

Rule of Thirds and Simplicity for Image Aesthetics using Deep Neural Networks

Steve Göring and Alexander Raake

Audiovisual Technology Group,
Technische Universität Ilmenau, Germany;
Email: [steve.goering, alexander.raake]@tu-ilmenau.de

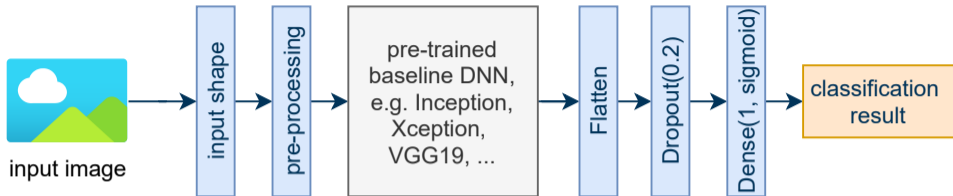
Code: <https://bit.ly/2Yy18mw>
MMSP 2021

September 10, 2021



- ▶ increasing upload of photos to social media platforms
- ▶ such photos not necessarily all of high appeal
- ▶ photo rules to increase appeal, e.g. rule of thirds, simplicity, balancing elements, and more [7]
- ▶ prediction whether a photo follows: rules of third, or image simplicity
→ How to automatically predict usage of photo rules?

Our Approach



- ▶ re-training/fine-tuning of pre-trained DNNs (17 different baseline models)
- ▶ for each rule: one model for a binary classification
- ▶ alternative:
 - rule prediction: [12, 11, 1]
 - prediction of overall appeal score: [4, 15, 3, 13, 10, 9, 2, 14, 8];
 - overall score: still challenging [16, 6]

Evaluation- rule of thirds

- ▶ dataset: Flickr urls [12]; 1808 "negative"; 1838 "positive"
- ▶ 90%-10% training validation split; 200 epochs, best reported

model	accuracy	precision	recall	f1	mcc
ResNet152	0.841	0.835	0.862	0.848	0.681
MobileNet	0.827	0.821	0.851	0.836	0.654
ResNet50	0.827	0.824	0.846	0.835	0.653

Table: **rule of thirds** prediction for top-3 DNN baseline models.

- ▶ better performance than *Mai et al.* [12] (80% accuracy)

Evaluation- image simplicity

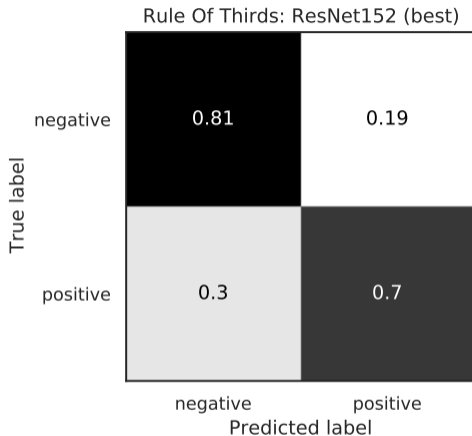
- ▶ dataset: urls [11]; 1832 "true"; 1980 "false".
- ▶ 90%-10% training validation split; 200 epochs, best reported

model	<i>accuracy</i>	<i>precision</i>	<i>recall</i>	<i>f1</i>	<i>mcc</i>
DenseNet121	0.940	0.952	0.927	0.939	0.880
ResNet50	0.934	0.941	0.927	0.934	0.869
VGG19	0.934	0.941	0.927	0.934	0.869

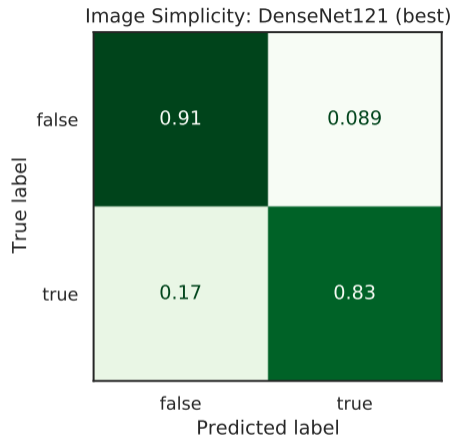
Table: **image simplicity** prediction for top-3 DNNs.

- ▶ better performance than *Mai et al.* [11] (89% accuracy)

Evaluation- confusion matrix



(a) Rule of thirds (ResNet152).



