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The Effects of Depth of Field on Subjective Evaluation of Aesthetic Appeal and Image Quality of Photographs

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ABSTRACT Aesthetic appeal and image quality are two important features of photographs, which play the dominant role when people clean their albums. Currently, the objective image quality assessment has been documented very well whereas the objective aesthetic appeal assessment algorithms are not developed well enough. This paper first subjectively evaluated image quality and aesthetic appeal separately of 339 photographs across different levels of depth of field. With the subjective data, the paper proposed two mathematical models to predict the subjective aesthetic appeal from subjective image quality. More specifically, depth of field, as a common photographic feature, was investigated to see how it influenced aesthetic appeal and image quality. 32 participants were asked to score for the aesthetic appeal and image quality. With these subjective scores, we used two methods - linear regression and deep neural networks - to build models separately to predict aesthetic appeal from image quality. We found that both models worked well on the valid dataset and the performance of the deep neural networks model was better than the linear regression model.

INDEX TERMS Aesthetic appeal, image quality, depth of field, linear regression, deep neural networks.

I. INTRODUCTION

Blur is an intrinsic property of retinal images, which also appears as out of focus [1]. Blur can be introduced mainly from two aspects: images and observers. From the aspect of images, the loss of power in the high spatial frequency domain makes image blurred. Photographs of a moving object always contain blur. In addition, image dithering, camera defocus, compression, format conversion, and transmission can also cause blur in photographs. From the aespect of observers, there are also many factors that can make retinal images blurred, such as their physilogical and mental state, visual ability, and viewing distance [2]. Most types of the blur is considered as image degradation, which decreases visual quality. Many researchers have put a lot of effort in investigating the effects of image blur on visual quality [3]–[6].

However, blur does not always play a negative role in photographs. Sometimes, blur is intentionally added into photographs, most frequently in the form of depth of field [7]. Depth of field is a high-frequency word in photography and cinematography, which is defined as the distance range in which objects are perceived as sharp. Depth of field can be controlled by focal distance, focal length, and aperture size. Small depth of field means there is a lot of blur in the image, probably only the focus object is sharp. Large depth of field can make photographs sharp everywhere. Blur in such photographs is not image degradation, and it can enhance the aesthetic appeal or stereopsis of the photographs [8], [9].

There is no unified standard on how much blur a photograph should contain. The effect of depth of field on visual quality is complicated since it is very subjective and it can be

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influenced by many other factors such as category, content, environment, and so on. Large depth of field make most areas of the photograph sharp, and there is no need to discuss blur. Researchers and photographs claim that a small depth of field can make photographs more beautiful [8], [10]. But data and materials that support these claims are not well documented yet. Hence, the main goal of this study is to investigate how depth of field influences aesthetic appeal and image quality of photographs in our daily life.

Researchers have concluded the reasons that how depth of field affects aesthetic appeal. First, a small depth of field can make the most important objects sharp and blur the other less important objects in the foreground and background. Hence, the clutters of the photograph are reduced, which directly influence the aesthetic appeal [11]. Luo et. al aslo found that depth of field could influence the clarity contrast and simplicity [12]. Second, depth of field is an important depth cue which can help enhance the perception of depth in photographs [13]–[16]. Enhanced depth perception can create stereoscopic impression of the photographs [17]. It can make the photograph more vivid and realistic. In addition, depth of field can also create a tilt-shift miniaturization or magnification effect, which is widely used in photographs and films [18], [19]. Miniaturization can make real objects appear toy-like while magnification effect can make architectural or toy models appear realistic. Therefore, it is difficult to conclude whether depth of field always play a positive effect on aesthetic appeal.

Previous studies found that aesthetic appeal and image quality are positively correlated [20], [21], which suggests that the effects of depth of field on aesthetic appeal and image quality are similar. IJsselsteijn et al. conclude that stereoscopic impression enhances the naturalness of the images, leading to a higher perceived image quality [22]. Vishwanath found that a small depth of field can make a photograph look stereoscopic [23]. According to these studies, it seems reasonable to make a hypothesis that a small depth of field can improve image quality.

