Efficient Deep Aesthetic Image Classification using Connected Local and Global Features

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\url{https://github.com/BestiVictory/ILGnet}

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ABSTRACT

In this paper we investigate the aesthetic image classification problem, also known as automatically classifying an image into low or high aesthetic quality, which is quite a challenging problem. Considering both the local and global information of images is quite important for image aesthetic quality assessment. Currently, a powerful inception module is proposed which shows very high performance in object classification. We have the observation that the inception module has the ability of considering both the local and global features in nature. Thus, in this paper, we propose a novel DCNN structure codenamed ILGNet for image aesthetics classification, which introduces the Inception module and connects intermediate Local layers to the Global layer for the output. In addition, the ILGNet is derived from part of the GoogLeNet. Thus, we can easily use a pre-trained image classification GoogLeNet model on the ImageNet dataset and fine tune our connected local and global layer on the large scale aesthetics assessment AVA dataset. The experimental results show that the proposed ILGNet outperforms the state of the art results in image aesthetics assessment in the AVA benchmark. The time cost of both training and test of the ILGNet are significantly less than those of full GoogLeNet with only a little reduction of the classification accuracy. Our ILGNet can achieve similar classification accuracy as that of 2/3 GoogLeNet, whose computational cost is nearly twice of ours. This makes the aesthetic assessment model more easily to be integrated into mobile and embedded systems.  

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1. Introduction

In practice, mastering the technical aspects of shooting good photos is an acquired skill that takes years of vigilant observation to learn. However, people often can easily distinguish whether an image is beautiful or not. As shown in [1], most people will prefer the left images as they are more beautiful than those in the right.

Nowadays, facilitate mobile devices, social networks, and cloud storages make fast increasing of the amount of images of home users or in the Internet. Thus the ability of automatically classify an image to low or high aesthetic quality can be used in various scenarios, such as follows.

- To return Internet image search results with high aesthetic quality;
- Today, people often make crazy shooting in daily life using their mobile phones. After that, they often struggle to select good photos from thousands of photos for sharing in their social network. Thus, the image aesthetics classification algorithm can help them to automatically select most beautiful images for sharing;

- Image aesthetics classification also helps to develop new image beautification tools to make images look better [Mai et al. 2016].
- The vast amount of work from graphic, architecture, industry, and fashion design can be automatically classified to low or high quality.

Subjective Image Aesthetic Quality Assessment (IAQA) is still challenging [Mai et al. 2016], which aim to automatically classify a image into low or high aesthetic quality or giving a numerical assessment of the aesthetic quality. The challenges mainly come from the followings.

- the large intra class difference of high or low aesthetics;
- plenty of low level features and high level aesthetics rules;

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been used to extract effective aesthetics features. After that, deep learning methods, which have shown great success in various computer vision tasks, have recently been used to extract effective aesthetics features.

Recently, an efficient deep neural network architecture for computer vision, codenamed Inception is proposed by Google (Szegedy et al., 2015). The inception module derives its name from the Network in network paper by Lin et al. (Lin et al., 2013). In general, one can view the inception module as a logical culmination of (Szegedy et al., 2015) while taking inspiration and guidance from the theoretical work by Arora et al (Arora et al., 2014). The benefits of the architecture are experimentally verified on the ILSVRC 2014 classification and detection challenges, where it significantly outperforms the state of the art before the year 2015. However, to the best of our knowledge, little attention has been paid to use inception for image aesthetic quality assessment in current literatures.

In this paper, we introduce the inception module into image aesthetics classification. We build a novel Deep convolutional neural network, codenamed ILGNet (I: Inception, L: Local, G: Global) using multiple inception modules. Recent work (Maire et al., 2014) (Szegedy et al., 2015) shows value in directly connecting intermediate layers to the output. Thus, we connect the layers of local features to the layer of global features. The network is 13 layers deep when counting only layers with parameters (or 17 layers if we also count pooling). Firstly, we train our ILGNet on the ImageNet (Deng et al., 2009), which is the largest available image dataset for 1000 categories object classification. Then we fixed the inception layers and fine tune the connected layer containing global and local features on the largest available image aesthetics dataset, the AVA dataset (Murray et al., 2012). The experimental results on the AVA dataset (Murray et al., 2012) outperform the state of the art in image aesthetics classification. We have published our trained models and codes at https://github.com/BestiVictory/ILGnet.

