aligned} \quad (2)$$

We will refer to the optimization in Eq. 2 as the *preservation game*. Masks (Fig. 2/b2)<sup>3</sup> generated by this game are sparse (*i.e.* many pixels are zero / appear black; enforced by minimizing  $\|\mathbf{m}_{c_T}\|_1$ ) and only contain large values at most important pixels. The corresponding explanation is computed by multiplying the mask with the image (Fig. 2/c2).

<sup>2</sup>Tensors  $\mathbf{x}, \mathbf{e}, \mathbf{r}$  are assumed to be normalized according to the training of the CNN. A value of zero for these thus corresponds to a grey color (*i.e.* the color of the data mean).

<sup>3</sup>Fig. 2/b2: Figure 2, column b, 2nd row

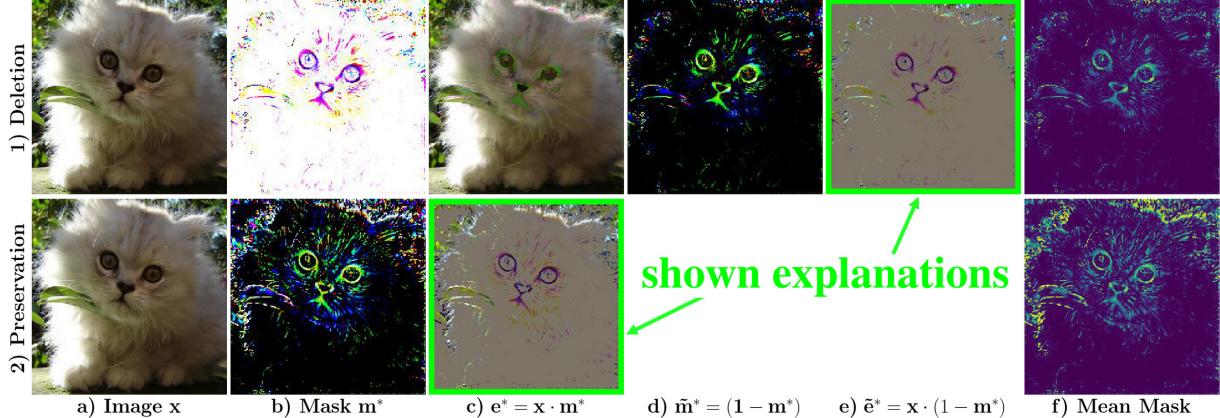


Figure 2: Visualization types calculated for VGG using *deletion / preservation game*. For the *reception / generation game* the same characteristics hold. Subscript  $c_T$  omitted to ease readability. a) Input image. b) Mask obtained by the optimization. Colors in a *deletion* mask are complementary to the image colors. c) Explanation directly obtained by the optimization. d) Complementary mask with a true-color representation for the *deletion game*. e) Explanation highlighting the important evidence for the *deletion game*. f) Mean mask: mask / comp. mask averaged over colors. — To underline important evidence, we use  $e$  for the explanation of the *preservation / generation game* and  $\tilde{e}$  for the *deletion / repression game*.

Alternatively, we can compute a *deleting explanation* using:

$$\begin{aligned} e_{c_T}^* &= \mathbf{m}_{c_T}^* \cdot \mathbf{x}, \\ \mathbf{m}_{c_T}^* &= \arg \max_{\mathbf{m}_{c_T}} \{\varphi(y_x^{c_T}, y_e^{c_T}) + \lambda \cdot \|\mathbf{m}_{c_T}\|_1\}. \end{aligned} \quad (3)$$

This optimization will be called *deletion game* henceforward. Masks (Fig. 2/b1) generated by this game contain mainly ones (*i.e.* appear white; enforced by maximizing  $\|\mathbf{m}_{c_T}\|_1$  in Eq. 3) and only small entries at pixels, which provide the most prominent evidence for the target class. The colors in a mask of the *deletion game* are complementary to the image colors. To obtain a true-color representation analogous to the *preservation game*, one can alternatively visualize the complementary mask (Fig. 2/d1):  $\tilde{\mathbf{m}}_{c_T}^* = (1 - \mathbf{m}_{c_T}^*)$ . A resulting explanation of the *deletion game*, as defined in Eq. 3, is visualized in Fig. 2/c1. This explanation is visually very similar to the original image as only a few pixels need to be deleted to change the model output. In the remaining of the paper for better visualization, we depict a modified version of the explanation for the *deletion game*:  $\tilde{e}_{c_T}^* = \mathbf{x} \cdot (1 - \mathbf{m}_{c_T}^*)$ . This explanation has the same properties as the one of the *preservation game*, *i.e.* it only highlights the important evidence. We observe that the *deletion game* generally produces sparser explanations compared to the *preservation game*, as less pixels have to be removed to delete evidence for a class than to maintain evidence by preserving pixels.

To solve the optimization in Eq. 2 and Eq. 3, we utilize Stochastic Gradient Descent and start with an explanation  $\mathbf{e}_{c_T}^0 = \mathbf{1} \cdot \mathbf{x}$  identical to the original image (*i.e.* a mask initialized with ones). As an alternative initialization of the masks, we additionally explore a zero initialization  $\mathbf{m}_{c_T}^0 = \mathbf{0}$ . In this setting the initial explanation contains

no evidence towards any class and the optimization iteratively has to add relevant (*generation game*) or irrelevant, not supporting the class  $c_T$ , information (*reception game*). The visualizations of the *generation game* are equivalent to those of the *preservation game*, the same holds for the *deletion* and *reception game*. In our experiments the *deletion game* produces the most fine-grained and visually pleasing explanations. Compared to the other games it usually needs the least amount of optimization iterations since we start with  $\mathbf{m}_{c_T}^0 = \mathbf{1}$  and comparatively few mask values have to be changed to delete the evidence for the target class. A comparison and additional characteristics of the four optimization settings (*i.e.* games) are included in Sec. A3.5.

### 3.2. Defending against Adversarial Evidence

CNNs have been proven susceptible to adversarial images [45, 19, 27], *i.e.* a perturbed version of a correctly classified image crafted to fool a CNN. Due to the computational similarity of adversarial methods and optimization based visual explanation approaches, adversarial noise is also a concern for the latter methods and one has to ensure that an explanation is based on true evidence present in the image and not on false adversarial evidence introduced during optimization. This is particularly true for the *generation/reception game* as their optimization start with  $\mathbf{m}_{c_T}^0 = \mathbf{0}$  and iteratively adds information.

[17] and [11] showed the vulnerability of optimization based explanation methods to adversarial noise. To avoid adversarial evidence, explanation methods use stochastic operations [17], additional regularizations [17, 11], optimize on a low-resolution mask with upsampling of the computed mask [17, 14, 6], or utilize a regularizing surrogate

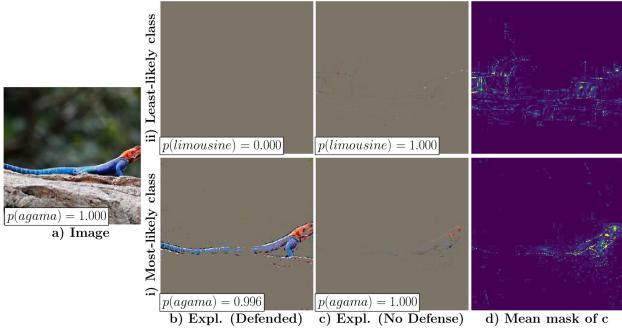


Figure 3: Explanations computed for the adversarial class *limousine* and the predicted class *agama* using the *generation game* and *VGG16* with and without our adversarial defense. An adversarial for class *limousine* can only be computed without the defense. d) Mean mask enhanced by a factor of 7 to show small adversarial structures.

model [11]. In general, these operations impede the generation of adversarial noise by obscuring the gradient direction in which the model is susceptible to false evidence, or by constraining the search space for potential adversarials. These techniques help to reduce adversarial evidence, but also introduce new drawbacks: 1) Defense capabilities usually depend on human-tuned parameters; 2) Explanations are limited to being low resolution and/or smooth, which prevents fine-grained evidence from being visualized.

**A novel Adversarial Defense.** To overcome these drawbacks, we propose a novel adversarial defense which filters gradients during backpropagation in a targeted way. The basic idea of our approach is: A neuron within a CNN is only allowed to be activated by the explanation  $\mathbf{e}_{c_T}$  if the same neuron was also activated by the original image  $\mathbf{x}$ . If we regard neurons as indicators for the existence of features (*e.g.* edges, object parts, …), the proposed constraint enforces that the explanation  $\mathbf{e}_{c_T}$  can only contain features which exist at the same location in the original image  $\mathbf{x}$ . By ensuring that the allowed features in  $\mathbf{e}_{c_T}$  are a subset of the features in  $\mathbf{x}$  it prevents the generation of new evidence.

This defense technique can be integrated in the introduced explanation methods via an optimization constraint:

$$\begin{cases} 0 \leq h_i^l(\mathbf{e}_{c_T}) \leq h_i^l(\mathbf{x}), & \text{if } h_i^l(\mathbf{x}) \geq 0, \\ 0 \geq h_i^l(\mathbf{e}_{c_T}) \geq h_i^l(\mathbf{x}), & \text{otherwise,} \end{cases} \quad (4)$$

where  $h_i^l$  is the activation of the  $i$ -th neuron in the  $l$ -th layer of the network after the nonlinearity. For brevity, the index  $i$  references one specific feature at one spatial position in the activation map. This constraint is applied after all nonlinearity-layers (*e.g.* ReLU-Layers) of the network, besides the final classification layer. It ensures that the absolute value of activations can only be reduced towards values representing lower information content (we assume that zero activations have the lowest information as commonly

applied in network pruning [22]). To solve the optimization with subject to Eq. 4, one could incorporate the constraints via a penalty function in the optimization loss. The drawback is one additional hyperparameter. Alternatively, one could add an additional layer  $\bar{h}_i^l$  after each nonlinearity which ensures the validity of Eq. 4:

$$\begin{aligned} \bar{h}_i^l(\mathbf{e}_{c_T}) &= \min(bu, \max(bl, h_i^l(\mathbf{e}_{c_T}))), \\ bu &= \max(0, h_i^l(\mathbf{x})), \\ bl &= \min(0, h_i^l(\mathbf{x})), \end{aligned} \quad (5)$$

where  $h_i^l(\mathbf{e}_{c_T})$  is the actual activation of the original nonlinearity-layer and  $\bar{h}_i^l(\mathbf{e}_{c_T})$  the adjusted activation after ensuring the bounds  $bu$ ,  $bl$  of the original input. For instance, for a ReLU nonlinearity, the upper bound  $bu$  is equal to  $h_i^l(\mathbf{x})$  and the lower bound  $bl$  is zero. We are not applying this method as it changes the architecture of the model which we try to explain. Instead, we clip gradients in the backward pass of the optimization, which lead to a violation of Eq. 4. This is equivalent to adding an additional clipping-layer after each nonlinearity which acts as the identity in the forward pass and uses the gradient update of Eq. 5 in the backward pass. When backpropagating an error-signal  $\bar{\gamma}_i^l$  through the clipping-layer, the gradient update rule for the resulting error  $\gamma_i^l$  is defined by:

$$\gamma_i^l = \bar{\gamma}_i^l \cdot [h_i^l(\mathbf{e}_{c_T}) \leq bu] \cdot [h_i^l(\mathbf{e}_{c_T}) \geq bl], \quad (6)$$

where  $[\cdot]$  is the indicator function and  $bl$ ,  $bu$  the bounds computed in Eq. 5. This clipping only affects the gradients of the similarity metric  $\varphi(\cdot, \cdot)$  which are propagated through the network. The proposed gradient clipping does not add hyperparameters and keeps the original structure of the model during the forward pass. Compared to other adversarial defense techniques ([11], [17], [6]), it imposes no constraint on the explanation (*e.g.* resolution/smoothness constraints), enabling fine-grained explanations.

**Validating the Adversarial Defense.** To evaluate the performance of our defense, we compute an explanation for a class  $c_A$  for which there is no evidence in the image (*i.e.* it is visually not present). We approximate  $c_A$  with the least-likely class  $c_{ll}$  considering only images which yield very high predictive confidence for the true class  $p(c_{true}) \geq 0.995$ . Using  $c_{ll}$  as the target class, the resulting explanation method without defense is similar to an adversarial attack (the *Iterative Least-Likely Class Method* [27]).

