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Deep Image Aesthetics Classification using Inception Modules and Fine-tuning Connected Layer

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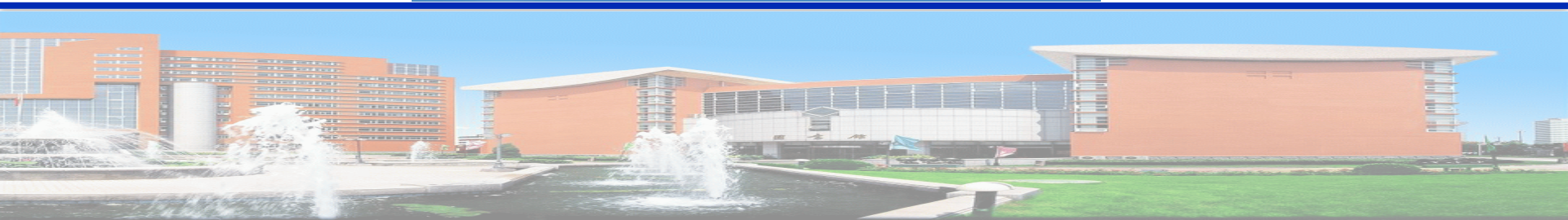

Outline

1. Motivation
2. Previous Work
3. Image Aesthetics Classfication Via ILGNET
4. Experiments and Results
5. Conclusion and Discussion

Motivation

(a)

(b)

For most people, they may consider that the left images in (a) are more attractive than those in (b).

Motivation

- To return Internet image search results with high aesthetic quality
- Image aesthetics classification also helps to develop new image beautification tools to make images look better
- The vast amount of work from graphic, architecture, industry, and fashion design can be automatically classified to low or high quality

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Previous Work

- Objective Image Quality Assessment
- Aesthetic Quality Assessment with Hand-crafted Features
- Deep Image Aesthetic Quality Assessment

Previous Work

1. They collect a dataset of images and manually separate them into two subjects, labelled as good or bad.
2. They design various aesthetics orientation features such as rule of third, visual balance, rule of simplicity.
3. 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

Previous Work

Recently, deep learning methods have shown great success in various computer vision tasks. Deep learning methods, such as deep convolutional neural network and deep belief network, have also been applied to image aesthetics assessment and have significantly improve the prediction precision against non-deep methods.

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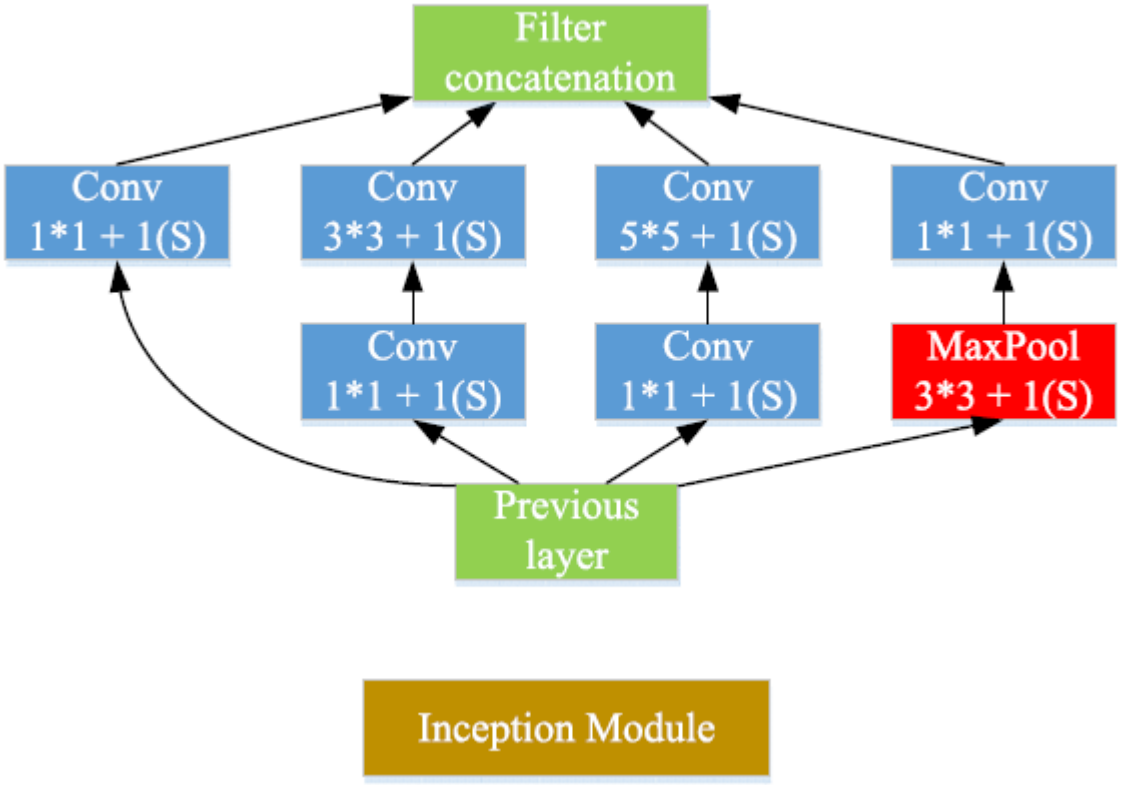
Image Aesthetics Classfication Via ILGNET



