Saliency Based Adjective Noun Pair Detection System

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Abstract: This paper investigates if it is possible to increase the accuracy of Convolutional Neural Networks trained on Adjective Noun Concepts with the help of saliency models. Although image classification reaches high accuracy rates, the same level of accuracy is not reached for Adjective Noun Pairs, due to multiple problems. Several benefits can be gained through understanding Adjective Noun Pairs, like automatically tagging large image databases and understanding the sentiment of these images. This knowledge can be used for e.g. a better advertisement system. In order to improve such a sentiment classification system a previous work focused on searching saliency methods that can reproduce the human gaze on Adjective Noun Pairs and found out that "Graph-Based Visual Saliency" belonged to the best for this problem. Utilizing these results we used the "Graph-Based Visual Saliency" method on a big dataset of Adjective Noun Pairs and incorporated these saliency data in the training phase of the Convolutional Neural Network. We tried out three different approaches to incorporate this information in three different cases of Adjective Noun Pair combinations. These cases either share a common adjective or a common noun or are completely different. Our results showed only slight improvements which were not significantly better besides for one technique in one case.

1 INTRODUCTION

Image classification is an important subject in computer science and can be applied for many different subjects, e.g. people or object recognition. In today's time with buzzwords like Big Data where massive amounts of data is created and saved within a short period of time a manual description of such images is not possible. Therefore an automatic way is needed, so that the images in these databases can be tagged and searching through them or generally working with them is possible. Currently methods work really well on general image classification, as it can be seen in the ImageNet challenge (Russakovsky et al., 2015), but they don't achieve the same level of performance on specifying these images with adjectives, such as "cute dog" for example, as it can be seen in (Chen et al., 2014b) or (Chen et al., 2014a), who tried to build a classifier for this problem. (Jou et al., 2015) also tried to solve this by using a multilingual approach and achieved better results, which are still not on the same level as the general image classification. Thus the classification of such Adjective Noun Pairs a.k.a ANPs still needs to be improved. One of the difficulties such methods need to face are objectivity vs. subjectivity, e.g. a "damaged building" is objectively damaged by a hole in a wall while deciding if a baby is cute is a subjective opinion dependent on the user. The other difficulty are localizable vs. holistic features. The feature hole in a damaged building is localized in a fixed sub-part of the image. On the other hand to estimate if a landscape is stormy the whole image needs to be taken into account. Sample images of this conflict can be found in Figure 1.
Another problem in ANP classification is the tagging of images. First, there may be multiple ANPs in one image, e.g. an ANP of "stormy landscape" probably also includes the ANP "dark clouds", which makes it more difficult to create a ground truth dataset. This is furthermore increased by the second problem of synonyms, e.g. the ANP image of a "cute dog" can also be used for "adorable dog". Nevertheless (Borth et al., 2013) created an ANP dataset which we will be using in this paper. A short description of this ANP dataset can be found in section 2.
In a previous work (Al-Naser et al., 2015) the authors investigated these problems with an Eye-Tracking experiment. In detail they asked if the participant agreed

with a certain ANP e.g. “beautiful landscape” and recorded their eye-gaze data. An example of how such eye gaze data look like can be seen in Figure 1. Under the sample images the heat maps are visualizing the most focused regions for the cases of agreement between user and ANP, disagreement and a combination of both. Each ground truth is the combination of all participants who were of the same opinion regarding this ANP. But only 8 out of 3000 ANPs (Borth et al., 2013) were used with just 11 human participants. A manual creation of such a database with all ANPs is not feasible. Following this problem (Stricker et al., 2017) investigated if there are saliency models capable of recreating the human gaze. They found out, that there are models which are better than other in handling this task. Figure 2 shows an image with its corresponding saliency map to visualize how such a saliency map may look like.
There are also similar works which are trying different approaches to detect the sentiment of an image or text. Some examples include (Cao et al., 2016), (You et al., 2016) or (Vadicamo et al., 2017)
This paper focuses on utilizing these results by using the saliency methods on the aforementioned larger dataset of ANPs (without eye-gaze data), which is described in section 2, as a preprocessing step. The images are then filtered and unsalient regions are discarded under the assumption that these new images will improve the accuracy of our saliency based ANP detection system. We trained a deep learning CNN with these data, which is described in section 3 while the explanation on how we incorporated the saliency data is done in section 4. Following this the results are presented and discussed in section 5. Lastly this paper ends with a conclusion on our findings in section 6.