A correct explanation for the adversarial class  $c_A$  should be “empty” (*i.e.* grey), as seen in Fig. 3 b, top row, when using our adversarial defense. If, on the other hand, the explanation method is susceptible to adversarial noise, the optimization procedure should be able to perfectly generate an explanation for any class. This behavior can be seen in Fig. 3 c, top row. The shown explanation for the adversarial

Model	No Defense	Defended
<i>VGG16</i> [39]	100.0 %	0.2 %
<i>AlexNet</i> [26]	100.0 %	0.0 %
<i>ResNet50</i> [23]	100.0 %	0.0 %
<i>GoogleNet</i> [44]	100.0 %	0.0 %

Table 1: Ratio how often an adversarial class  $c_A$  was generated, using the *generation game* with no sparsity loss on *VGG16* with and without our defense.

class ( $c_A$ : *limousine*) contains primarily artificial structures and is classified with a probability of 1 as *limousine*.

We also depict the explanation of the predicted class ( $c_{pred}$ : *agama*). The explanation with our defense results in a meaningful representation of the *agama* (Fig. 3 b, bottom row); without defense (Fig. 3 c/d, bottom row) it is much more sparse. As there is no constraint to change pixel values arbitrarily, we assume the algorithm introduces additional structures to produce a sparse explanation.

A quantitative evaluation of the proposed defense is reported in Tab. 1. We generate explanations for 1000 random ImageNet validation images and use a class  $c_A$  as the explanation target<sup>4</sup>. To ease the generation of adversarial examples, we set the sparsity loss to zero and only use the similarity metric which tries to maximize the probability of the target class  $c_A$ . Without an employed defense technique, the optimization is able to generate an adversarial explanation for 100% of the images. Applying our defense (Eq. 6), the optimization nearly never was able to do so. The two adversarial examples generated in *VGG16* have a low confidence, so we assume that there has been some evidence for the chosen class  $c_A$  in the image. Our proposed technique is thus well suited to defend against adversarial evidence.

## 4. Qualitative Results

Implementation details are stated in Sec. A2.

### 4.1. Interpretability

**Comparison of methods.** Using the *deletion game* we compute mean explanation masks for *GoogleNet* and compare these in Fig. 5 with state-of-the-art methods. Our method delivers the most fine-grained explanation by deleting important pixels of the target object. Especially explanations b), f), and g) are coarser and, therefore, tend to include background information not necessary to be deleted to change the original prediction. The majority of pixels highlighted by FGVis form edges of the object. This cannot be seen in other methods. The explanations from c) and d) are most similar to ours. However, our masks are computed to directly produce explanations which are viable network

<sup>4</sup>For  $c_A$  we used the least-likely class, as described before. We use the second least-likely class, if the least-likely class coincidentally matches the predicted class for the zero image.

inputs and are, therefore, verifiable — The deletion of the highlighted pixels prevents the model from correctly predicting the object. This statement does not necessarily hold for explanations calculated with methods c) and d).

**Architectural insights.** As first noted in [31] explanations using backpropagation based approaches show a grid-like pattern for ResNet. In general, [31] demonstrate that the network structure influences the visualization and assume that for ResNet the skip connections play an important role in their explanation behavior. As shown in Fig 6 this pattern is also visible in our explanations to an even finer degree. Interestingly, the grid pattern is also visible to a lesser extent outside the object. A detailed investigation of this phenomenon is left for future research. See A3.4 for a comparison of explanations between models.

### 4.2. Class Discriminative / Fine-Grained

Visual explanation methods should be able to produce class discriminative (*i.e.* focus on one object) and fine-grained explanations [35]. To test FGVis with respect to these properties, we generate explanations for images containing two objects. The objects are chosen from highly different categories to ensure little overlapping evidence. In Fig. 4, we visualize explanations of three such images, computed using the *deletion game* and *GoogleNet*. Additional results can be found in Sec. A3.2.

FGVis is able to generate class discriminative explanations and only highlights pixels of the chosen target class. Even partially overlapping objects, as the elkhound and ball in Fig. 4, first row, or the bridge and schooner in Fig. 4,

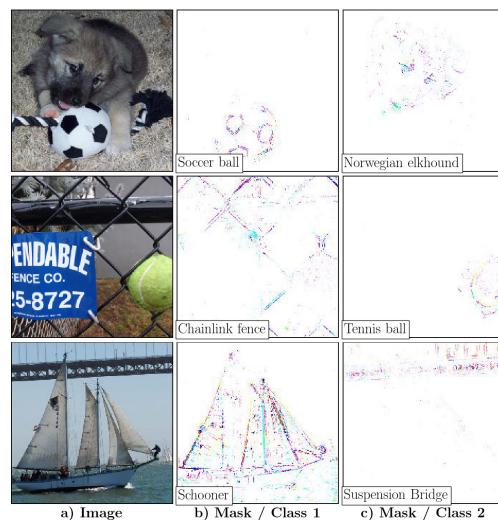


Figure 4: Explanation masks for images with multiple objects computed using the *deletion game* and *GoogleNet*. FGVis produces class discriminating explanations, even when objects partially overlap. Additionally, FGVis is able to visualize fine-grained details down to the pixel level.

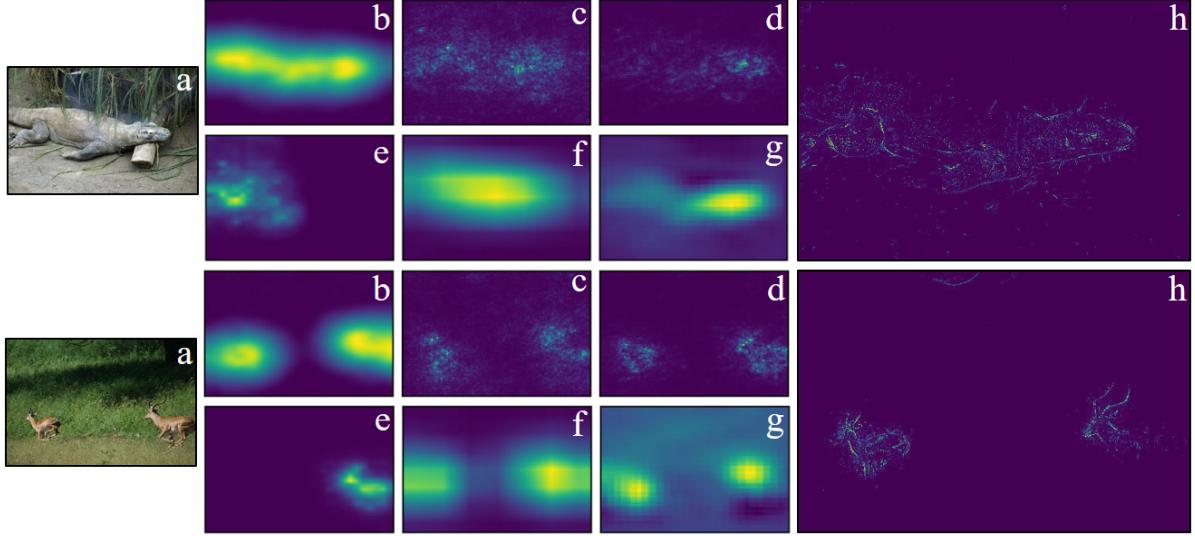


Figure 5: Comparison of mean explanation masks: a) Image, b) BBMP [17], c) Gradient [38], d) Guided Backprop [42] , e) Contrastive Excitation Backprop [49], f) Grad-CAM [35], g) Occlusion [48], h) FGVis (ours). The masks of all reference methods are based on work by [17]. Due to our detailed and sparse masks, we plot them in a larger size.

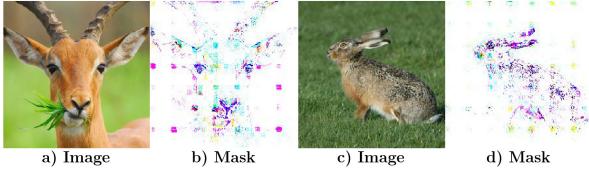


Figure 6: Visual explanations computed using the *deletion game* for *ResNet50*. The masks (b, d) show a grid-like pattern, as also observed in [31] for *ResNet50*.

third row, are correctly discriminated. One major advantage of FGVis is its ability to visualize fine-grained details. This property is especially visible in Fig 4, second row, which shows an explanation for the target class fence. Despite the fine structure of the fence, FGVis is able to compute a precise explanation which mainly contains fence pixels.

### 4.3. Investigating Biases of Training Data

An application of explanation methods is to identify a bias in the training data. Especially for safety-critical, high-risk domains (*e.g.* autonomous driving), such a bias can lead to failures if the model does not generalize to the real world.

**Learned objects.** One common bias is the coexistence of objects in images which can be depicted using FGVis. In Sec. A3.3, we describe such a bias in ImageNet for sports equipment appearing in combination with players.

**Learned color.** Objects are often biased towards specific colors. FGVis can give a first visual indication for the importance of different color channels. We investigate if a *VGG16* model trained on ImageNet shows such a bias using the *preservation game*. We focus on images of school

buses and minivans and compare explanations (Fig. 7; all correctly predicted images in Fig. A6 and A8). Explanations of minivans focus on edges, not consistently preserving the color compared to school buses with yellow dominating those explanations. This is a first indication for the importance of color for the prediction of school buses.

To verify the qualitative finding, we quantitatively give an estimation of the color bias. As an evaluation we swap each of the three color channels *BGR* to either *RBG* or *GRB* and calculate the ratio of maintained true classifications on the validation data after the swap. For minivans 83.3% (averaged over *RBG* and *GRB*) of the 21 correctly classified images keep their class label, for school buses it is only 8.3% of 42 images. For 80 ImageNet classes at least 75% of images are no longer truly classified after the color swap. We show the results for the most and least affected 19 classes and minivan / school bus in Tab. A3.

To the best of our knowledge, FGVis is the first method used to highlight color channel importance.

## 5. Quantitative Results

### 5.1. Faithfulness of Explanations

The faithfulness of generated visual explanations to the underlying neural network is an important property of explanation methods [35]. To quantitatively compare the faithfulness of methods, Petsiuk *et al.* [32] proposed causal metrics which do not depend on human labels. These metrics are not biased towards human perception and are thus well suited to verify if an explanation correctly represents the evidence on which a model bases its prediction.

We use the deletion metric [32] to evaluate the faith-

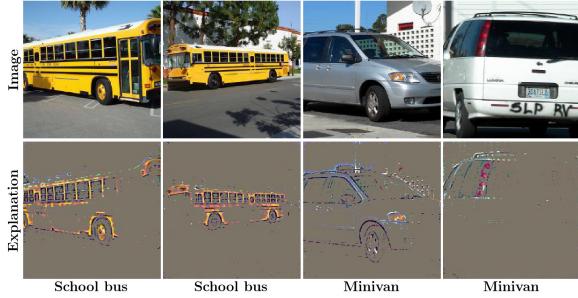


Figure 7: Explanations computed using the *preservation game* for *VGG16*. Explanations of the class minivan focus on edges, hardly preserving the color, compared to the class school bus, with yellow dominating the explanations.

fulness of explanations generated by our method. This metric measures how the removal of evidence effects the prediction of the used model. The metric assumes that an importance map is given, which ranks all image pixels with respect to their evidence for the predicted class  $c_{ml}$ . By iteratively removing important pixels from the input image and measuring the resulting probability of the class  $c_{ml}$  a deletion curve can be generated, whose *area under the curve* AUC is used as a measure of faithfulness (Sec. A4.1).

In Tab. 2, we report the deletion metric of FGVis, computed on the validation split of ImageNet using different models. We use the *deletion game* to generate masks  $\mathbf{m}_{ml}$ , which determine the importance of each pixel. A detailed description of the experiment settings as well as additional figures, can be found in Sec. A4.1. FGVis outperforms the other explanation methods on both models by a large margin. This performance increase can be attributed to the ability of FGVis to visualize fine-grained evidence. All other approaches are limited to coarse explanations, either due to computational constraints or due to the used measures to avoid adversarial evidence. The difference between the two model architectures can most likely be attributed to the superior performance of *ResNet50*, resulting in on average higher softmax scores over all validation images.

Method	<i>ResNet50</i>	<i>VGG16</i>
Grad-Cam [35]	0.1232	0.1087
Sliding Window [48]	0.1421	0.1158
LIME[33]	0.1217	0.1014
RISE [32]	0.1076	0.0980
FGVis (ours)	<b>0.0644</b>	<b>0.0636</b>

Table 2: Deletion metric computed on the ImageNet validation dataset (lower is better). The results for all reference methods were taken from Petsiuk *et al.* [32].