Inception Module

Image Aesthetics Classfication Via ILGNET

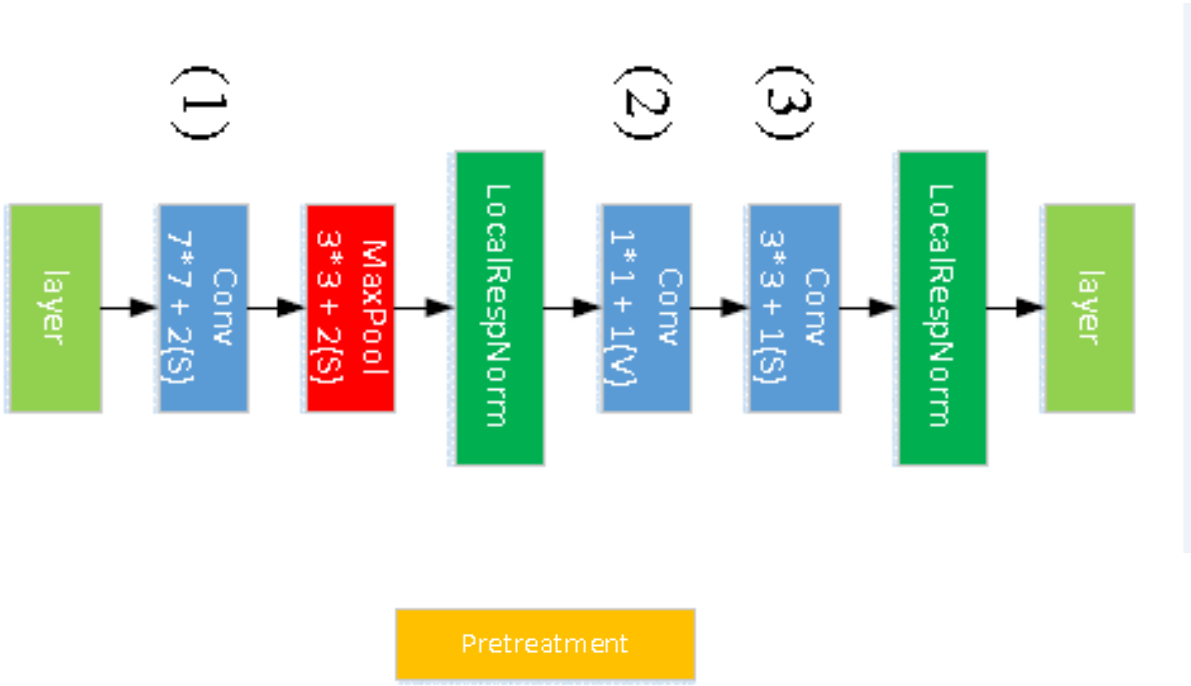
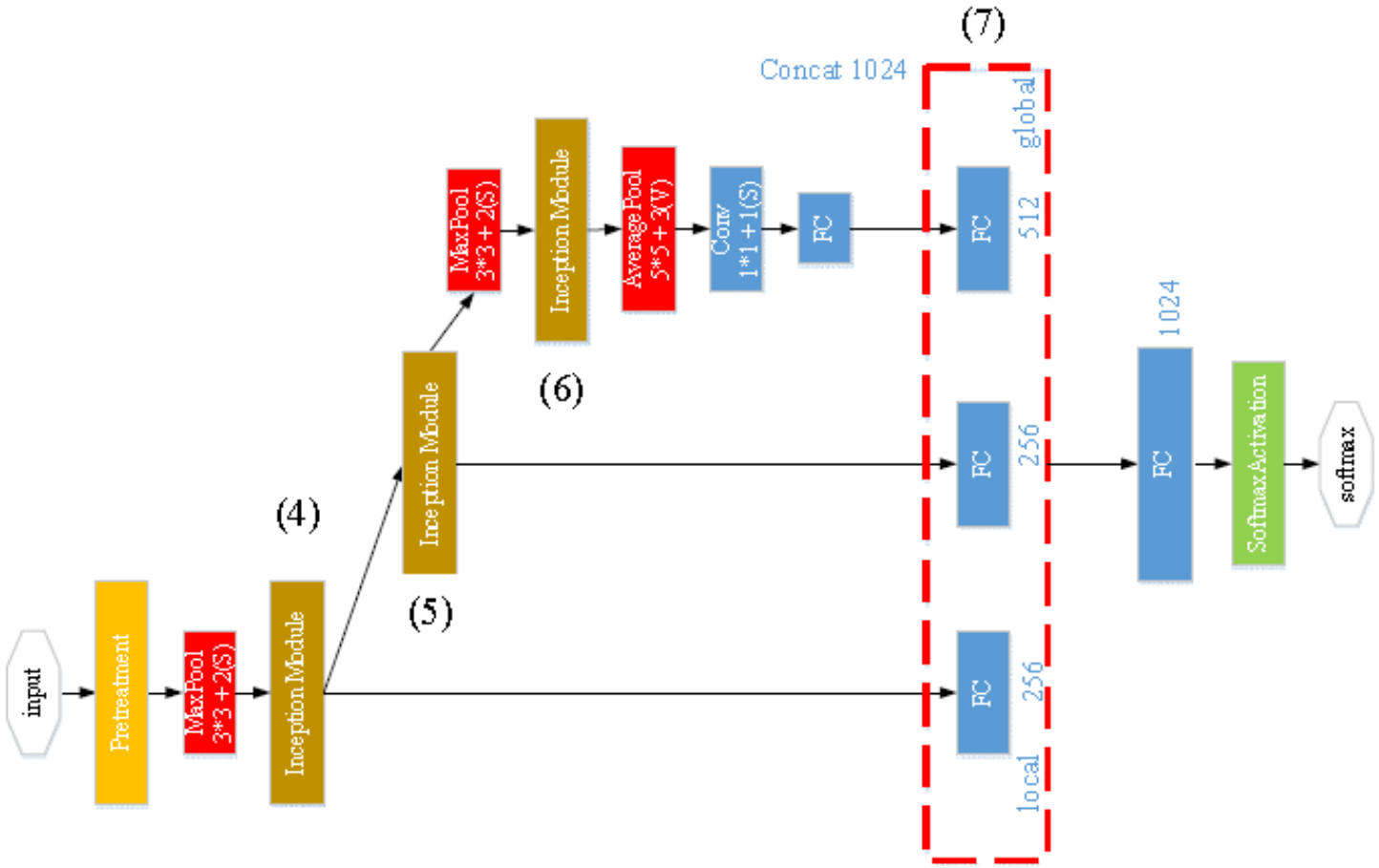