(a) Stormy Landscape (Holistic, Objective)

(b) Damaged Building (Localized, Objective)

(c) Beautiful Landscape (Holistic, Subjective)

(d) Cute Baby (Localized, Subjective)

Figure 1: This figure shows the four ANP samples: “stormy landscape”, “damaged building”, “beautiful landscape” and “cute baby”. Below these images are the three forms of ground truth. The order is from left to right: disagreement, agreement and combination. Not all ground truth images are showing eye gaze data. This is because for that image no participant disagreed or agreed with the ANP and therefore no gaze data was recorded in combination with this answer. Furthermore these four images are showing the problems of objective vs. subjective ANPs and holistic vs. localizable ANPs.

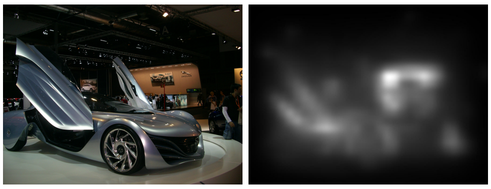


Figure 2: An image of an “amazing car” with its corresponding saliency map calculated by “Graph-Based Visual Saliency”.

2 THE ANP DATASET

In this paper a subset of the Visual Sentiment Ontology (Borth et al., 2013) was used. We are now briefly describing the creation of this dataset.
First of all Plutchnik’s Wheel of Emotions (Plutchik, 1980) was used as an emotional model. It consists of eight basic emotions and each of them is further separated into three more. This leads to a total of 24 emotions which are named in table 1. These 24 emotions were used to look for images on Flickr including their tags. With this procedure 310k images and 3M tags were retrieved. The tags were analyzed by removing stop-words and performing stemming. Furthermore a ranking of the top 100 tags was created by using tag frequency analysis. This resulted in 1146 distinct tags. As a last preprocessing step a sentiment value is calculated for each tag so that all tags have a value from -1 to +1 where negative numbers represent a negative association and positive numbers represent a positive association. After this preprocessing the ANPs can be constructed by combining adjectives with nouns, in order to give neutral nouns a sentiment value. The resulting ANPs are now analyzed to find ANPs which are an already existing concept, like “hot” + “dog”. These images were removed. Furthermore if the values of the noun and the adjective contradict each other the noun will get the value of the adjective. This was done in order to solve cases like “abused” + “child”. Otherwise the senti-

Table 1: The 24 emotions divided into eight basic emotions as described by Plutchnik's Wheel of Emotions.

Ecstasy	Joy	Serenity
Admiration	Trust	Acceptance
Terror	Fear	Apprehension
Amazement	Surprise	Distraction
Grief	Sadness	Pensiveness
Loathing	Disgust	Boredom
Rage	Anger	Annoyance
Vigilance	Anticipation	Interest

ment value of the ANP is just the sum of both. Lastly rare constructs are removed.

Two problems the dataset is facing are false positive and false negative. False positive means that an image is labeled with an ANP but doesn't show. it, e.g. an image which clearly shows a flower, but is labeled as "abandoned area". This problem was analyzed with the Amazon Mechanical Turk which showed that 97% of the labels are correct. False negative represents the problem that an image is not tagged with a label although it clearly shows it. Unfortunately this problem is still an open issue and could only be minimized.
As earlier stated we used a subset of the aforementioned Visual Sentiment Ontology. To show if our approach can really improve the performance for ANP specific tasks we created three subsets as shown in table 2. The first one "Normal" consists of ten classes where no adjective or noun appears more than once. "Same Adjective" consists of ten classes with the same adjective, namely "amazing". Similarly "Same Noun" consists of ten classes sharing the same noun "car". The goal of these three test cases is to show if our modified network will perform better at learning certain adjectives or different kinds of nouns.