## 5.2. Visual explanation for medical images

We evaluate FGVis on a real-world use case to identify regions in eye fundus images which lead a CNN to classify

the image as being affected with referable diabetic retinopathy (RDR). Using the *deletion game* we derive a weakly-supervised approach to detect RDR lesions. The setup, used network, as well as details on the disease and training data are described in A4.2. To evaluate FGVis, the DiaretDB1 dataset [25] is used containing 89 fundus images with different lesion types, ground truth marked by four experts. To quantitatively judge the performance, we compare in Tab. 3 the image level sensitivity of detecting if a certain lesion type is present in an image. The methods [54, 28, 21, 29] use supervised approaches on image level without reporting a localization. [51] propose an unsupervised approach to extract salient regions. [18] use a comparable setting to ours applying CAM [53] in a weakly-supervised way to highlight important regions. To decide if a lesion is detected, [18] suggest an overlap of 50% between proposed regions and ground truth. As our explanation masks are fine-grained and the ground truth is coarse, we compare using a 25% overlap and for completeness report a 50% overlap.

It is remarkable that FGVis performs comparable or outperforms fully supervised approaches which are designed to detect the presence of one lesion type. The strength of FGVis is especially visible in detecting RSD, as these small lesions only cover some pixels in the image. In Fig. A21 we show fundus images, ground truth and our predictions.

Method	H	HE	SE	RSD
Zhou <i>et al.</i> [54]	94.4	-	-	
Liu <i>et al.</i> [28]	-	83.0	83.0	-
Haloi <i>et al.</i> [21]	<b>96.5</b>	-	-	
Mane <i>et al.</i> [29]	-	-	-	<b>96.4</b>
Zhao <i>et al.</i> [51]	98.1	-	-	
Gondal <i>et al.</i> [18]	97.2	93.3	81.8	50
Ours (25% Overlap)	<b>100</b>	94.7	<b>90.0</b>	88.4
Ours (50% Overlap)	90.5	81.6	80.0	86.0

Table 3: Image level sensitivity in % (higher is better) for four different lesions H, HE, SE, RSD: Hemorrhages, Hard Exudates, Soft Exudates and Red Small Dots.

## 6. Conclusion

We propose a method which generates fine-grained visual explanations in the image space using a novel technique to defend adversarial evidence. Our defense does not introduce hyperparameters. We show the effectiveness of the defense on different models, compare our explanations to other methods, and quantitatively evaluate the faithfulness. Moreover, we underline the strength in producing class discriminative visualizations and point to characteristics in explanations of a *ResNet50*. Due to the fine-grained nature of our explanations, we achieve remarkable results on a medical dataset. Besides, we show the usability of our approach to visually indicate a color bias in training data.

## References

- [1] Julius Adebayo, Justin Gilmer, Ian Goodfellow, and Been Kim. Local explanation methods for deep neural networks lack sensitivity to parameter values. In *Workshop at the International Conference on Learning Representations (ICLR)*, 2018. 2
- [2] Ankita Agrawal, Charul Bhatnagar, and Anand Singh Jalal. A survey on automated microaneurysm detection in diabetic retinopathy retinal images. In *International Conference on Information Systems and Computer Networks (ISCON)*, pages 24–29. IEEE, 2013. 10
- [3] R. Arunkumar and P. Karthigaikumar. Multi-retinal disease classification by reduced deep learning features. *Neural Computing and Applications*, 28(2):329–334, 2017. 10
- [4] Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller, and Wojciech Samek. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PloS one*, 10(7):e0130140, 2015. 2
- [5] David Baehrens, Timon Schroeter, Stefan Harmeling, Motoaki Kawanabe, Katja Hansen, and Klaus-Robert Müller. How to explain individual classification decisions. *Journal of Machine Learning Research*, 11(Jun):1803–1831, 2010. 2
- [6] Chun-Hao Chang, Elliot Creager, Anna Goldenberg, and David Duvenaud. Explaining image classifiers by counterfactual generation. *arXiv e-prints*, page arXiv:1807.08024, Jul 2018. 2, 3, 4, 5
- [7] Aditya Chattpadhyay, Anirban Sarkar, Prantik Howlader, and Vineeth N. Balasubramanian. Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks. In *Winter Conference on Applications of Computer Vision (WACV)*, pages 839–847, 2018. 2
- [8] E. Colas, A. Besse, A. Orgogozo, B. Schmauch, N. Meric, and E. Besse. Deep learning approach for diabetic retinopathy screening. *Acta Ophthalmologica*, 94(S256), 2016. 10
- [9] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3213–3223, 2016. 1
- [10] Jorge Cuadros and George Bresnick. EyePACS: an adaptable telemedicine system for diabetic retinopathy screening. *Journal of Diabetes Science and Technology*, 3(3):509–516, 2009. 10
- [11] Piotr Dabkowski and Yarin Gal. Real time image saliency for black box classifiers. In *Advances in Neural Information Processing Systems (NIPS)*, pages 6967–6976, 2017. 1, 2, 3, 4, 5
- [12] P. Dollár, C. Wojek, B. Schiele, and P. Perona. Pedestrian detection: A benchmark. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2009. 1
- [13] Mengnan Du, Ninghao Liu, and Xia Hu. Techniques for interpretable machine learning. *arXiv e-prints*, page arXiv:1808.00033, Jul 2018. 2
- [14] Mengnan Du, Ninghao Liu, Qingquan Song, and Xia Hu. Towards explanation of dnn-based prediction with guided feature inversion. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1358–1367, 2018. 2, 3, 4
- [15] EyePACS. <https://www.kaggle.com/c/diabetic-retinopathy-detection>. assessed on 2018-09-23, 2015. 10
- [16] EyePACS. <https://www.kaggle.com/c/diabetic-retinopathy-detection/discussion/15617>. assessed on 2018-09-23. 10
- [17] Ruth C. Fong and Andrea Vedaldi. Interpretable explanations of black boxes by meaningful perturbation. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 3429–3437, 2017. 1, 2, 3, 4, 5, 7
- [18] Waleed M. Gondal, Jan M. Köhler, René Grzesick, Gernot A. Fink, and Michael Hirsch. Weakly-supervised localization of diabetic retinopathy lesions in retinal fundus images. In *IEEE International Conference on Image Processing (ICIP)*, pages 2069–2073, 2017. 1, 8, 10
- [19] Ian Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. In *International Conference on Learning Representations (ICLR)*, 2015. 4
- [20] Varun Gulshan, Lily Peng, Marc Coram, Martin C Stumpe, Derek Wu, Arunachalam Narayanaswamy, Subhashini Venugopalan, Kasumi Widner, Tom Madams, Jorge Cuadros, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *Journal of the American Medical Association (JAMA)*, 316(22):2402–2410, 2016. 1, 10
- [21] Mirnal Haloi, Samarendra Dandapat, and Rohit Sinha. A gaussian scale space approach for exudates detection, classification and severity prediction. *arXiv e-prints*, page arXiv:1505.00737, May 2015. 8
- [22] Song Han, Jeff Pool, John Tran, and William Dally. Learning both weights and connections for efficient neural network. In *Advances in Neural Information Processing Systems (NIPS)*, pages 1135–1143, 2015. 5
- [23] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. 6
- [24] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv e-prints*, page arXiv:1503.02531, Mar 2015. 3
- [25] Tomi Kauppi, Valentina Kalesnykiene, Joni-Kristian Kamaraainen, Lasse Lensu, Iiris Sorri, Asta Raninen, Raija Voutilainen, Hannu Uusitalo, Heikki Kälviäinen, and Juhani Pietilä. The DIARETDB1 diabetic retinopathy database and evaluation protocol. In *British Machine Vision Conference (BMVC)*, pages 1–10, 2007. 8, 10
- [26] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NIPS)*, pages 1097–1105, 2012. 6, 1
- [27] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. *arXiv e-prints*, page arXiv:1607.02533, Jul 2016. 4, 5

- [28] Qing Liu, Beiji Zou, Jie Chen, Wei Ke, Kejuan Yue, Zailiang Chen, and Guoying Zhao. A location-to-segmentation strategy for automatic exudate segmentation in colour retinal fundus images. *Computerized Medical Imaging and Graphics*, 55:78–86, 2017. 8
- [29] Vijay M Mane, Ramish B Kawadiwale, and DV Jadhav. Detection of red lesions in diabetic retinopathy affected fundus images. In *IEEE International Advance Computing Conference (IACC)*, pages 56–60, 2015. 8
- [30] Rowan McAllister, Yarin Gal, Alex Kendall, Mark Van Der Wilk, Amar Shah, Roberto Cipolla, and Adrian Vivian Weller. Concrete problems for autonomous vehicle safety: Advantages of Bayesian deep learning. In *International Joint Conferences on Artificial Intelligence (IJCAI)*, 2017. 1
- [31] Weili Nie, Yang Zhang, and Ankit Patel. A theoretical explanation for perplexing behaviors of backpropagation-based visualizations. *arXiv e-prints*, page arXiv:1805.07039, May 2018. 6, 7
- [32] Vitali Petsiuk, Abir Das, and Kate Saenko. Rise: Randomized input sampling for explanation of black-box models. In *British Machine Vision Conference (BMVC)*, 2018. 1, 2, 7, 8, 10
- [33] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. Why should I trust you?: Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1135–1144, 2016. 2, 8
- [34] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet large scale visual recognition challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. 1
- [35] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-CAM: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 618–626, 2017. 1, 2, 6, 7, 8
- [36] Dasom Seo, Kanghan Oh, and Il-Seok Oh. Regional multi-scale approach for visually pleasing explanations of deep neural networks. *arXiv e-prints*, page arXiv:1807.11720, Jul 2018. 2
- [37] Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. Learning important features through propagating activation differences. In *Proceedings of the 34th International Conference on Machine Learning (ICML)*, pages 3145–3153, 2017. 2
- [38] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Deep inside convolutional networks: Visualising image classification models and saliency maps. *International Conference on Learning Representations (ICLR)*, 2014. 2, 7
- [39] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv e-prints*, page arXiv:1409.1556, Sep 2014. 6
- [40] Daniel Smilkov, Nikhil Thorat, Been Kim, Fernanda Viégas, and Martin Wattenberg. Smoothgrad: removing noise by adding noise. *arXiv e-prints*, page arXiv:1706.03825, Jun 2017. 2
- [41] Sharon D. Solomon, Emily Chew, Elia J. Duh, Lucia Sobrin, Jennifer K. Sun, Brian L. VanderBeek, Charles C. Wykoff, and Thomas W. Gardner. Diabetic retinopathy: a position statement by the American diabetes association. *Diabetes care*, 40(3):412–418, 2017. 10, 16
- [42] Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. Striving for simplicity: The all convolutional net. In *International Conference on Learning Representations (ICLR)*, 2015. 1, 2, 7
- [43] Mukund Sundararajan, Ankur Taly, and Qiqi Yan. Axiomatic attribution for deep networks. In *Proceedings of the 34th International Conference on Machine Learning (ICML)*, pages 3319–3328, 2017. 2
- [44] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 6
- [45] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In *International Conference on Learning Representations (ICLR)*, 2014. 4
- [46] Daniel Shu Wei Ting, Carol Yim-Lui Cheung, Gilbert Lim, Gavin Siew Wei Tan, Nguyen D Quang, Alfred Gan, Haslina Hamzah, Renata Garcia-Franco, Ian Yew San Yeo, Shu Yen Lee, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. *Jama*, 318(22):2211–2223, 2017. 10
- [47] Joanne WY Yau, Sophie L. Rogers, Ryo Kawasaki, Ecosse L. Lamoureux, Jonathan W. Kowalski, Toke Bek, Shih-Jen Chen, Jacqueline M. Dekker, Astrid Fletcher, Jakob Grauslund, et al. Global prevalence and major risk factors of diabetic retinopathy. *Diabetes care*, 35(3):556–564, 2012. 10
- [48] Matthew D. Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 818–833, 2014. 2, 7, 8
- [49] Jianming Zhang, Zhe Lin, Jonathan Brandt, Xiaohui Shen, and Stan Sclaroff. Top-down neural attention by excitation backprop. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 543–559, 2016. 1, 2, 7
- [50] Quan-shi Zhang and Song-Chun Zhu. Visual interpretability for deep learning: A survey. *Frontiers of Information Technology & Electronic Engineering*, 19(1):27–39, 2018. 2
- [51] Yitian Zhao, Yalin Zheng, Yifan Zhao, Yonghuai Liu, Zhili Chen, Peng Liu, and Jiang Liu. Uniqueness-driven saliency analysis for automated lesion detection with applications to retinal diseases. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 109–118. Springer, 2018. 8
- [52] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Object Detectors Emerge in Deep Scene CNNs. *arXiv e-prints*, page arXiv:1412.6856, Dec 2014. 2

- [53] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2921–2929, 2016. [1](#), [2](#), [8](#)
- [54] Lei Zhou, Penglin Li, Qi Yu, Yu Qiao, and Jie Yang. Automatic hemorrhage detection in color fundus images based on gradual removal of vascular branches. In *IEEE International Conference on Image Processing (ICIP)*, pages 399–403, 2016. [8](#)

# Interpretable and Fine-Grained Visual Explanations for Convolutional Neural Networks

## -Supplementary Material-

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The supplementary material provides details, additional results, and further comparisons.