(b) Simplicity (DenseNet121).

Figure: Confusion matrices for best performing models considering both rules of thumbs.

- ▶ 1133 images [5]; extended by 5 annotators for rule of thirds and simplicity

rule	model	<i>accuracy</i>	<i>precision</i>	<i>recall</i>	<i>f1</i>	<i>mcc</i>
rule of thirds	ResNet152	0.672	0.549	0.292	0.381	0.202
image simplicity	DenseNet121	0.794	0.708	0.721	0.714	0.553

Table: performance of prediction in comparison to binary mean annotations.

- ▶ both prediction results within range of pairwise comparison of annotators

Conclusion, Summary and Future Work

- ▶ overview of re-trained DNN models for photo rule prediction
 - example rules: rule of thirds, image simplicity
 - DNNs show good results; better than SoA reported values
- ▶ additional annotation of AVT-Image-Database
- ▶ open and next steps:
 - apply models to other rules
 - handle rules as regression
 - analyze subjective influence for rule annotations

- [1] Larbi Abdenebaoui et al. “UNNA: a unified neural network for aesthetic assessment”. In: *2018 International Conference on Content-Based Multimedia Indexing (CBMI)*. IEEE. 2018, pp. 1–6.
- [2] Simone Bianco et al. “Predicting image aesthetics with deep learning”. In: *International Conference on advanced concepts for intelligent vision systems*. Springer. 2016, pp. 117–125.
- [3] Sagnik Dhar, Vicente Ordonez, and Tamara L Berg. “High level describable attributes for predicting aesthetics and interestingness”. In: *CVPR 2011*. IEEE. 2011, pp. 1657–1664.
- [4] Steve Göring, Konstantin Brand, and Alexander Raake. “Extended Features using Machine Learning Techniques for Photo Liking Prediction”. In: *QoMEX*. Sardinia, Italy, May 2018.

- [5] Steve Göring and Alexander Raake. “Evaluation of Intra-coding based image compression”. In: *8th European Workshop on Visual Information Processing (EUVIP)*, IEEE. 2019, pp. 1–6.
- [6] Shu Kong et al. “Photo aesthetics ranking network with attributes and content adaptation”. In: *European Conference on Computer Vision*. Springer. 2016, pp. 662–679.
- [7] B. Krages. *Photography: The Art of Composition*. Allworth, 2012.
- [8] Hui-Jin Lee et al. “Photo aesthetics analysis via DCNN feature encoding”. In: *IEEE Transactions on Multimedia* 19.8 (2017), pp. 1921–1932.
- [9] Xin Lu et al. “Rating image aesthetics using deep learning”. In: *IEEE Trans. on Multimedia* 17.11 (2015), pp. 2021–2034.

- [10] Jana Machajdik and Allan Hanbury. “Affective image classification using features inspired by psychology and art theory”. In: *Proc. of the 18th int. conf. on Multimedia*. 2010, pp. 83–92.
- [11] Long Mai et al. “Detecting rule of simplicity from photos”. In: *20th ACM int. conf. on Multimedia*. 2012, pp. 1149–1152.
- [12] Long Mai et al. “Rule of thirds detection from photograph”. In: *Int. Symposium on Multimedia*. IEEE. 2011, pp. 91–96.
- [13] Luca Marchesotti et al. “Assessing the aesthetic quality of photographs using generic image descriptors”. In: *Int. Conference on Computer Vision*. IEEE. 2011, pp. 1784–1791.

- [14] Hironori Takimoto, Fumiya Omori, and Akihiro Kanagawa. “Image Aesthetics Assessment Based on Multi-stream CNN Architecture and Saliency Features”. In: *Applied Artificial Intelligence* 35.1 (2021), pp. 25–40.
- [15] Hossein Talebi and Peyman Milanfar. “NIMA: Neural image assessment”. In: *IEEE Trans. on Image Processing* 27.8 (2018), pp. 3998–4011.
- [16] Yunlan Tan et al. “Photograph aesthetical evaluation and classification with deep convolutional neural networks”. In: *Neurocomputing* 228 (2017), pp. 165–175.

Thank you for your attention



..... are there any questions?

This work has been partially supported by the CYTEMEX project funded by the Free State of Thuringia, Germany (FKZ: 2018-FGI-0019) and the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 437543412.