3 DEEP LEARNING CLASSIFIER FOR ANPS

To train the deep learning classifier on the dataset we used Tensorflow as a framework. Within it we trained a simple convolutional neural network. Since the goal of this paper is not to develop a state of the art classifier for ANPs but to investigate the effects of including saliency data, a simple network suffices for this proof of concept. We want to check if saliency data is capable of increasing the accuracy. Therefore we have taken a simple convolutional neural network as described by Tensorflow's introduction to convolutional neural networks (Tensorflow, 2017).
We are now going to briefly describe the architecture. The proposed network was made in order to solve the CIFAR-10 classification problem (Krizhevsky and Hinton, 2009). This means that the network is capable of classifying 32x32 pixels into ten categories. These categories are: airplane, automobile, bird, cat, deer, dog, frog, horse, ship and truck. Furthermore the accuracy of this network is about 86%.
This is also our reason for choosing this network. It achieves a good performance on a similar problem, which is categorizing images into ten classes. Nevertheless our classes are more complex because now the network doesn't need to learn ten simple concepts (nouns) which are clearly different from each other but also needs to learn an adjective description. Furthermore our classes with which we test the network are not always distinct from each other. This can be best seen in our test case for similar nouns where the network needs to learn to distinguish between an "amazing car" and an "awesome car". Even humans would not be able to reliably perform this task due to many difficult problems. These problems are, that such adjective are sometimes subjective, e.g. what person A thinks might be beautiful might be ugly for person B. Furthermore many ANPs are similar to each other like the earlier example of "amazing" and "awesome" where both can be used to describe the same object. Unfortunately this dataset doesn't support that a single image is described by multiple ANPs. This also includes the problem that an image shows a fitting ANP but we don't have it included in our list of ANPs. This leads to the conclusion that our accuracy will be far worse than the accuracy on the CIFAR-10 dataset.
The proposed network as it can be seen in figure 3 (a), consists of three major steps, which will be described in detail later. First the input images are read and preprocessed. Secondly a classification will be done on the images. Lastly the training is done to compute all variables.

3.1 Training Preparation

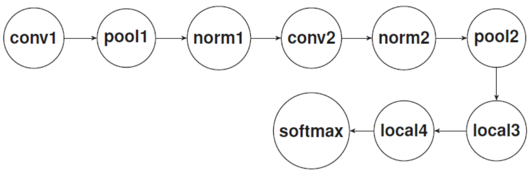
The images are simply read from a binary file. After that the proposed network crops the images to 24x24 pixels. But we skip this step, because our testset performed better with images size being 32x32 pixels. All other steps were not modified. Therefore our second step was to whiten the images so that the model is insensitive to dynamic range.

3.2 Classification

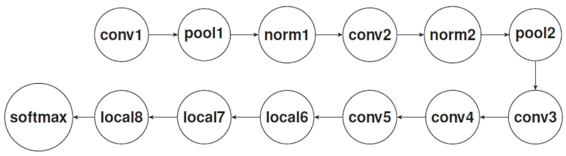
The layers of the CNN for classification are build as shown by figure 3 (a).

Table 2: A list of all ten classes for each subset. The number after the class marks how many images belong to each of the classes.