### A1. Defending against Adversarial Evidence

Our method produces explanations based on evidence in the image and suppresses hallucination of adversarial evidence. Without our adversarial defense the optimization can produce an explanation for any class (*i.e.* even for a class visually not present in the image).

To illustrate this differently to the experiment reported in Sec. 3.1 (Tab. 1 and Fig. 3), we show an alternative version of the evaluation, only using a black image as input. Fig. A1 shows an explanation for the adversarial class *iguana* with and without defense. For Tab. A1 we create explanations for each of the 998 ImageNet classes, using always the same black input image. We omit the predicted class of the black image and the class of the starting condition (image · zero mask). Without defense an explanation can always be generated due to hallucination of adversarial evidence. The results are comparable to the evaluation in the main paper.

### A2. Implementation Details

Unless otherwise specified, the explanations are computed for the most-likely class using SGD with a learning rate of 0.1, running for 500 iterations. To improve optimization and avoid instabilities, we initialize the masks  $\mathbf{m}$  with noise sampled for each pixel from a uniform distribution  $\mathcal{U}(a, b)$ , with  $\mathcal{U}(0, 0.01)$  for the *generation* and *repression game* and  $\mathcal{U}(0.99, 1)$  for the *preservation* and *deletion game*. We normalize the gradient using its maximum value to avoid large changes of individual mask pixels.

For the similarity metric  $\varphi(\cdot, \cdot)$  we use the cross-entropy

\*contributed while working at BCAI. We additionally thank Volker Fischer, Michael Herman, Anna Khoreva for discussions and feedback.

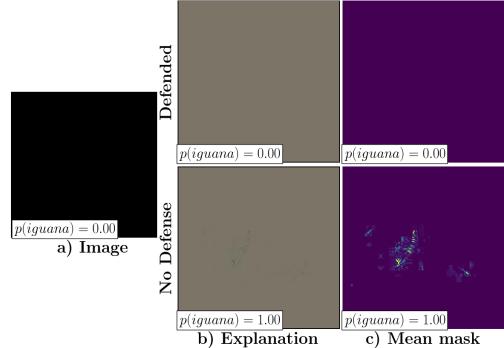


Figure A1: Explanation for the adversarial class *iguana* starting from a black image. An adversarial can only be computed without defense (*generation game*, *GoogleNet*). Mean masks are enhanced by a factor of 10.

Model	<i>GoogleNet</i>	<i>VGG16</i>	<i>AlexNet</i>	<i>ResNet50</i>
No Defense	100 %	100 %	100 %	100 %
Defended	0.0 %	0.1 %	0.1 %	0.0 %

Table A1: How often an adversarial class could be generated from a black image averaged over 998 ImageNet classes (*generation game*,  $\lambda = 0$ ).

for the *generation* and *preservation game* and the negative probability for the *deletion* and *repression game*.

When computing an explanation for the most-likely class, we use a line-search for the parameter  $\lambda$  to determine its optimal value. Unless otherwise noted, we iteratively use 13 equally spaced  $\lambda$  values between  $10^{-4}$  and  $10^{-10}$  and stop when the resulting most-likely class of  $\mathbf{e}_{ml}$  shifts (*deletion* and *repression game*) or achieves the highest probability among all classes (*preservation* and *generation game*). We use images of the ImageNet [26] validation set and pre-trained model weights.

A comparison of resulting masks for different learning rates and  $\lambda$  values for *GoogleNet* computed with the *deletion game* are shown in Fig. A2.

A higher  $\lambda$  value causes sparser masks due to a higher weighting of the sparsity invoking part  $\|\mathbf{m}_{C_T}\|_1$  within the loss function (Eq. 2 and Eq. 3). Especially for higher  $\lambda$  values, the resulting masks are rather independent of the chosen learning rate of the SGD optimization.

### A3. Qualitative Results

#### A3.1. Entropy of Reference Images

FGVis computes explanations  $\mathbf{e}_{c_T}$  by optimizing for a perturbed version of the input image  $\mathbf{x}$ . The perturbation is modelled via a removal operator  $\Phi$  [17, 14, 6, 11], which computes a weighted average between the image  $\mathbf{x}$  and a reference image  $\mathbf{r}$ , using a mask  $\mathbf{m}_{C_T}$ :

$$\mathbf{e}_{c_T} = \Phi(\mathbf{x}, \mathbf{m}_{c_T}) = \mathbf{x} \cdot \mathbf{m}_{c_T} + (1 - \mathbf{m}_{c_T}) \cdot \mathbf{r}. \quad (7)$$

A good reference image  $\mathbf{r}$  should carry little information and lead to a model prediction with a high entropy, meaning, ideally all classes are assigned the same softmax score (see ‘Maximum (1000 classes)’ in Tab. A2 for the resulting maximum entropy). To compare references, we report their entropy for different models in Tab. A2.

For all models except *GoogleNet* the zero image reference has the highest entropy. Interestingly, for the zero image reference, the more recent architectures (*GoogleNet*, *ResNet50*) have a lower entropy. This indicates that these architectures do not assign a roughly equally distributed softmax score to all classes (as *AlexNet* or *VGG16*).

As expected, an increasing noise level  $\sigma_n$  for a Gaussian noise image as well as a decreasing standard deviation of the Gaussian blur filter  $\sigma_b$  reduces the entropy. Only *GoogleNet* does not fully follow this characteristic.

For comparison, we report the entropy for 1000 random ImageNet validation images for the different models.

Due to the high entropy as well as the low computational effort of a zero reference image, we choose this reference

for FGVis.

#### A3.2. Class Discriminative / Fine-Grained

In Fig. A3 and Fig. A4 we show additional explanation masks for images containing two distinct objects. The objects are chosen from highly different categories to ensure little overlapping evidence. The explanations are computed using the *deletion game*, which generates the most pleasing class-discriminative explanations, and *GoogleNet*.

Note that FGVis discriminates well even if the two objects partially overlap. The figures additionally highlight the ability of FGVis to generate fine-grained explanations.

To determine  $\lambda$  we use for the most-likely class the strategy as described in Sec. A2. For the second class  $\lambda$  is optimized to significantly drop the softmax score of this class.

#### A3.3. Investigating Biases of Training Data

**Learned objects.** The coexistence of objects in images often results in a learned bias. In Fig. A5, we visualize such a bias for *GoogleNet* trained on ImageNet.

Sports equipment like hockey pucks or ping-pong balls frequently appear in combination with players. This bias is learned by the neural network and results in explanations that also contain pixels belonging to the players. Without deleting these pixels, the *deletion game* is not able to shift the class of the images.

**Learned color.** We quantitatively verify the color bias reported in Sec. 4.3 and show the 19 classes of ImageNet which are most and least affected by swapping the color in Tab. A3. We swap each of the three color channels *BGR* to either *RGB* or *GRB* and calculate the ratio of maintained true classifications on the validation data after the swap.

Fig. A6 shows explanations for the class school bus computed using the *preservation game* for *VGG*. The yellow color, also visible in the original images (Fig. A7), is dominant in most of the explanations.

Fig. A8 shows explanations for the class minivan computed using the *preservation game* for *VGG*. The original color of the car is not consistently preserved. Especially for

Reference image $\mathbf{r}$	<i>AlexNet</i>	<i>GoogleNet</i>	<i>VGG16</i>	<i>ResNet50</i>
Zero image	6.90	4.08	6.31	5.09
Gaussian noise image ( $\sigma_n = 8$ )	$5.11 \pm 0.16$	$4.62 \pm 0.16$	$5.59 \pm 0.09$	$4.56 \pm 0.14$
Gaussian noise image ( $\sigma_n = 32$ )	$2.61 \pm 0.29$	$4.67 \pm 0.22$	$4.38 \pm 0.23$	$4.07 \pm 0.30$
Blurred ImageNet image ( $\sigma_b = 5$ )	$3.67 \pm 1.12$	$3.15 \pm 1.31$	$4.08 \pm 1.43$	$2.38 \pm 1.58$
Blurred ImageNet image ( $\sigma_b = 10$ )	$4.56 \pm 0.88$	$4.09 \pm 1.08$	$4.83 \pm 0.86$	$3.22 \pm 1.25$
ImageNet image	$1.73 \pm 1.43$	$1.09 \pm 1.14$	$1.06 \pm 1.22$	$0.67 \pm 0.91$
Maximum (1000 classes)	6.91	6.91	6.91	6.91

Table A2: Entropy of reference images  $\mathbf{r}$  for different models. The entropy is averaged over 1000 random instances of each reference image. Gaussian noise images are generated by independently sampling for each pixel from a Gaussian distribution with zero-mean and a standard deviation of  $\sigma_n$ . The blurred ImageNet images are computed using a Gaussian blur filter with a standard deviation of  $\sigma_b$ . For all random references we report the mean  $\pm$  standard deviation of the entropy.

white or grey cars (original images in Fig. A9) the visible color in the explanation is reduced to a greenish-blue color.

Fig. A6 and A8 show all correctly classified images for school bus and minivan.

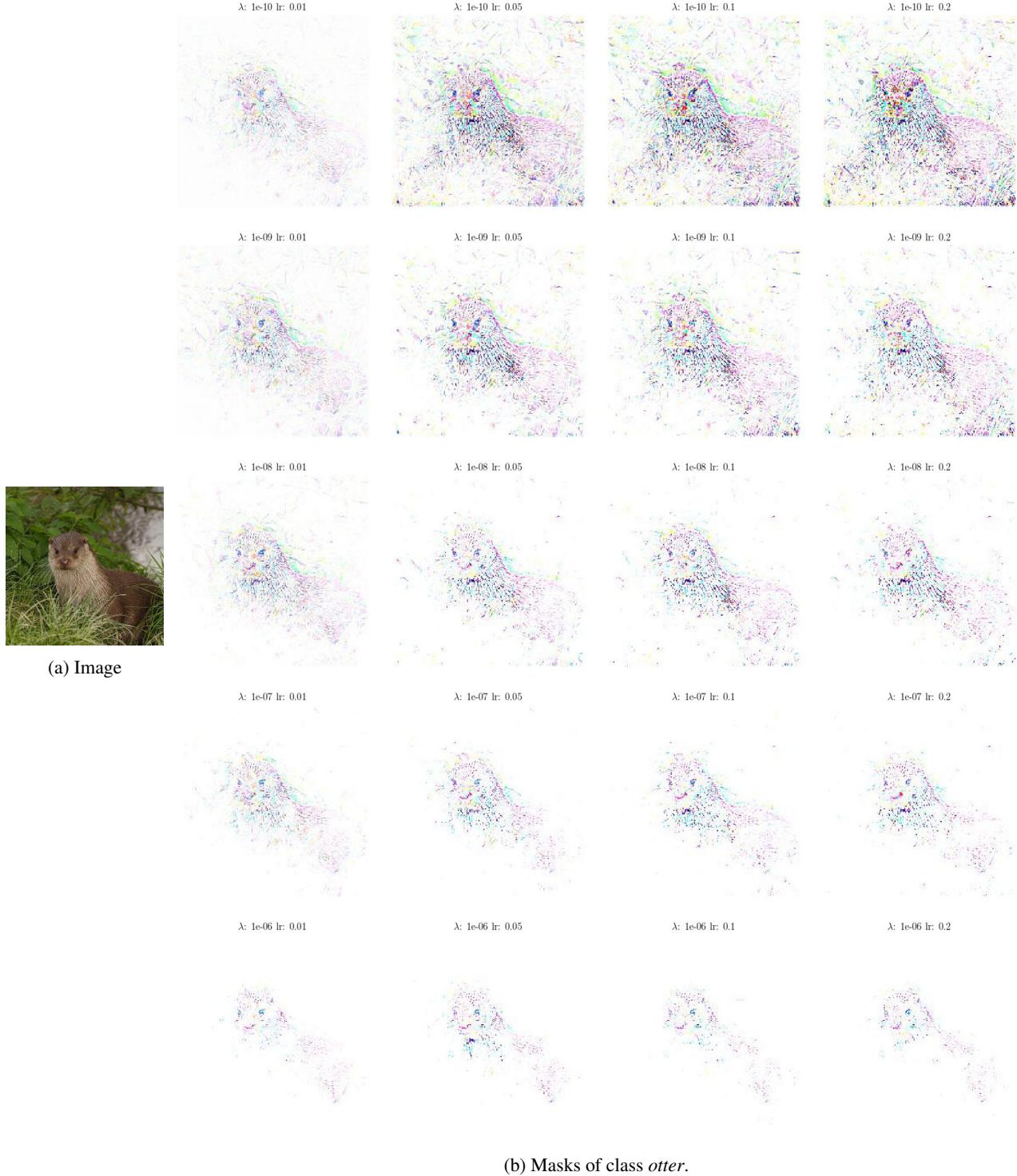


Figure A2: Comparison of resulting masks for different learning rates (lr) and  $\lambda$  values computed using the *deletion game* and *GoogleNet*.