2. Related Work

In this section we briefly investigate the related work of our image aesthetics classification: The objective image quality assessment, the image aesthetic quality assessment using hand-crafted features, the deep image aesthetic quality assessment.

2.1. Objective Image Quality Assessment

Objective image quality assessment aim to evaluate image quality distorted by imaging, transmission, and compression. They detect and measure various distortions including blocking, ringing, mosaic patterns, blur, noise, ghosting, jerkiness, smearing, etc (Mai et al., 2016). These low-level distortion measurement-based metrics can not well model human perception of the image aesthetic quality.

2.2. Aesthetic Quality Assessment with Hand-crafted Features

Subjective image aesthetic quality assessment aim to automatically classify a image into low or high aesthetic quality or giving a numerical assessment of the aesthetic quality. In this area, researchers usually follow three standard steps.

- They collect a dataset of images and manually separate them into two subjects: (1) the images with high aesthetic quality, labelled as good or high, (2) the ones with low aesthetic quality, labelled as bad or low. Some work pick up some of the images and make psychological experiments to obtain numerical assessment of the aesthetic quality of images.
- They design various aesthetics orientation features such as rule of third, visual balance, rule of simplicity (Datta et al., 2006) Ke et al., 2006 Luo and Tang, 2008 Li and Chen 2009 Bhattacharyya et al., 2010 Jiang et al., 2010 Li et al., 2010 Jin et al., 2010 Gray et al., 2010 Chen et al., 2015 Dhar et al., 2011 Joshi et al., 2011 Nishiyama et al., 2011 Luo et al., 2011 Tang et al., 2013 Wu et al., 2011 Khan and Vogel 2012 Niu and Liu 2012). In another way, they use generic image features for object recognition, such as low level image features (Jong et al., 2004), Fisher Vector (Marchesotti et al., 2011) and bag of visual words (Su et al., 2011 2012) to predict image aesthetics.
- They use machine learning tools such as SVM, Adaboost, and Random Forest to train a classifier on the collected datasets to automatically predict the aesthetic label of image (high or low, good or bad). They regress the hand-crafted design features to the human evaluated scores to predict the numerical assessment results of the image aesthetic quality.

2.3. Deep Image Aesthetic Quality Assessment

Recently, deep learning methods have shown great success in various computer vision tasks, such as object recognition, object detection, and image classification (Szegedy et al., 2015 He et al., 2016). Deep learning methods, such as deep convolutional neural network and deep belief network, have also been used to extract effective aesthetics features. After that, deep learning methods, which have shown great success in various computer vision tasks, have recently been used to extract effective aesthetics features.

Thus, this problem has becoming a hot topic in the communities of Computer Vision (CV), Computational Aesthetics (CA) and Computational Photography (CP). In early work, various hand-crafted aesthetic features (i.e. aesthetic rule based features) are designed and connected with a machine classification or regression. Another line is to use generic image description features. After that, deep learning methods, which have shown great success in various computer vision tasks, have recently been used to extract effective aesthetics features.

In early work, various computer vision tasks, such as object recognition, object detection, and image classification (Szegedy et al., 2015) shows value in directly connecting intermediate layers to the output. Thus, we connect the layers of local features to the layer of global features. The network is 13 layers deep when counting only layers with parameters (or 17 layers if we also count pooling). Firstly, we train our ILGNet on the ImageNet (Deng et al., 2009), which is the largest available image dataset for 1000 categories object classification. Then we fixed the inception layers and fine tune the connected layer containing global and local features on the largest available image aesthetics dataset, the AVA dataset (Murray et al., 2012). The experimental results on the AVA dataset (Murray et al., 2012) outperform the state of the art in image aesthetics classification. We have published our trained models and codes at https://github.com/BestiVictory/ILGnet.