Image Aesthetics Classfication Via ILGNET



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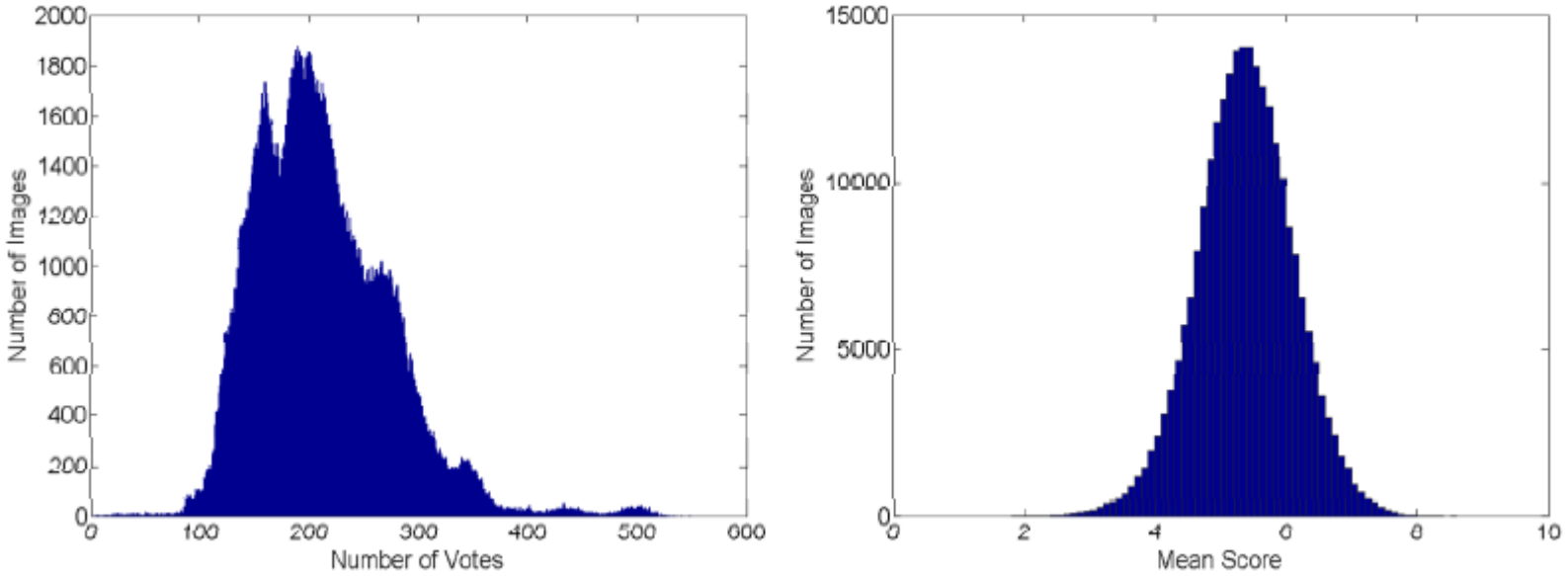
Experiments and Results

- The AVA Dataset
  - Aesthetic Visual Analysis (AVA)
  - more than 250 thousands of images [25].
  - specifically for image aesthetics.
  - DPChallenge.com
  - Scores (0-10) voted by different viewers.
  - the number of votes that per image in 78-549
  - with an average of 210

N. Murray, L. Marchesotti, and F. Perronnin, "AVA: A large-scale database for aesthetic visual analysis," in 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence, RI, USA, June 16-21, 2012, 2012, pp. 2408 - 2415.