However, as we know that distortion blur is a very annoying negative feature of a photograph [3], [5], [24]. Many scientists do research about blur detection and annoyance quantification as well as sharpen algorithms [6], [25]–[28]. Very few studies made an explicit distinction between depth of field blur and distortion blur. Liu et al. conclude that blur quality metrics and sharpening algorithms should be able to discriminate between depth of field blur and unwanted distortion blur, towards preserving the former and, as a consequence, the image quality of an image [29]. Hence, the current conclusions about the effects of distortion blur on image quality are not suitable to be directly used to predict the effects of depth of field on image quality. Moreover, Vishwanath's work is inconclusive on how variations in depth of field blur affect the impression of stereopsis while Ijsselsteijn et al's conclusions about the effects of depth of field on image quality are not always consistent with later studies [30]–[33]. Hence, the investigation of depth of field on image quality was necessary.

As we mentioned before, depth of field is a high-frequency word in photography. Observers who are interested in photography are very familiar with the term while most of the people may not know the term even they use the depth of field effect in their daily life. Previous studies preferred to use experts as their participants to avoid the learning process [34], [35]. Hence, we guess the performance of participants on the evaluation of aesthetic appeal and image quality may be different across their background. Therefore, we added a quesionnaire in our experiment to investigate the effects of participants'level of expertise on the results.

Both aesthetic appeal and image quality can be achieved subjectively or objectively. Subjective evaluation is precise, but also expensive and time-consuming. Hence, researchers have developed different kinds of image quality assessment algorithms to measure image quality automatically [36]–[39]. However, such kinds of algorithms for aesthetic appeal are much fewer because the aesthetic appeal features are more complicated and the definition is too subjective [40]–[42]. Previous studies have already shown that aesthetic appeal and image quality is positively correlated. Hence, if we can find a good model between image quality and aesthetic appeal, it is possible to predict aesthetic appeal accurately with the model and the image quality assessment algorithms. In this paper, to get the effects of depth of field on aesthetic appeal and image quality, participants were invited to do a lot of subjective evaluation. However, the researches on aesthetic appeal are not as many as image quality and the no-reference metrics for predicting aesthetic appeal are not well developed.

In this study, to get the effects of depth of field on aesthetic appeal and image quality, participants were invited to do a lot of subjective evaluation. After the analysis of the subjective data, we used linear regression and deep neural networks to develop models between aesthetic appeal and image quality.

II. SUBJECTIVE EXPERIMENTS

To build a model between aesthetic appeal and image quality, we used 339 photographs and asked participants to score them on aesthetic appeal and image quality. These photographs included eight categories and were blurred at different levels. Hence, we first subjectively classified the photographs according to their blurry and then scored them. Two different groups of participants were involved in the experiment.

A. CLASSIFICATION EXPERIMENT

1) PARTICIPANTS

Sixteen participants classified the 339 photographs according to the definition of depth of field. All the participants were staff or students from TUDelft. Their mean age was 29 years with a standard deviation of ±3.5 years. The experiment was approved by the ethics committee of Delft University of Technology.

FIGURE 1. **Stimuli with controlled depth of field.**

2) STIMULI

The photographs used in the experiment were mainly from photo.net, Flickr, Google+, and personal collections. The copyright of these photographs allowed the use for academic purpose. We labelled these photographs into eight categories according to their content: animals, architecture, flowers, food, sports, street, landscape and artificial. The artificial photographs were created by the authors, and the details can be found in prevous papers [15], [16]. The depth of field was fully controlled in our own photographs, and there were three levles: 5.7mm, 18.4mm, and 68.9mm respectively. An example can be seen in Fig. 1.

3) PROCEDURE

The photographs were shown on a PLE48 19'' Iiyama display, with the resolution of 1280∗1024. Before the experiment, the display was calibrated with a ColorMunki spectrophotometer towards sRGB. The experiment conductor need to make sure that the participants understood the definition or meaning of depth of field since it was a technical term usually used by photographers. The experimental conductor used the words: ''the distance within which objects are perceived as sharp'' to describe depth of field. All the photographs were displayed in a random order, and the participants were required to decide the depth of field of each photograph was small, medium or large by clicking the corresponding button on the experimental interface. The experiment took about 30 minutes.