Fig. 1. For most people, they may consider that the left image in (a) is more attractive than that in (b). Images are from the AVA dataset. (Murray et al., 2012)
been applied to image aesthetics assessment and have significantly improve the prediction precision against non-deep methods (Karayev et al., 2014; Lu et al., 2014; 2015ab; Dong and Tian, 2015; Wang et al., 2016; Ma et al., 2016; Kong et al., 2016; Kao et al., 2017; Wang et al., 2017; Ma et al., 2017). Most of the architectures follow the AlexNet (Krizhevsky et al., 2012), which is an 8 layers network with 5 convolutional layers and 3 full-connected layers. Although they obtain good performance, inspired by the recent achievement by Google in the ILSVRC challenge, going deeper allows us to train a deeper neural network model that captures large receptive field, enabling us to, not only obtain features of local images, but also whole image layout as global features. Besides, recent work (Maire et al., 2014) (Szegedy et al., 2015) (Lu et al., 2014, 2015a,b) shows value in directly connecting intermediate layers to the output. The inception module has the ability of considering both the local and global features in nature. Thus we change our network by connecting the intermediate local feature layers to the global feature layer.

3. Image Aesthetics Classification via ILGNet

In this section we will describe the details of our proposed ILGNet. As shown in Fig. 2, our network is 13 layers deep when counting only layers with parameters or 17 layers if we also count pooling. Three inception layers and one pre-treatment layer are involved. We connect the two intermediate layers of local features to the layer of global features to form a concat layer of 1024 dimension, following a full connected layer. The output layer is 1 dimension which directly gives the classification result of low or high aesthetic quality. We build this network on the first 1/3 part of GoogLeNetV1 (Szegedy et al., 2015) and batch normalization, which is an important feature of GoogLeNetV2 (Ioffe and Szegedy, 2015).

3.1. The Inception Module

The Inception module is proposed by Szegedy et al. (2015). The main ideas of the Inception module are:

1. Convolution kernels with different sizes represent receptive fields with different sizes. This design means fusing features of different scales.
2. The kernel sizes are set to 1 ∗ 1, 3 ∗ 3 and 5 ∗ 5 so as to align the features conveniently. The stride is 1. The pad is set to 0, 1, 2.
3. The features extracted by the higher layer are increasingly abstract. The receptive field involved by each feature is larger. Thus, the ratio of 3 ∗ 3 and 5 ∗ 5 kernels should be increased.

3.2. The ILGNet for Aesthetics Prediction

All the convolutions, including those inside the Inception modules, use rectified linear activation. The size of the receptive field in our network is 224 ∗ 224 in the RGB color space with zero mean. All these reduction/projection layers use rectified linear activation as well (Szegedy et al., 2015).

The first and the second inception layers are considered to extract local image features. The last inception layer is considered to extract global image features after two max pooling and one average pooling. Then, we connect the output of the first two inception layers (256 dimension for each) and last inception layer (512 dimension) to form a 1024 dimension concat layer. This contact layer is followed by a full connected layer with the same dimension. The output of our ILGNet is bypass a softmax layer to a binary output, which indicates low or high aesthetic quality of an image.

The ILGNet is derived from the part of the GoogLeNet, which can be used with a pre-trained image classification GoogLeNet model on the ImageNet dataset by fine tuning our connected local and global layer on the large scale aesthetics assessment AVA dataset (Murray et al., 2012).

4. Experiments

In this section, we report the experimental results to verify the effectiveness of our proposed ILGNet when dealing with image aesthetics classification. It will be compared with several state-of-the-art methods. Most of them are based on deep neural networks. All the experiments are conducted on the large scale and reliable public datasets AVA, which is specifically designed for the research of photo quality assessment (Murray et al., 2012). The main training parameters of the Caffe package Jin et al. (2014) are listed in Table 1.

4.1. Dataset

4.1.1. The ImageNet Dataset

The ILSVRC 2014 classification challenge involves the task of classifying the image into one of 1000 leaf-node categories in the Imagenet hierarchy. There are about 1.2 million images for training, 50,000 for validation and 100,000 images for testing. Each image is associated with one ground truth category. Our ILGNet are derived from the GoogLeNet, thus we can easily share the parameters of the pre-trained GoogLeNet models on the on the 1.2 million training images from ILSVRC 2014 classification challenge for 1000 categories.