Normal	Same Adjective	Same Noun
Abandoned Area (799)	Amazing Baby (644)	Abandoned Car (844)
Active Child (958)	Amazing Cars (959)	Amazing Car (959)
Adorable Cat (741)	Amazing Dog (787)	Antique Car (985)
Aerial View (955)	Amazing Flowers (840)	Awesome Car (876)
Amateur Sport (603)	Amazing Food (918)	Beautiful Car (825)
Amazing Cars (959)	Amazing Girls (834)	Big Car (967)
Ancient Building (822)	Amazing Nature (835)	Classic Car (963)
Antique Airplane (738)	Amazing People (923)	Cool Car (989)
Arctic Ice (842)	Amazing Sky (899)	Exotic Car (935)
Artificial Leg (454)	Amazing Wedding (882)	Large Car (961)



(a) The first CNN



(b) The second CNN

Figure 3: The two CNN architectures we have used. The second one has more convolutional layers.

The layers take over different tasks. ConvX represents a convolution layer which uses a rectified linear activation function. PoolX takes over the pooling task by using maximum values. NormX performs a normalization. LocalX are fully connected layers. Finally softmax is a linear transformation.
We also trained a second network, as shown in figure 3 (b) which has three more convolutional layers and a third fully connected layer.

3.3 Training

The model was trained using gradient descent. We trained this model on the different datasets as described in section 2. We used 80% of the images for training and 20% for testing. During training we reached 350 Epochs and stopped after running 5000 batches with a size of 128. Furthermore our training set contained the three different approaches of incorporating saliency data and one set without saliency data in order to get accuracy values against which we can compare later.

4 INCORPORATING SALIENCY DATA

The CNN from section 3 is for the most cases the same and we tried different approaches how to incorporate the saliency data. All the different approaches share the same preprocessing which will be now described.
First of all we used all the images and applied the saliency method "Graph-Based Visual Saliency" a.k.a GBVS (Harel et al., 2006) on them. We decided to use GBVS as a saliency method because it performed as one of the best saliency methods overall for detecting important regions on ANPs according to (Stricker et al., 2017).
The approach of GBVS is inspired by biology. It forms activation maps on certain feature channels and normalizes them to highlight conspicuity. Furthermore all images were resized to 32x32 pixels. This leads to two sets of images. The first one contains all original images at size 32x32 pixels while the second one contains all saliency maps at size of 32x32 pixels. We have in total investigated three ways of incorporating these saliency maps into the image in order to help the network to concentrate on the important regions. The first method is a simple masking method and the second one is exploiting tensorflows option to train on four dimensional images with an alpha value additionally to the standard RGB channel. This approach does have two possibilities of incorporating saliency data. Lastly we also used a way of cutting out the important parts of the image to train on a smaller image which only contains the relevant data.

4.1 Simple Salient Masking Filtering

The simple masking method compares the original image with the saliency map pixel per pixel. It creates the new image with the condition, that if the value of the saliency map is greater than 127, which is half of the maximum of 255, the corresponding pixel's RGB data in the original image will be taken to the new image without modification. Otherwise the RGB value in the new image will be (0, 0, 0). This means that if the saliency map's value on position x1, y1 is e.g. 223, then the RGB value of the original image at position x1, y1 will be written at the new image's position x1, y1. But if the value at position x2, y2 in the saliency map is 100, then the value of new image at position x2, y2 will be zero on all three colour channels. We didn't experiment with values different from 127, because another approach showed better results and was therefore more interesting to investigate.

4.2 Exploiting the Salient Alpha Channel Filters

Tensorflow offers the option to define how many dimensions each image has on which the network will train. Currently it only supports the dimensions one to four. One means a simple image where each pixel has the value of zero to 255 e.g. something like a greyscale map, like our saliency map. Two would be the same including the alpha channel. Three is the standard way of RGB and four is RGB with an alpha channel.

We create the image on which the network will train by taking the original image and copying all RGB values one to one. Setting the alpha value is done in two different ways, where both are using the saliency map to calculate the alpha value:

- The first possibility is to simply take the saliency map. Each value in the saliency map is a single number ranging from zero to 255. This fits the value range of the alpha channel. Therefore we simply copy the value from the saliency map and set it as the alpha value.
- For the second possibility we utilize the findings from (Stricker et al., 2017). One of the important contributions was observing that the performance of saliency methods like GBVS significantly increased after binarizing the saliency map with a threshold determined by Otsu's method (Otsu, 1975). Thus we binarized the saliency map and set the alpha value to 255 if the corresponding saliency map pixel had the value one. If the saliency map pixel value is zero we also set the corresponding pixel's alpha value to zero.