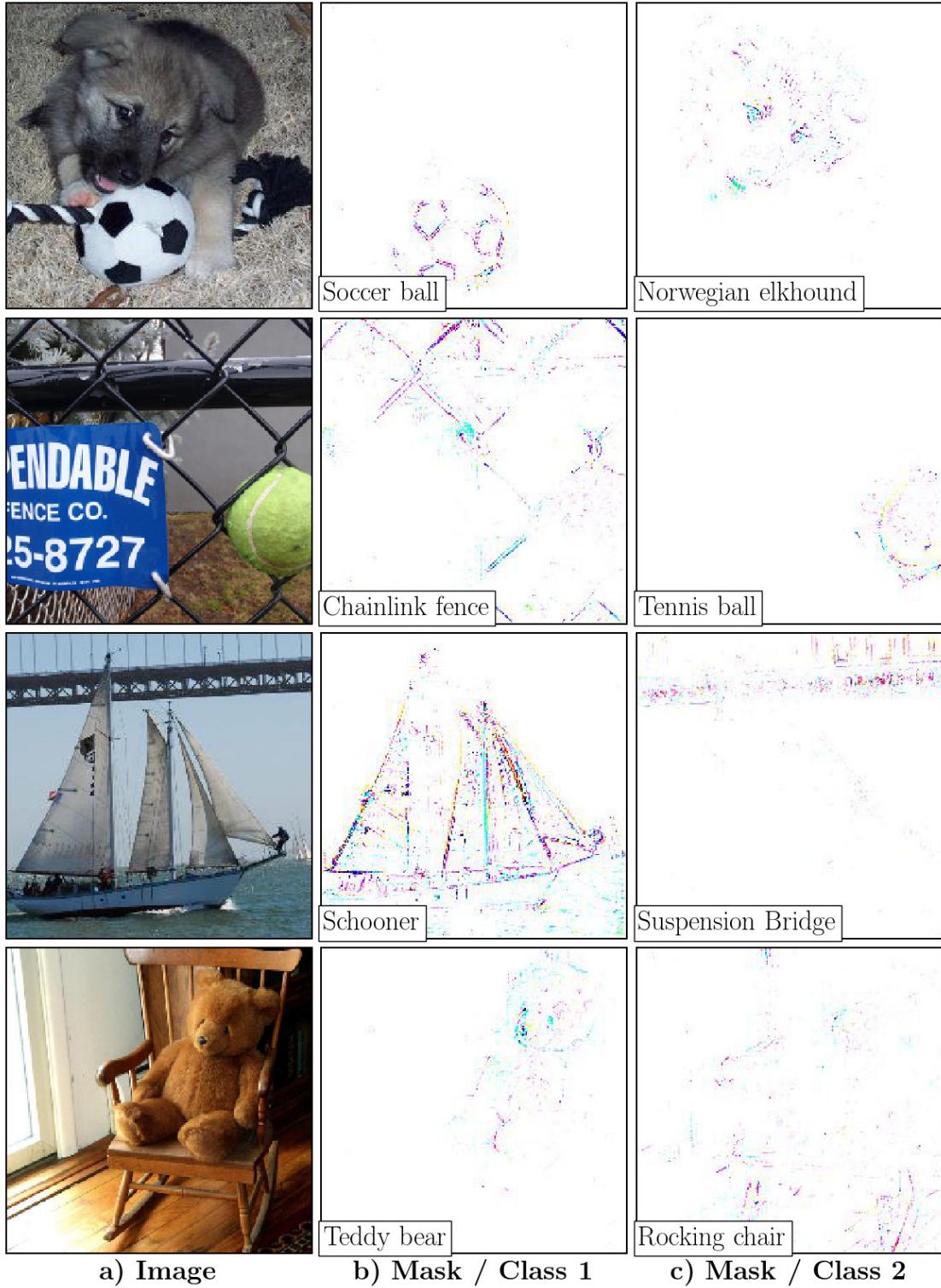


Figure A3: Explanation masks for images with multiple objects computed using the *deletion game* and *GoogleNet*. FGVis produces class discriminative explanations, even when objects partially overlap. Note that objects not belonging to either class, *e.g.* the rug in the top row, the blue sign on the chainlink fence, or the window in the bottom row vanish in the explanation. Additionally, FGVis is able to visualize fine-grained details down to the pixel level.

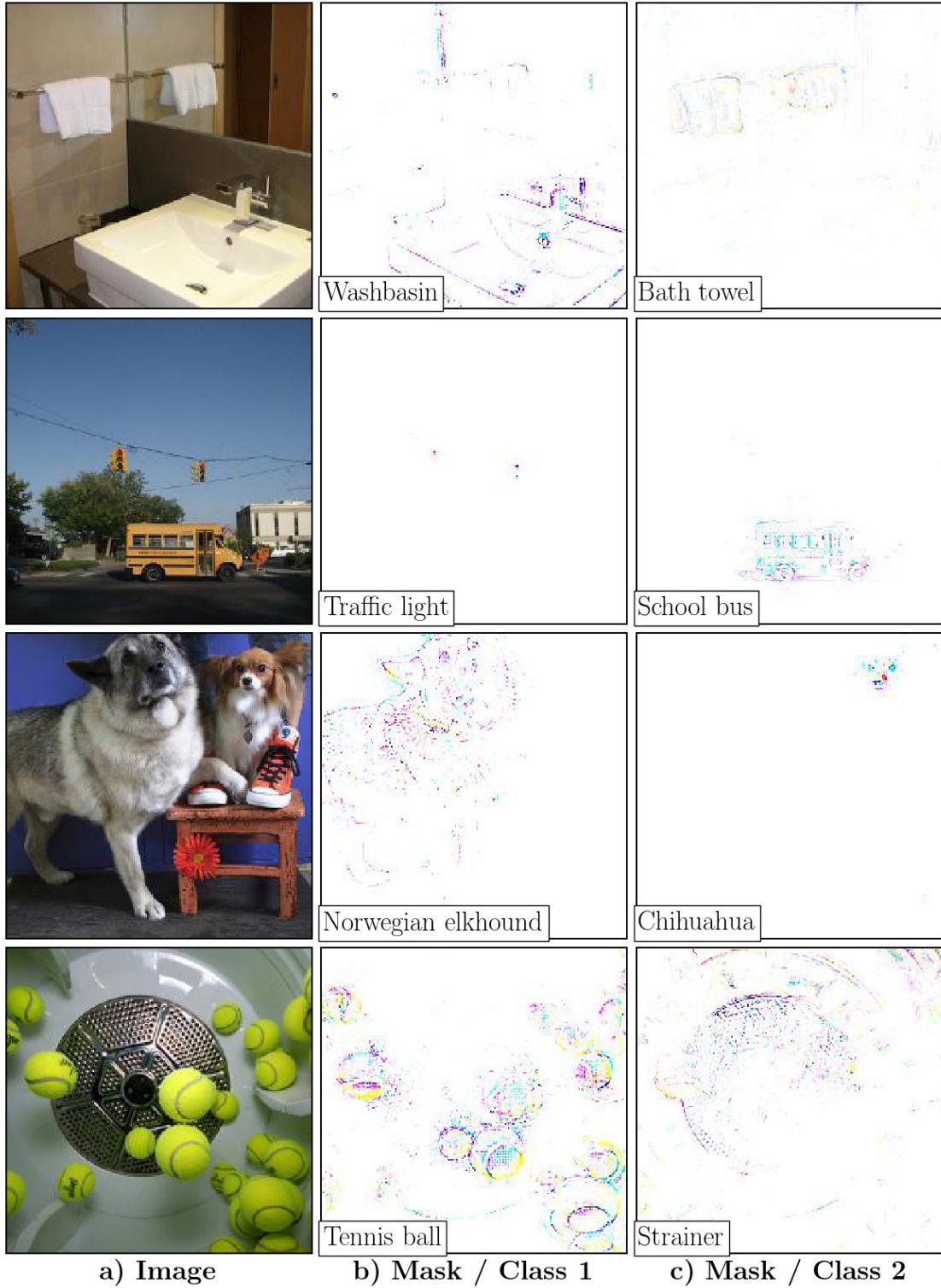


Figure A4: Explanation masks for images with multiple objects computed using the *deletion game* and *GoogleNet*. FGVis produces class discriminative explanations, even when objects partially overlap. This is especially visible in the last row where the tennis balls are almost all removed in the explanation mask for the class strainer.



Figure A5: Visual explanations computed using the *deletion game* for *GoogleNet*. For both classes (hockey puck and ping-pong ball) the explanation method has to additionally delete pixels of the players and the table tennis bat/ice-hockey stick to shift the prediction of the model. This clearly highlights a bias of the data towards images which contain a puck/ball, a player and sports equipment.

ID	Class name	#Images	Avg. RBG, GRB	RBG	GRB
168	redbone	31	0.00 %	0.00 %	0.00 %
964	potpie	28	0.00 %	0.00 %	0.00 %
159	Rhodesian ridgeback	35	0.00 %	0.00 %	0.00 %
930	French loaf	27	0.00 %	0.00 %	0.00 %
234	Rottweiler	42	1.19 %	0.00 %	2.38 %
214	Gordon setter	36	1.39 %	2.78 %	0.00 %
963	pizza, pizza pie	35	1.43 %	2.86 %	0.00 %
950	orange	35	1.43 %	2.86 %	0.00 %
184	Irish terrier	33	1.52 %	0.00 %	3.03 %
962	meat loaf, meatloaf	29	1.72 %	3.45 %	0.00 %
984	rapeseed	47	2.13 %	4.26 %	0.00 %
211	vizsla, Hungarian pointer	35	2.86 %	2.86 %	2.86 %
11	goldfinch, Carduelis carduelis	48	3.12 %	0.00 %	6.25 %
934	hotdog, hot dog, red hot	40	3.75 %	2.50 %	5.00 %
218	Welsh springer spaniel	39	3.85 %	2.56 %	5.13 %
191	Airedale, Airedale terrier	37	5.41 %	5.41 %	5.41 %
163	bloodhound, sleuthhound	18	5.56 %	5.56 %	5.56 %
961	dough	15	6.67 %	0.00 %	13.33 %
263	Pembroke, Pembroke Welsh corgi	41	7.32 %	7.32 %	7.32 %
...	...	...	...	...	...
779	school bus	42	8.33 %	9.52 %	7.14 %
...	...	...	...	...	...
656	minivan	21	83.33 %	71.43 %	95.24 %
...	...	...	...	...	...
528	dial telephone, dial phone	36	95.83 %	91.67 %	100.00 %
866	tractor	37	95.95 %	91.89 %	100.00 %
572	goblet	26	96.15 %	96.15 %	96.15 %
47	African chameleon, Chamaeleo chamaeleon	40	96.25 %	95.00 %	97.50 %
302	ground beetle, carabid beetle	27	96.30 %	96.30 %	96.30 %
463	bucket, pail	27	96.30 %	96.30 %	96.30 %
717	pickup, pickup truck	28	96.43 %	100.00 %	92.86 %
178	Weimaraner	44	96.59 %	93.18 %	100.00 %
669	mosquito net	44	96.59 %	97.73 %	95.45 %
661	Model T	46	96.74 %	97.83 %	95.65 %
769	rule, ruler	36	97.22 %	100.00 %	94.44 %
771	safe	40	97.50 %	97.50 %	97.50 %
829	streetcar, tram, tramcar, trolley, ...	41	97.56 %	97.56 %	97.56 %
713	photocopier	44	97.73 %	100.00 %	95.45 %
916	web site, website, internet site, site	47	97.87 %	100.00 %	95.74 %
423	barber chair	31	98.39 %	96.77 %	100.00 %
190	Sealyham terrier, Sealyham	39	98.72 %	97.44 %	100.00 %
340	zebra	47	100.00 %	100.00 %	100.00 %
545	electric fan, blower	37	100.00 %	100.00 %	100.00 %

Table A3: Ratio of maintained true classifications on the validation data of ImageNet after swapping color channels for the most and least affected 19 classes and minivan / school bus. Each of the three color channels *BGR* are swapped to either *RBG* or *GRB*. The class ID, class name, number of truly classified images before the color swap (#Images) and percentage of maintained classification after the swap for the average over *RBG* or *GRB* and each swap individually are reported. Most color-dependent classes are redbone or potpie. Most color-independent classes zebra or electric fan.