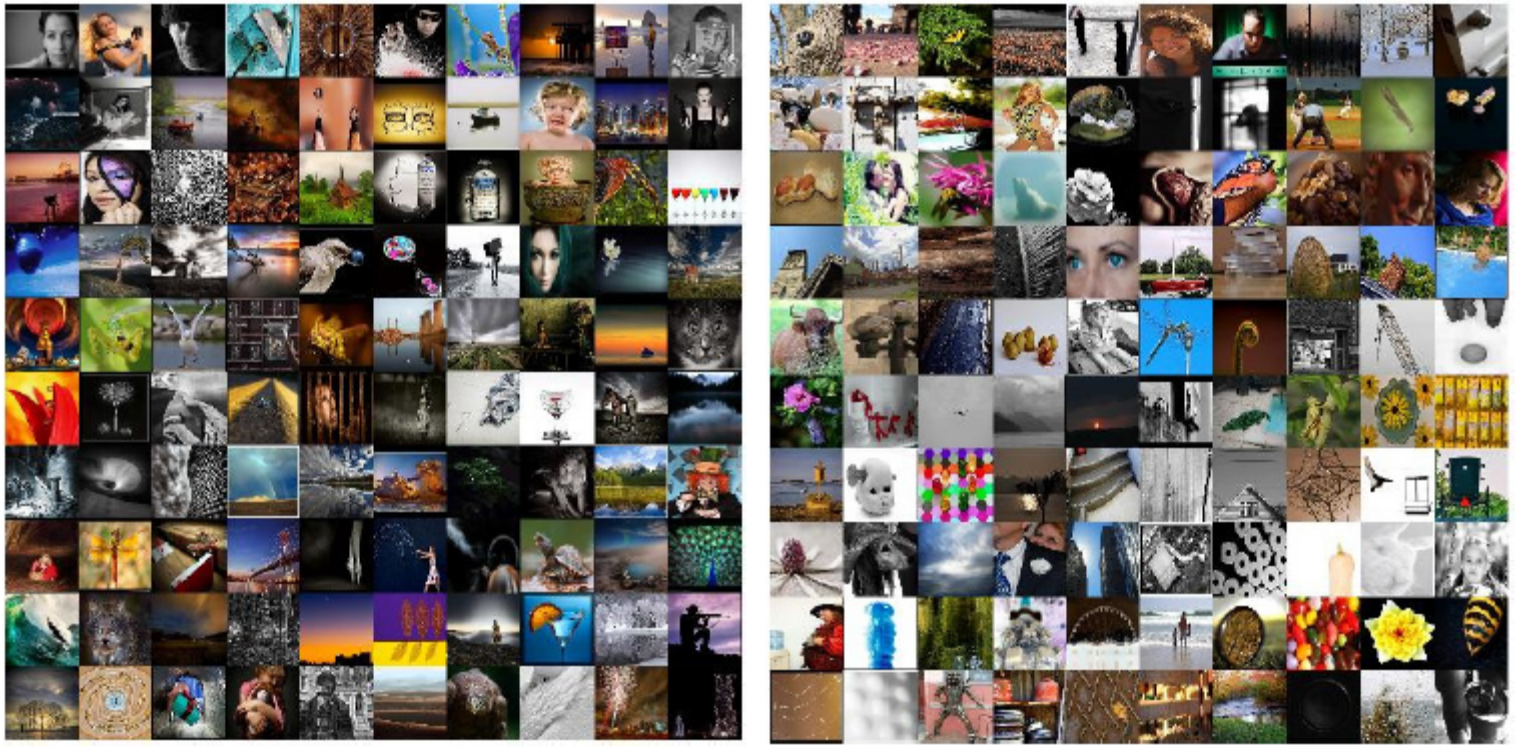
Experiments and Results

- The AVA Dataset



The histogram/distribution of the mean scores and the number of votes per image in the AVA dataset.

Experiments and Results



High Aesthetic Quality　　Low Aesthetic Quality

An embedding of the AVA dataset. The left and right part are the high (mean score above 5) and low aesthetic quality (mean score below 5).

Experiments and Results

- AVA1 Dataset

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

- AVA2 Dataset

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.

Experiments and Results

Methods	Accuracy
MurrayCVPR2012 [1]	67.0%
WangSP2016 [30]	76.94%
WangCORR2016 [33]	76.8%
KongECCV2016 [32]	77.33%
LuTMM2015 [28]	74.46%
LuICCV2015 [27]	75.41%
MaiCVPR2016 [2]	77.1%
Our ILGNet	**79.25%**

The Classification Accuracy in AVA1 Dataset

Experiments and Results

Methods	Accuracy
LuoECCV2008 [5]	61.49%
LoICPR2012 [42]	68.13%
DattaECCV2006 [3]	68.67%
KeCVPR2006 [4]	71.06%
MarchesottiICCV2011 [22]	68.55%
DongNC2015 [29]	78.92%
DongMMM2015 [43]	83.52%
WangSP2016 [30]	84.88%
Our ILGNet	**85.62%**