4.1.2. The AVA Dataset

Aesthetic Visual Analysis (AVA) (Murray et al., 2012) is a large dataset formed by more than 250 thousands of images [25]. This database is specifically constructed for the purpose of learning more about image aesthetics. All those images are directly downloaded from the DPCChallenge.com. For each image in AVA, there is an associated distribution of scores (0-10) voted by different viewers. As reported in Murray et al. (2012), the number of votes that per image gets is ranged in 78-549, with an average of 210.

4.2. Classification Results

For a fair comparison, we adopted same strategy to construct two sub dataset of AVA as the previous work.
Inception Module

Previous layer

Conv 1*1 + 1(S)

Conv 1*1 + 1(S)

MaxPool 3*3 + 1(S)

Conv 3*3 + 1(S)

Conv 5*5 + 1(S)

Conv 1*1 + 1(S)

Conv 1*1 + 1(S)

Filter concatenation

Conv 7*7 + 2(S)

Conv 1*1 + 1(V)

MaxPool 3*3 + 2(S)

LocalRespNorm 3*3 + 1(S)

LocalRespNorm

Pretreatment layer

input

MaxPool 3*3 + 2(S)

MaxPool 3*3 + 2(S)

AveragePool 5*5 + 3(V)

Conv 1*1 + 1(S)

FC

SoftmaxActivation

softmax

Fig. 2. The architecture of the proposed ILGNet: Inception with connected Local and Global layers. We build this network on the first 1/3 part of GoogLeNetV1 (Szegedy et al., 2015) and batch normalization, which is a important feature of GoogLeNetV2 (Ioffe and Szegedy, 2015). We use one pre-treatment layer and three inception layers. The first two inception layers extract local features and the last one extracts global features. Recent work (Maire et al., 2014) (Szegedy et al., 2015) shows value in directly connecting intermediate layers to the output. Thus, we connect the two layers of local features to the layer of global features to form a concat layer of 1024 dimension to a full connected layer. The output layer is 1 dimension which indicate low or high aesthetic quality. The network is 13 layers deep when counting only layers with parameters (or 17 layers if we also count pooling). The labels (1)-(7) are used for the visualization in section 4.

Table 1. The main training parameters of the Caffe package.

| Parameters       | AVA1 (δ = 0) | AVA1 (δ = 1) | AVA2 |
|------------------|--------------|--------------|------|
| base_lr          | 0.0001       | 0.00001      | 0.00001 |
| lr_policy        | "step"       | "step"       | "step" |
| stepsize         | 100000       | 19000        | 13325 |
| gamma            | 0.96         | 0.96         | 0.96  |
| max_iter         | 475000       | 760000       | 533000 |
| momentum         | 0.9          | 0.9          | 0.9   |
| weight_decay     | 0.0002       | 0.0002       | 0.0002 |

AVA1: We chose the score of 5 as the boundary to divide the dataset into high quality class and low quality class. In this way, there are 74,673 images in low quality and 180,856 images in high quality. the training and test sets contain 235,599 and 19,930 images respectively (Murray et al., 2012; Wang et al., 2016; Wang et al., 2017; Kong et al., 2016; Lu et al., 2015b,a; Mai et al., 2016).

AVA2: to increase the gap between images with high aesthetic quality and images with low aesthetic quality, we firstly sort all images by their mean scores. Then we pick out the top 10% images as good and the bottom 10% images as bad. Thus, we select 51,106 images form the AVA dataset. And all images are evenly and randomly divided into training set and test set, which contains 25,553 images respectively (Luo and Tang, 2008; Lo et al., 2012; Datta et al., 2006; Ke et al., 2006; Marchesotti et al., 2011; Dong and Tian, 2015; Dong et al., 2015; Wang et al., 2016).

The sample classification results using our ILGNet are shown in the first column of Fig. 3. Differences between low-aesthetic images and high-aesthetic images heavily lie in the amount of textures and complexity of the entire image (Lu et al., 2015b).