Figure A6: Explanations computed using the *preservation game* for VGG for the class school bus.

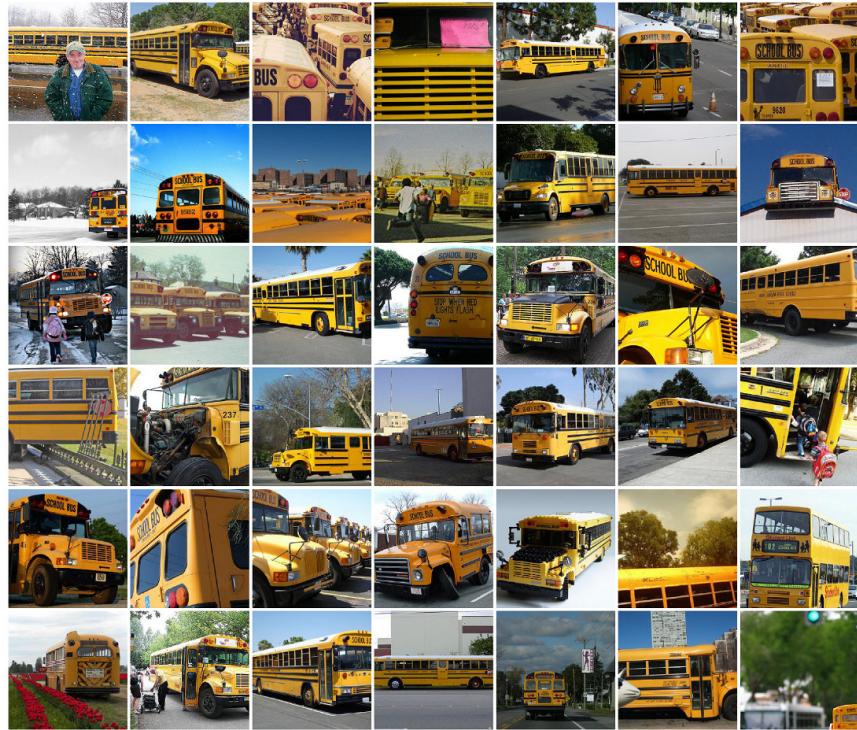


Figure A7: Input images for the explanations in Fig. A6



Figure A8: Explanations computed using the *preservation game* for *VGG* for the class minivan.



Figure A9: Input images for the explanations in Fig. A8

### A3.4. Comparison of Networks

In Fig. A10 and Fig. A11 we compare the mask and explanation for four network architectures (*GoogleNet*, *VGG16*, *AlexNet*, *ResNet50*) using the *deletion game*. Respectively, in Fig. A12 and Fig. A13 we use the *preservation game* for the same comparison.

For all settings the explanations of *ResNet50* and *VGG16* are more dense, meaning more pixels have to be deleted/preserved to change/preserve the class prediction. This could be an indicator that these models are more robust, though, a detailed explanation would require further research. Besides, the grid-like pattern for the explanations from *ResNet50*, described in Sec. 4.1 are visible.

The importance of the color to classify the school bus (described in Sec. 4.3) can be seen in Fig. A13.

For *VGG16* we have observed that the pixels at the image edge are in many cases highlighted in the explanations. Furthermore, *VGG16* shows pronounced edges in the explanation compared to the other networks.

### A3.5. Comparison of Games

In Fig. A14 and A15 the different game types (see Sec. 3.1) are visually compared for *GoogleNet*.

The resulting explanations for the *relegation* and *deletion game* are qualitatively similar. The similarity among the two games is due to both using the same optimization with only a different starting condition  $\mathbf{m} = 0$  for the *relegation* vs.  $\mathbf{m} = 1$  for the *deletion game*. The same observation holds for the *generation / preservation game*.

The explanations of the *relegation* and *deletion game* are more sparse compared to the *generation / preservation game*. This is most likely due to the fact that only small parts of the image need to be suppressed to change the model output (e.g. shifting one breed of dog to another), though, to evoke a certain model output one needs to create sufficient amount of evidence for this class.

During the optimization only class pixels containing evidence towards the target class need to be changed for the *generation* and *deletion game*. After optimization most of the mask values stay zero for the *generation game* and one

for the *deletion game*. The optimized masks are thus similar to its starting conditions.

Vice versa, the opposite holds for the *preservation* and *repression game*.

### A3.6. Further Examples

In Fig. A16, A17, A18, and A19 further explanations computed using FGVis are shown.

## A4. Quantitative Results

### A4.1. Faithfulness of Explanations

To evaluate the faithfulness of our approach, we use the deletion metric of Petsiuk *et al.* [32]. This metric measures how the removal of evidence affects the prediction of the used model. The metric assumes that an importance map is given, which ranks all image pixels with respect to their evidence for the predicted class  $c_{ml}$  (*i.e.* the most-likely class). We use the mean mask (see Sec. A3.5) as the pixel-wise importance map. The mean mask is computed for all images in the ImageNet validation dataset using the *deletion game* with a learning rate of 0.3 and a line-search to determine the  $\lambda$  value. We iteratively use 4 equally spaced  $\lambda$  values between  $10^{-7}$  and  $10^{-10}$  and stop when  $y_e^{ct} < 0.02 \cdot y_x^{ct}$ , where  $y_e^{ct}$  is the softmax score of class  $ct$  given the explanation and  $y_x^{ct}$  the corresponding score given the image.

Using the importance map, the deletion curve is generated by successively removing pixels from the input image according to their importance and measuring the resulting probability of the class  $c_{ml}$  (see Fig. A20c). The removed pixels are set to zero, as proposed in Petsiuk *et al.* [32]. The fraction of removed pixels is increased in increments of 0.25% for the first 100 steps and in increments of 1% for the remaining 75 steps. In Fig. A20b, we visualize for an example image the binary masks used to successively set pixels to zero. For a clearer illustration, we reduced the number of deletion steps in this figure. The deletion metric is computed by measuring the *area under the curve* AUC of the deletion curve (see Fig. A20c) using the trapezoidal rule.

### A4.2. Visual Explanation for Medical Images

**Background of the disease:** As people with diabetes have a high prevalence for RDR [47], a frequent retinal screening is recommended and deep learning algorithms have been successfully developed to classify fundus images ([8], [20], [3], [46]). The black box character of these algorithms can be reduced by visual explanation techniques as shown in [18].

Of the publicly available 88,702 images [15] from Eye-PACS [10], we use 80% for training and 20% for validation for a classifier with binary outcome (referable diabetic retinopathy (RDR) vs. non-RDR) which is later used for

the weakly-supervised localization. We use a similar setup as in [18] to train the binary classifier (RDR vs. non-RDR).

Training was conducted with the same implementation settings as described in [18] using an adopted version of the CNN architecture proposed by [16] for classifying retinal images. We use leaky ReLUs as non-linearities and include batch normalization.

The DiaretDB1 dataset [25] used to evaluate the weakly-supervised localization is a dataset of 89 color fundus images collected at the Kuopio University Hospital, Finland. All images have a resolution of 1500x1152 pixels and are scaled to the input dimension of the model.

The dataset is ground truth marked by four experts. As proposed in [25] we consider pixels as lesions if at least three experts have agreed.

We use FGVis with a fixed  $\lambda = 10^{-10}$  and a learning rate of 0.25 stopping if the softmax score for RDR falls below 10% with a maximum of 500 iterations.

In Fig. A21 retinal images overlaid with the ground truth (top row) are compared to our prediction (bottom row). To be consistent with [18] the masks  $m$  are binarized for better visualization and to be able to quantitatively report the sensitivity (see Tab. 3). Values greater or equal than 4% of the maximum are set to one, the remaining pixels to zero. The predicted pixels in the fine-grained masks  $m$  map to the ground truth. Note that FGVis detects these pixels as they are the important ones to be deleted to reduce the softmax score for RDR.

A medical expert would also look at mutations in the optic disk or blood vessels which additionally are an indicator for the disease [41]. These mutations are also highlighted by our method. They are not labelled in the ground truth markings leading to visual false positives (FPs).

The strength of FGVis to visualize fine-grained structures can be seen in the detection of red small dots (microaneurysm) which are the earliest sign of diabetic retinopathy [2]. As these often merely cover some pixels in the image, it is hard to detect them (zooming in Fig. A21 is necessary to spot these).

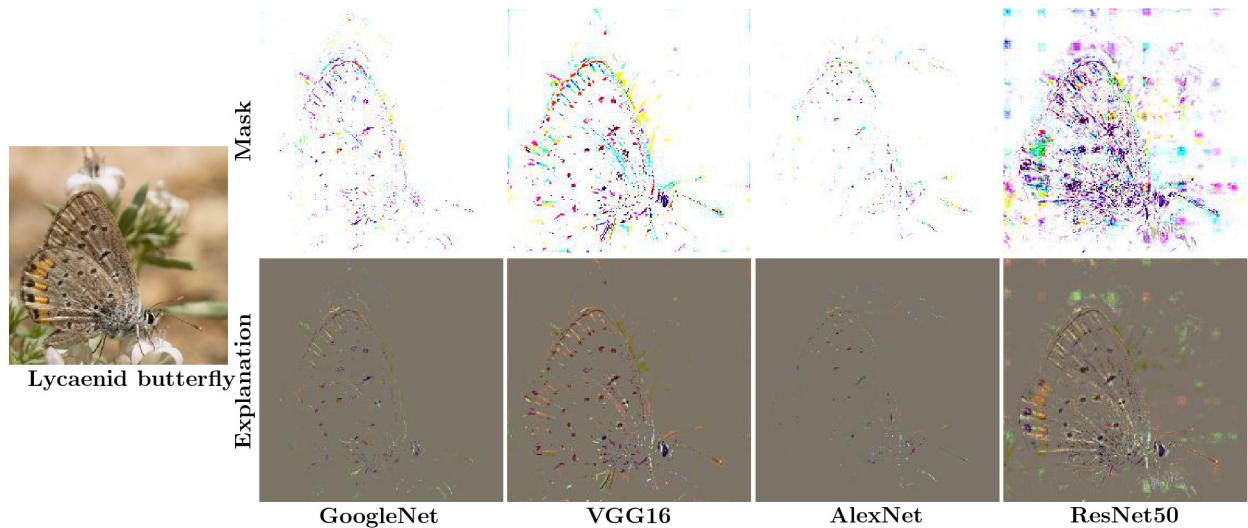


Figure A10: Masks and explanations computed using the *deletion game* for different networks.