The Classification Accuracy in AVA2 Dataset

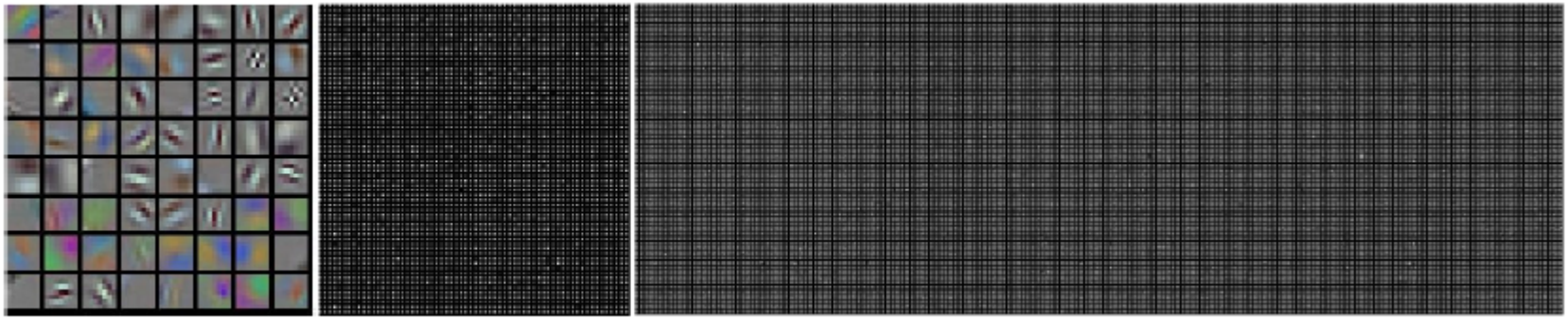
Experiments and Results

High

Low

Experiments and Results

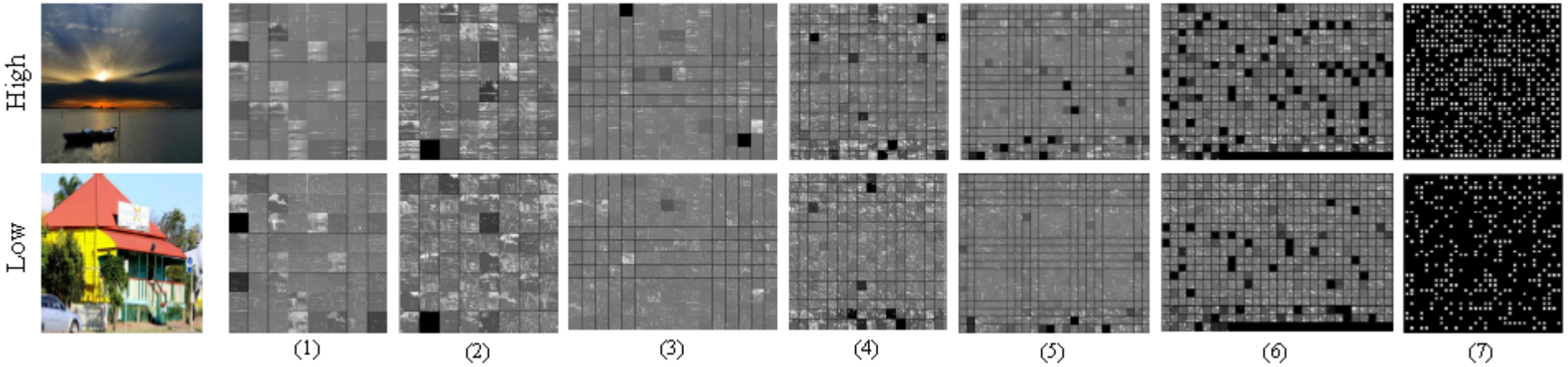
- The Network Weights



The visualization results of the weights of the first three convolutional layers

Experiments and Results

- The Features



The visualization results of the weights of the features extracted by our ILGNet in important layers for images with high (top) and low (bottom) labels.

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Conclusion and Discussion

- 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.
- 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.

Thanks !

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