4.3 Salient Region Patch Extraction

Lastly we investigated the effects of cutting out the important regions of an image and patching them together to create a new smaller image on which the network learns.

In detail we searched for the n most important regions of the image. In our case we set n to four. In a naive approach those n regions can be found easily. We have our saliency map from which we can derive the salient regions. Therefore in a simple way we could have just taken the pixels where we found the n highest values. But this does have one major problem. How can we assure that we have taken points that actually represent different regions of the image and not just the pixels on position (x,y), (x+1,y), (x,y+1) and (x+1,y+1). It is highly probable that if pixel (x,y) has the highest value, then the surrounding pixels will have a very high value themselves. We need to avoid the case where we choose pixels right beside each other to achieve our goal of covering a big part of the image. Therefore we cannot take the first n pixels with the highest value or choose them randomly. Figure 4 illustrates this problem.

This problem can be solved by the following procedure. We define a set A which contains all pixels where each pixel has maximum value. We will explain later how we build the set in detail. After that we take a look at all possible subsets of A with length n. This means that each subset is a possible solution to our problem. For all subsets we calculate the distance between all points. As a distance measure we used the euclidean distance. Then we sum up the length of all distances. The solution to our problem is the subset where this sum is maximal, because this will give us the points whose distance is maximal to each other. In a more formal way we choose the subset which maximizes the following sum:

$$\sum_{i=0}^{n} \sum_{j=i+1}^{n} distance(p_i, p_j) \tag{1}$$

Figure 4 also showcases this solution.

Another problem is how to calculate the set A. The problem lies in how to define a maximal value, which is the condition for the points inside set A. If we take a look at figure 5 we can see again the same image as before, where there are again three red circles which illustrate the three salient regions. This time they are filled with three colours. Red, orange and yellow. If the circle is filled with red, this means that all pixels inside it have the value of 253 to 255 according to the saliency map. An orange filling represents the values 250 to 252. Lastly the yellow points represent a value between 247 and 249. It is obvious that set

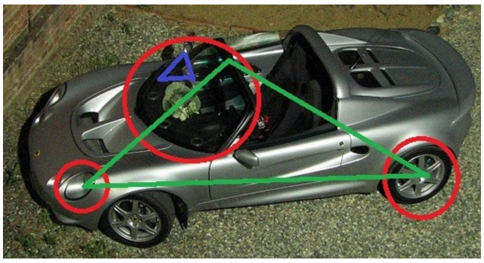


Figure 4: This image shows a car where multiple areas have been marked as salient (marked by the red circle). To cover the whole image we want to choose a part of the image from the three shown salient regions, meaning we want to include the tire, lights and window, instead of choosing to cut out the tire multiple times. This image also illustrates the solution to this problem . We take a look at all subsets and connect all points inside a subset with each other. This results in multiple triangles, e.g. the green and the blue one. All points of the blue triangle are inside the same salient region and therefore the sum of the lines is rather small. Instead the green triangle who has points in all salient regions has a higher sum of the lines. Thus deciding to take the points defined by the green triangle is the better choice.

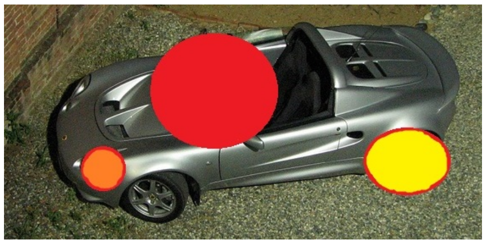


Figure 5: This image showcases the problem of how to define the set A. Red pixels inside the red circle have a value of 253 to 255. Orange pixels inside the red circle have a value of 250 to 252. Yellow pixels inside the red circle have a value of 247 to 240. It is obvious that the set A needs to consider all red, orange and yellow pixels as a pixel with maximal value and not only the red ones.