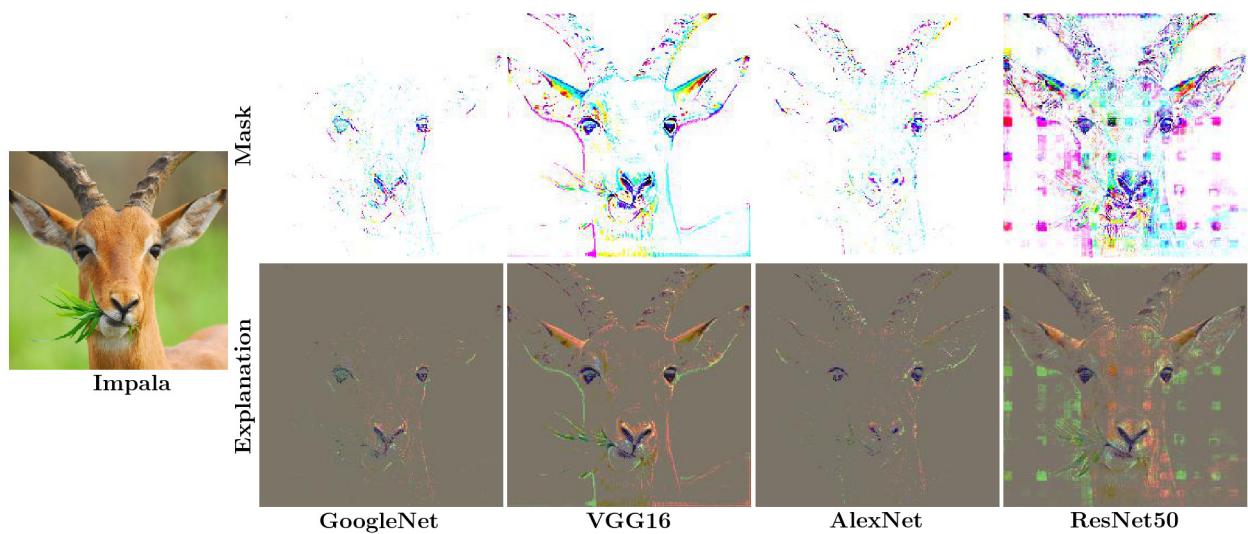


Figure A11: Masks and explanations computed using the *deletion game* for different networks.

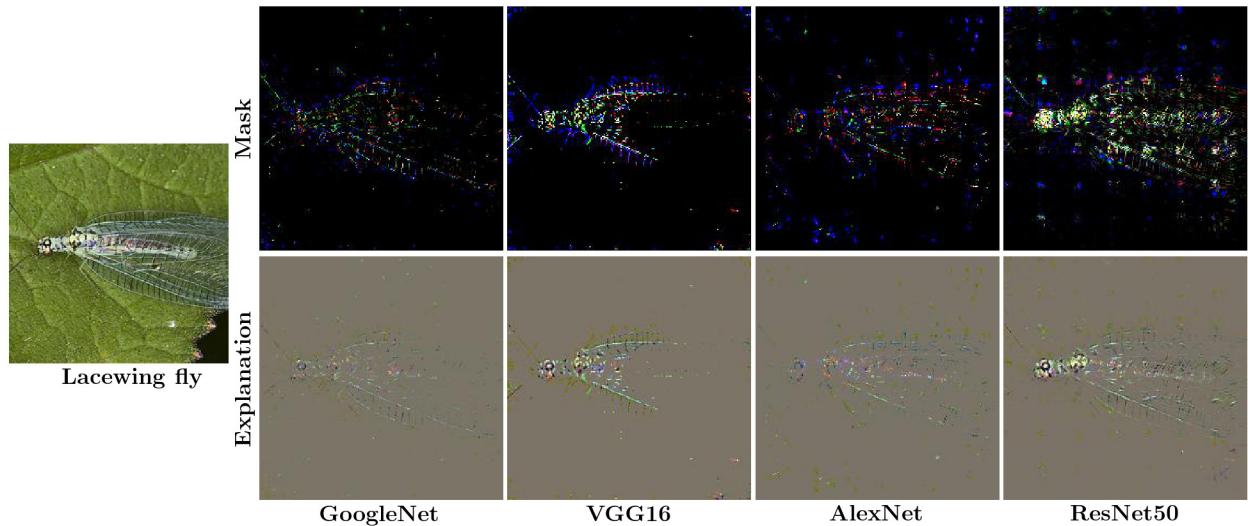


Figure A12: Masks and explanations computed using the *preservation game* for different networks.

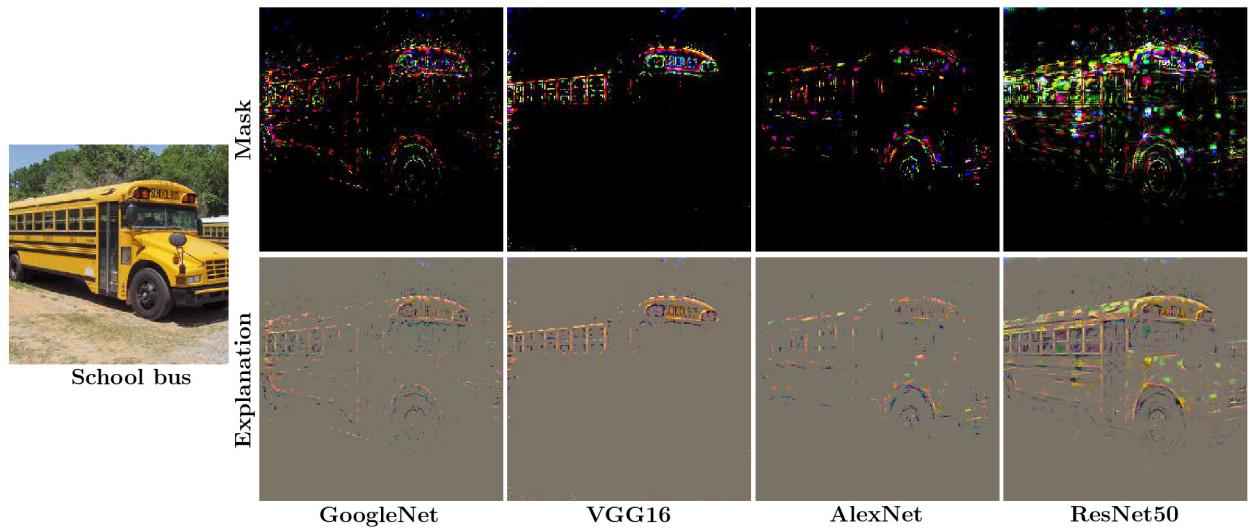


Figure A13: Masks and explanations computed using the *preservation game* for different networks.

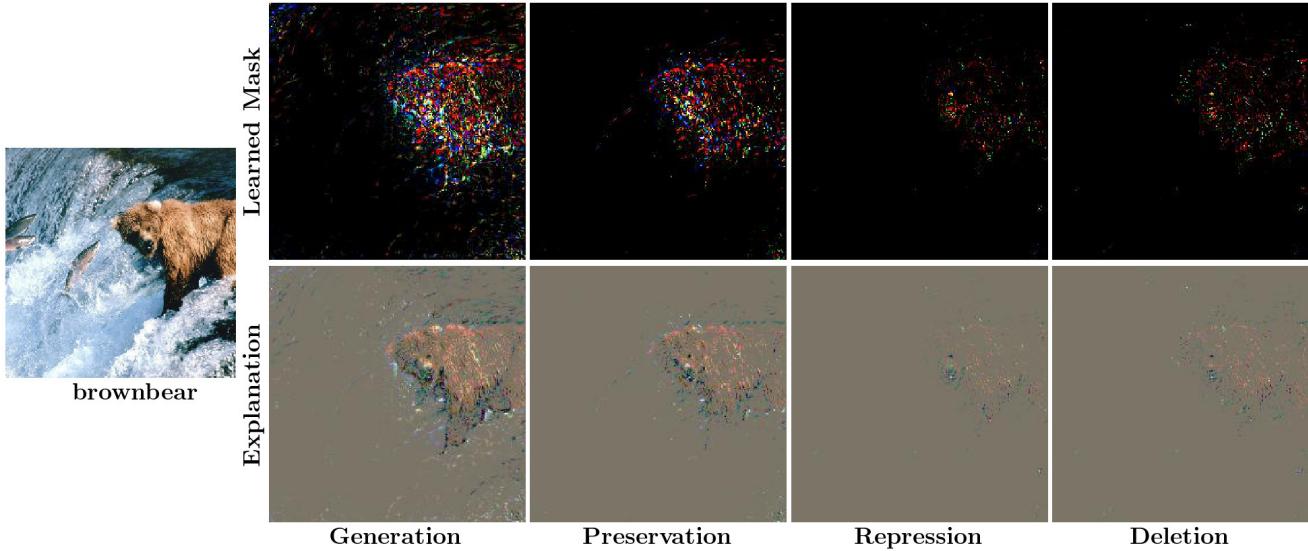


Figure A14: Explanations and masks computed using the different games for *GoogleNet*. For the *repression* and *deletion game* the complementary masks ( $1 - m$ ) are plotted to have true-color representations (see Sec. A3.4).

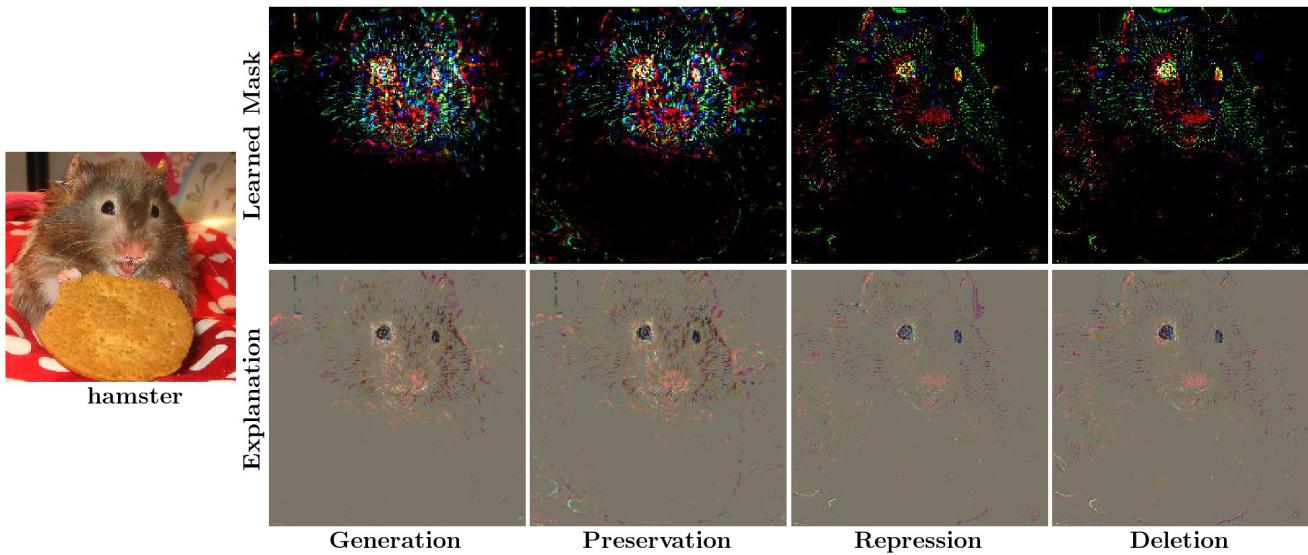


Figure A15: Explanations and masks computed using the different games for *GoogleNet*. For the *repression* and *deletion game* the complementary masks ( $1 - m$ ) are plotted to have true-color representations (see Sec. A3.4).

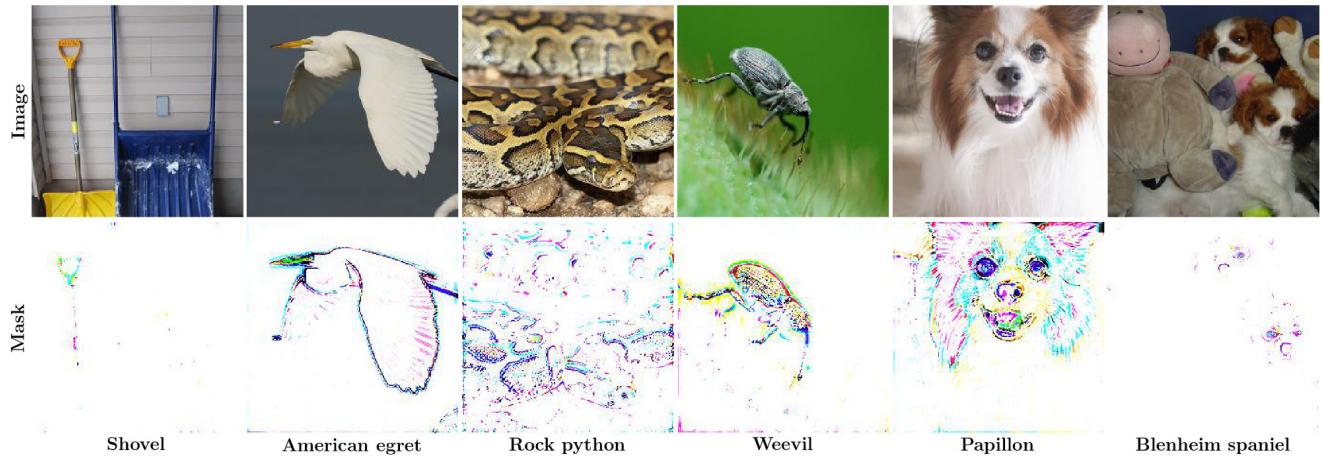


Figure A16: Explanation masks computed using the *relegation game* for VGG16.