Table 2. The Classification Accuracy in AVA1 dataset.

| Methods                | δ = 0    | δ = 1    |
|------------------------|----------|----------|
| Murray et al. (2012)   | 66.70%   | 67.00%   |
| AVG SCNN Lu et al. (2014) | 69.91%   | 71.26%   |
| Lu et al. (2015b)      | 74.46%   | 73.70%   |
| Lu et al. (2015a)      | 75.41%   | –        |
| Schwarz et al. (2016)  | 75.83%   | –        |
| Wang et al. (2016)     | 76.94%   | –        |
| Mai et al. (2016)      | 77.10%   | 76.10%   |
| Kong et al. (2016)     | 77.33%   | –        |
| Wang et al. (2017)     | 78.08%   | 77.27%   |
| Kao et al. (2017)      | 79.08%   | 76.04%   |
| Ma et al. (2017)       | 82.5%    | –        |
| ILGNet-without-Inc.    | 75.29%   | 73.25%   |
| 1/3 GoogLeNetV1-BN     | 80.74%   | 79.09%   |
| ILGNet-Inc.V1-BN       | 81.68%   | 80.71%   |
| ILGNet-Inc.V3          | 81.71%   | 80.65%   |
| ILGNet-Inc.V4          | 82.66%   | 80.83%   |

The original ILGNet is build on the first 1/3 of GoogLeNet V1, as shown in Fig. 2. We add batch normalization (GoogLeNet V2 (Szegedy et al., 2015) features), which form our ILGNet-Inc-V1-BN. After that we further build our ILGNet on the first 1/3 of recent GoogLeNet V3 (Szegedy et al., 2016) and V4 (Szegedy et al., 2017), which form our ILGNet-Inc.V3 and ILGNet-Inc.V4.

We present the experimental results in the AVA1 dataset in
Fig. 3. The visualization results of the weights of the features extracted by our ILGNet-Inc.V1-BN in important layers for images with high (top) and low (bottom) labels. The labels of (1)-(7) correspond to the same labels in Fig. 2. We have an interesting observation that in the last layer, the density of the active features are often higher in the ones with high aesthetic quality than those with low aesthetic quality.
Table 3. The Classification Accuracy in AVA2 dataset.

| Methods                  | Accuracy |
|--------------------------|----------|
| Luo and Tang (2008)      | 61.49%   |
| Lo et al. (2012)         | 68.13%   |
| Datta et al. (2006)      | 68.67%   |
| Ke et al. (2006)         | 71.06%   |
| Marchesotti et al. (2011)| 68.55%   |
| Dong and Tian (2015)     | 78.92%   |
| Tian et al. (2015)       | 80.38%   |
| Dong et al. (2015)       | 83.52%   |
| Wang et al. (2016)       | 84.88%   |
| ILGNet-Inc.V1-BN         | 85.50%   |
| ILGNet-Inc.V3            | 85.51%   |
| ILGNet-Inc.V4            | 85.53%   |

Table 2. It can be observed that our ILGNet-Inc.V4 outperforms the state of the art DCNN architectures with the accuracy 82.66%. The best performance obtained by the methods based on hand-crafted features is 67.0% (Murray et al., 2012), which is worse than the DCNN features. Similar results are shown when δ = 1.

To verify the effectiveness of inception module, we test a modified network of ILGNet-Inc.V1-BN: the ILGNet-without-Inc., in which we replace all the inception module with corresponding ordinal convolutional layer that is adaptive with the original pre and next layers. The performance (75.29%) of this InGNet-without-Inc. is significantly worse than that (81.68%) of the ILGNet-Inc.V1-BN. This verifies the usefulness of the inception module in capture features of both local patch and global view.

To verify the effectiveness of the connected local and global layer, we compare our ILGNet-Inc.V1-BN with the first 1/3 of original GoogLeNet with batch normalization: 1/3 GoogleNetV1-BN. The performance (80.74%) of the 1/3 GoogleNetV1-BN on AVA1 is also worse than that (81.68%) of the ILGNet-Inc.V1-BN. This verifies the usefulness of our proposed connected local and global layer.