A needs to include pixels from all three circles. The value range is close enough (247 to 253 are only 6 points difference) to be considered maximal. Nevertheless such a case is possible were such a salient region may have an upper bound which is lower than the maximum value in the whole image. Therefore we cannot take the absolute best value in the whole image and look only for pixels with the same one. Then we would only take the red pixels and couldn't achieve the big coverage of the image.

Our solution to this problem was to take a sorted list of all the saliency values with descending order. Then we took the nth element and looked at its value v. Now we need to define a lower bound depending of v where all pixels with a higher value than v are considered to be a maximal for set A. We chose the lower bound to be 10% smaller than v. Therefore our set A is defined by:

$$A = \{p | p \geq (t * 0.9) \forall p \in P\} \quad (2)$$

With t being the nth highest value over all pixels and P containing all pixels.

It is not advised to choose a high percentage for this, because we are looking at all possible subsets of length n of A the number of subsets we need to check drastically increases which results in a significant longer computation time.

After this preprocessing we have a set of n pixels. We set the pixel to be the center of a 8x8 pixels big sub-part of the image. Because we are doing this for four pixels we will get four 8x8 pixels sub-parts of the image. These four sub-parts are cut out and then combined to create the new image on which the network will train.

5 DISCUSSION

We are now going to present the results we have gathered with our methods. Table 3 shows all values for the first network. The columns represent the different datasets which were used. These are “Normal”, “Same Adjective” and “Same Noun”. “Normal” consists of ten classes where each classes adjective and noun is different from each other. Contrary to this “Same Adjective” consists of ten classes all containing the same adjective but different nouns. Similar to this “Same Noun” consists of ten classes all containing the same noun but different adjectives.

The rows are showing which technique was used to train the CNN. “Standard” means using the CNN as described in section 3 on unfiltered images, while the other rows represent the methods used for filtering the images, as described in section 4.

Following these results, we again tried this method with using the deeper network as shown in section 3. The results can be seen in table 4.

Taking the not enhanced images, as seen in the results table of the standard row, as a baseline, we can see that the techniques of simple masking and patches have failed to increase the accuracy and performed worse in both CNNs.

The patches method probably failed due to the reason that the saliency map did not create multiple disconnected areas on the images, as it can be seen in figure 4 but instead created a connected area, where high salient regions are close to each other. Furthermore those high salient regions mostly lie close to each other, therefore the method to patch the image often took similar parts of the image and threw away important information. An example of how such a

Table 3: Accuracy's on the different datasets "Normal", "Same Adjective" and "Same Noun" using the standard CNN and the different methods of incorporating the saliency datas.

Saliency Data Incorporation	**Normal**	**Same Adjective**	**Same Noun**
Standard	**0.404**	0.241	0.173
Simple Masking	0.239	0.220	0.137
Alpha Value (Binarized)	0.132	**0.343**	**0.181**
Alpha Value (Not Binarized)	0.333	0.32	0.163
Patches	0.226	0.197	0.109

Table 4: Accuracy's on the different datasets "Normal", "Same Adjective" and "Same Noun" using a CNN with more layers and the different methods of incorporating the saliency datas.

Saliency Data Incorporation	**Normal**	**Same Adjective**	**Same Noun**
Standard	0.411	0.327	0.171
Simple Masking	0.255	0.208	0.140
Alpha Value (Binarized)	0.413	**0.338**	**0.21**
Alpha Value (Not Binarized)	**0.421**	**0.338**	0.178
Patches	0.252	0.196	0.13

saliency map looks like can be seen in figure 2. Furthermore figure 6 shows some example images and their corresponding images as created by the patches method. These images are highlighting this problem.