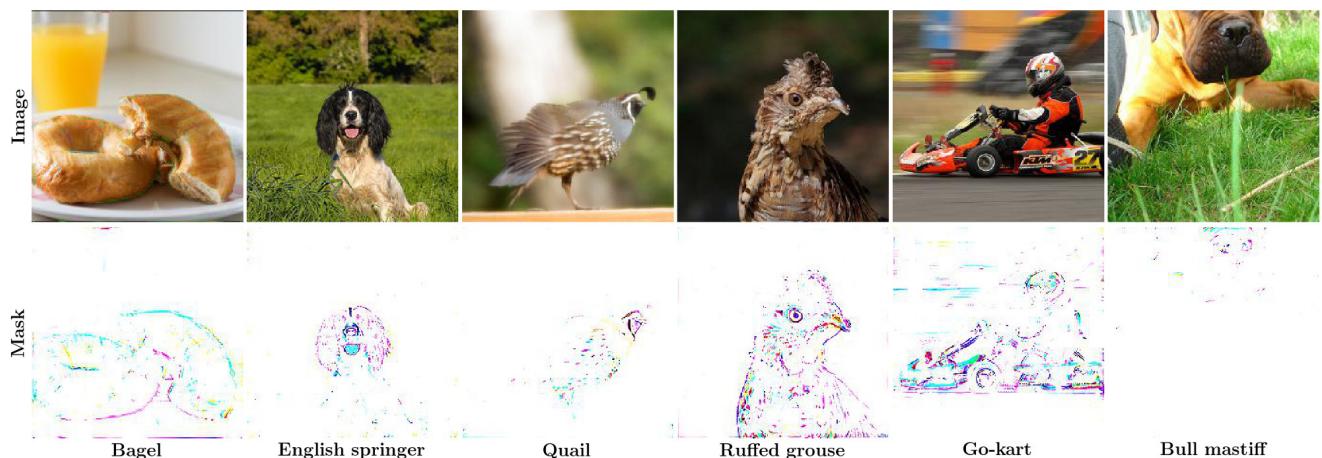


Figure A17: Explanation masks computed using the *relegation game* for VGG16.

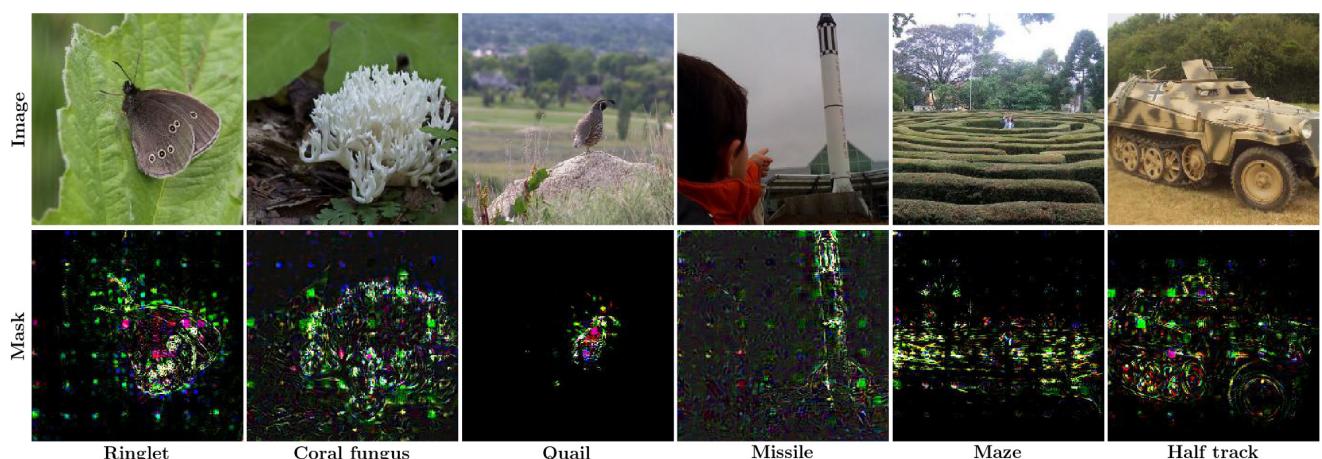


Figure A18: Explanation masks computed using the *preservation game* for ResNet50.

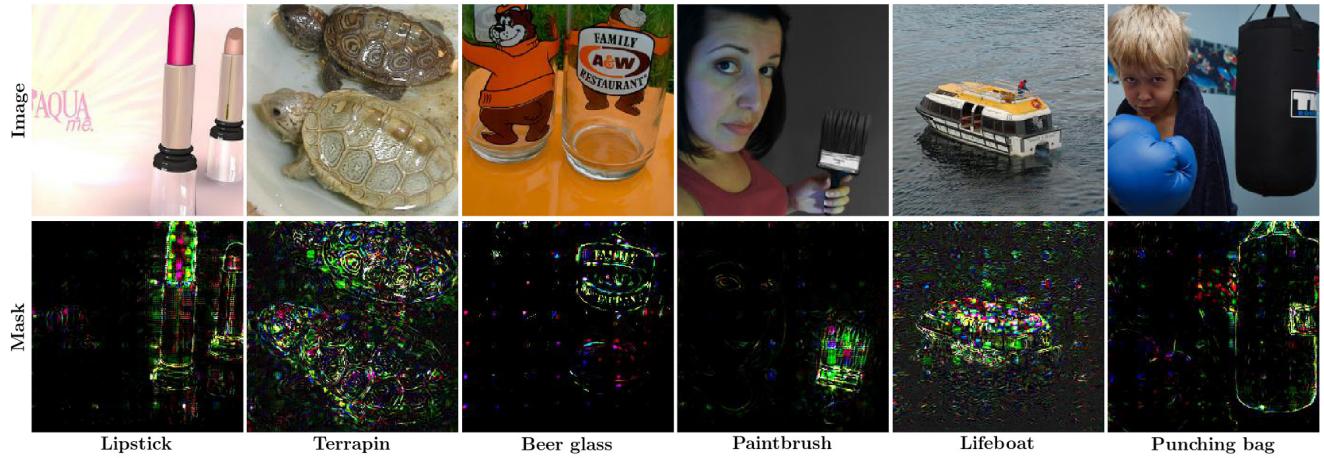


Figure A19: Explanation masks computed using the *preservation game* for ResNet50.

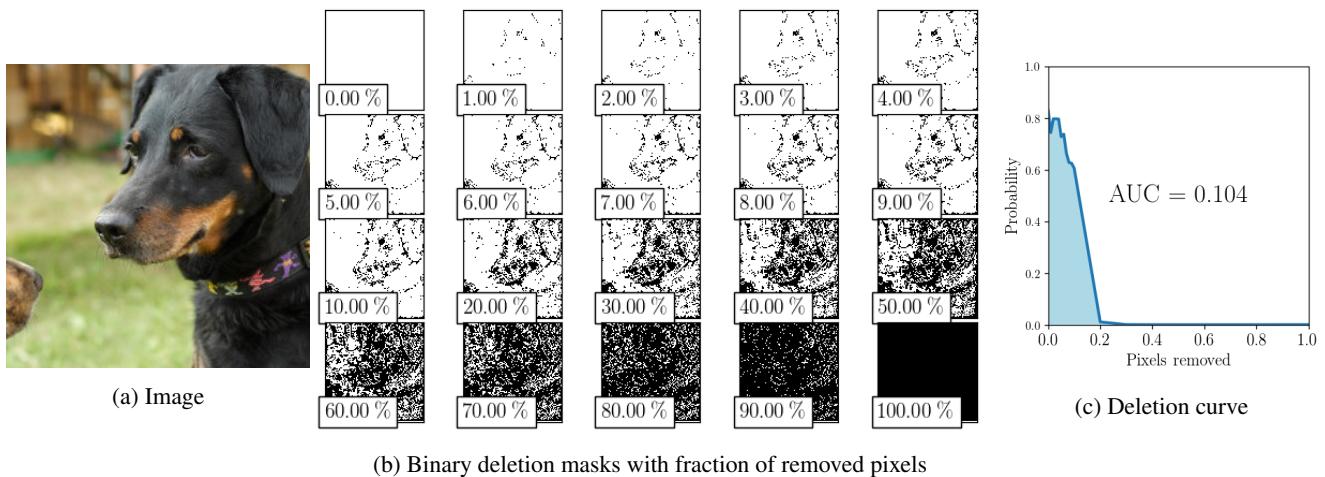


Figure A20: The deletion curve (c) is computed by successively deleting pixels (b) from the image according to their importance and measuring the resulting probability of the class  $c_{ml}$ .

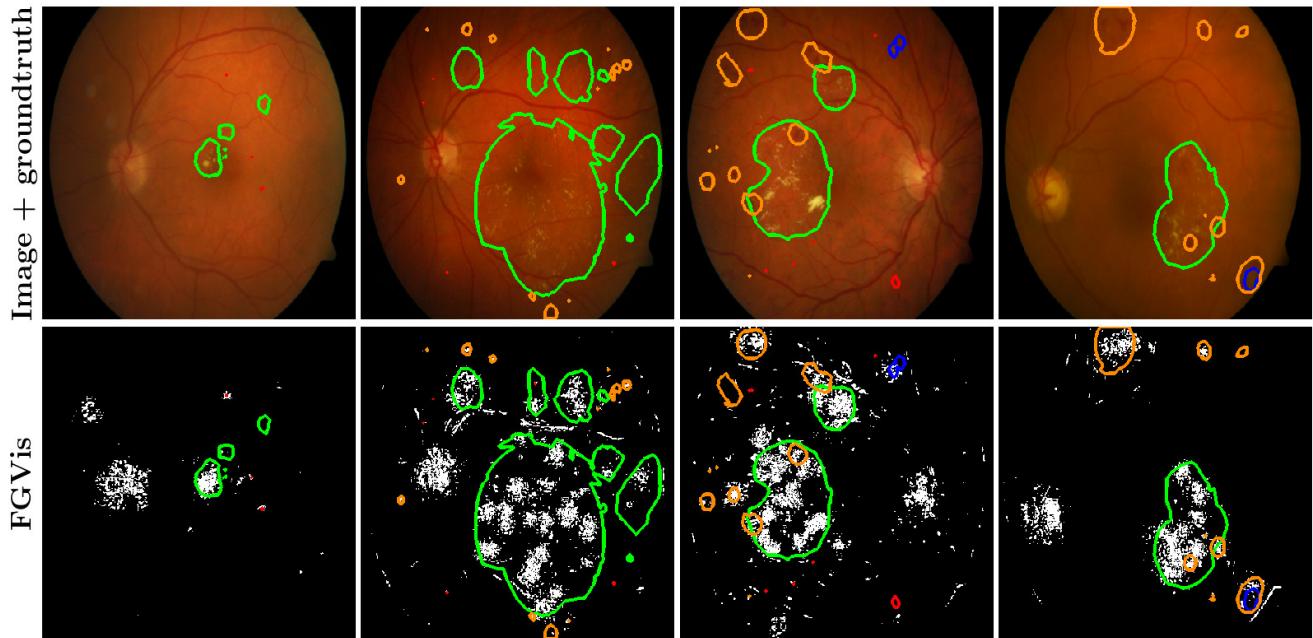


Figure A21: Weakly-supervised localization results on DiaretDB1 images. The top row shows fundus images, the bottom row our detection. All images are overlaid with ground truth markings in green (hard exudates), blue (soft exudates), orange (hemorrhages), red (red small dots). Though the network was trained in a weakly-supervised way given only the image label, most of the regions highlighted by FGVis fall within the ground truth markings. Note that mutations in the optic disk or blood vessels are an indicator for the disease [41] but these are not covered by the ground truth markings leading visually to false positives. FGVis highlights part of the blood vessels and optic disks.