The classification accuracy in the AVA2 dataset is shown in Table 3. Our ILGNet-Inc.V1-BN outperforms the state of the art DCNN architectures with the accuracy 85.50%. The best performance obtained by the methods based on hand-crafted features is 68.55% (Marchesotti et al., 2011), which is still worse than DCNN architectures.

4.3. The Efficiency Comparison

We take the ILGNet-Inc.V1-BN as an example to compare the efficiency with the first 1/3, 2/3 and full GoogLeNetV1 plus batch normalization. The time costs are summarized in Table 4. The time cost of both training and test of the ILGNet-Inc.V1-BN are significantly less than those of full GoogLeNetV1-BN with only a little reduction of the classification accuracy. This makes the aesthetic assessment model more easily to be integrated into mobile and embedded systems.

The performance of our ILGNet-Inc.V1-BN is better than that of 1/3 GoogLeNetV1-BN. The training and test times of our ILGNet-Inc.V1-BN is similar as those of 1/3 GoogLeNetV1-BN. This is because that our ILGNet-Inc.V1-BN is built on the 1/3 GoogLeNetV1-BN, which has similar computational efficiency as ours. With our strategy of connected local and global layer, our ILGNet-Inc.V1-BN can even achieve nearly the same performance (81.68%) to that (81.72%) of 2/3 GoogleNetV1-BN. While the training and test times of 2/3 GoogleNetV1-BN are much more than those of our ILGNet-Inc.V1-BN. In addition, we show the loss vs. epoch curves in Fig. 4. Our ILGNet-Inc.V1-BN achieve the fastest convergence speed, which further verifies the efficiency of our method.

4.4. The Features Visualization

We visualize the extracted features by our LGNet-Inc.V1-BN from images with high and low aesthetic quality. As shown in Fig. 3 our LGNet can extract features from the low level to high level. The last feature maps shown the features extracted by the connected layer of local and global feature extractors, which are nearly binary patterns. We have an interesting observation that in the last layer, the density of the active features are often higher in the ones with high aesthetic quality than those with low aesthetic quality. This verifies that the extracted features can well represent the aesthetic quality.

5. Conclusion and Discussion

In this paper, we propose a novel DCNN to predict the aesthetic label of low or high for images, codenamed ILGNet, which introduces multiple power inception modules and a connected local and global layer. We approximately fixed the shared inception layers of a pre-trained GoogLeNet model on
the ImageNet (Deng et al., 2009) and fine tune the connected layer on the AVA dataset (Murray et al., 2012). This architecture goes in deeper than current DCNN used for image aesthetic quality assessment and outperforms the state of the art in the largest aesthetic image dataset: the AVA dataset with both two strategies of the dataset partition. In the future work, we will introduce more domain knowledge in this field into the design of the DCNN for image aesthetic quality assessment and try to make the architecture itself *learnable*, which means that some architecture parameters such as the number of layers and the number of nodes on the full connected layers can also be automatically determined from the training on large-scale aesthetic dataset. Besides, now the input image is scaled to a fixed size of 224*224, which loses high quality local image patches and destroys the composition aesthetics of the original image. In the future work, we will use technologies such as spatial pyramid pooling to handle this limitation. Because of the bias of AVA dataset (the number of high quality images is higher than that of low quality images), we will explore other aesthetic criteria such as numerical assessment or ranking in the future.

**Acknowledgments**

Parts of this paper have previously appeared in our previous work (Jin et al., 2016). This is the extended journal version of that conference paper. The main differences between this archival version and the conference version are:

1. The title has been changed to capture essential idea of our work.
2. A more clear explanation of the power of the Inception module.
3. The performance of our ILGNet is increased to the state of the art (79.25% to 82.66% with the new network combination ILGNet-Inc.V4 reported in this version).
4. More experimental results are shown and more related methods (including the state of the art method published after our last version of manuscript submitted to PRL journal) are compared.
5. We have published our newly trained models and codes at [https://github.com/BestiVictory/ILGNet](https://github.com/BestiVictory/ILGNet).

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