The simple masking method may have failed due to the same reason. Because pixels are either taken or completely disregarded some important information has been lost.

On the other hand the methods exploiting the alpha value have shown some improvements for the standard CNN, with the exception of the "Normal" case. There we can see a big drop in accuracy of 30%. For the case of "Same Noun" we can see a tiny improvements in the binarized alpha method while the results for the not binarized method showed slightly worsened. On the other hand both methods increased the accuracy in the "Same Adjective" case by 8% - 10%.

Therefore for this network, the use of saliency guided data, incorporated by the binarized alpha value method has shown success in the case of using it for data where the ANPs are not distinct from each other, e.g. they share either adjectives or nouns. If they don't share adjectives or nouns, the approach doesn't improve the accuracy.

In the case of the deeper CNN, we can see some differences compared to the standard one. First of all the big accuracy loss in the "Normal" case does not happen and it even slightly increased, for both alpha value methods, compared to the not saliency guided method. Nevertheless the deeper architecture of the network has also improved the accuracy of the not saliency guided method in the "Same Adjective" case. While both alpha value methods are still better, the improvements are now only small by 1%. Contrary to this, the new architecture did not increase the accuracy for the not saliency guided method in the "Same Noun" case but it did improve the accuracy's for the saliency guided methods. Therefore now both alpha value methods are better by a small value. The not binarized one is better by only 0.7% while the binarized one showed improvements of 3.9%.

Therefore in the deeper CNN, both alpha value methods showed slight improvements in all cases. The binarized one was better in the "Same Noun" case compared to the not binarized one while the not binarized one was better in the "Normal" case.

We think that the alpha value methods are better than the other saliency guided methods, because the other methods strictly remove information, while the alpha methods only guide the CNN as to where important regions may be but does not remove the information of the other regions and instead only reduces their impact.

Lastly we also performed a significance test on the accuracy's of the deeper network, to check if the accuracy's are also significantly better. We compared the results in each of the cases "Normal", "Same Adjective" and "Same Noun". In each of the cases we checked if the accuracy of "Alpha Value (Binarized)" and "Alpha Value (Not Binarized)" are significantly better than the accuracy of the "Standard" way.

We conducted a t-test with our findings. Our results show that only the accuracy's of "Alpha Value (Binarized)" in the case of "Same Noun" is significantly better than the standard model. The two-tailed P value equals 0.0024 in this case.

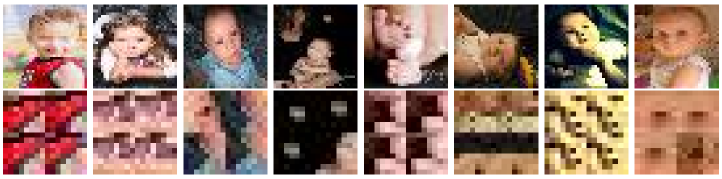


Figure 6: This figure shows eight example images from the ANP "amazing baby" in the upper row. The lower row shows their corresponding images as they are created by the patches method. (The patched image belongs to the image above it). This highlights the problem of the method to create those patched images. Namely that it is not capable of selecting distinct areas but instead very similar ones are used.

6 CONCLUSION

In this paper we investigated the impact of saliency data on CNNs trained to recognize a small set of ANPs. This set of ANPs was divided into three categories, "Normal", "Same Adjective" and "Same Noun". We found out that our deeper network showed some slight improvements by incorporating saliency data using the alpha value in all three categories. But these improvements were not statistically significant besides for the case of "Same Noun" with the technique of "Alpha Value (Binarized)". But we expect better improvements with a bigger dataset, where each class contains more images. A huge dataset which satisfies all the needs, e.g. the support of multiple ANPs and synonyms, for this problem. Creating such a dataset is a difficult and interesting problem for future work. Furthermore our results are showing big differences between the different the two CNNs, which we used. Therefore the impact of different network architectures can also be investigated in future work to maximize the precision of the approach.

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