4) RESULTS

If more than eight participants decided the photograph as having ''small'' depth of field, the photograph was labelled as ''small depth of field''. With this method, 67 photographs were classified in the group of ''small depth of field'', 96 in the group of ''medium depth of field'', and 156 in the group of ''large depth of field''. There were 20 photographs left, which we classified in ''ambiguous'' group because the number of the participants choosing a given value of depth of field was smaller than eight for each of three labels. The classified stimuli were shown in Fig. 2(a), (b), and (c), respectively.

B. SUBJECTIVE ASSESSMENT OF AESTHETIC APPEAL AND IMAGE QUALITY

1) PARTICIPANTS

16 male and 16 female college students or staff took part in the experiment. They were from nine different countries and the age was from 17 to 39 years with the mean of 27 years (SD = ± 3.7). This group of participants did not took part in the classification experiment, which meant they did not view the stimuli before. The participants did not know the purpose of our experiment, and they just did the task as the experimental conductor asked.

2) STIMULI

All the photographs used in the classification experiment were used in this scoring experiment.

3) PROCEDURE

The total 339 photographs were separated into three groups randomly for each participant. And they had to score these three groups of photographs twice, once for the image quality and the other time for the aesthetic appeal. Hence, there were six sessions in total with the image quality session and aesthetic appeal session shown up alternatively. When one photograph was displayed on the screen, a continuous rating scale was under it, ranging from ''1'' to ''7''. For image quality session, 1 means ''bad'' and 7 means ''excellent''. For aesthetic appeal session, 1 means ''ugly'' and 7 means ''beautiful''. Between 1 and 7, there was no extra marks on the rating scale. During the experiment, the participants could spend as much time as they wanted on each trial and they were also allowed to take a break during sessions.

There was a training session before the real experiment started to make sure that the participants understand the definition of aesthetic appeal (i.e., concerned with beauty and art, the understanding of beautiful things, and made in an artistic way and beautiful to look at) and image quality (i.e., if no degradation or artifact is perceived in an image, it is considered to be of high quality) [8]. The training session can also make them be familiar with the experimental interface. During the training session, the participants were also recommended the standard for a high score in aesthetic appeal such as ''looks good, pleasing to your eyes, attracts attention, good colour and composition''. However, we did not force people to use these standard, and they could give the score completely according to their own judgement. In the end of the experiment, we did a questionnaire to collect more information about their background. The questionnaire includes questions about their standard for the scoring, whether they like taking photographs, and how much do they know about depth of field.

(a). Stimuli which are labled as 'small depth of field'.

(b). Stimuli which are labled as 'medium depth of field'.

(c). Stimuli which are labled as 'large depth of field'.

FIGURE 2. **Stimuli used in the experiment.**

C. RESULTS OF THE SUBJECTIVE ASSESSMENT OF AESTHETIC APPEAL AND IMAGE QUALITY

1) SUBJECTIVE ASSESSMENT OF AESTHETIC APPEAL AND IMAGE QUALITY

For each participant, they scored 339 photographs which were classified into four categories, named as "small depth of field", "medium depth of field", "large depth of field", and "ambiguous". We calculated the mean aesthetic appeal score and the mean image quality score of each category for every participant. In the following analysis, we did not take the "ambiguous" group data into account. The results of the subjective assessment of aesthetic appeal and image quality are shown in Fig. 3. We then performed a repeated-measures ANOVA on the aesthetic appeal and image quality with Depth of Field as the independent factor. We found that depth of field influenced the aesthetic appeal significantly ($F(1, 31) = 4.87$, $p = 0.035$). However, the effect size was not very big with the partial eta-squared was 0.136. A post-hoc LSD test showed that only small depth of field significantly differed from large depth of field. The effect of medium depth of field was not signiciant.

For image quality, we also found depth of field to be a signicant main factor ($F(2, 62) = 4.38$, $p = 0.017$), but the effect size was still very small (partial eta-squared = 0.124). The post-hoc LSD comparisons revealed that the subjective image quality scores of photographs with a large depth of field were significantly higher than that of the photographs with a small or medium depth of field. There was no significant difference between the image quality score of photographs with a small and a medium depth of field.

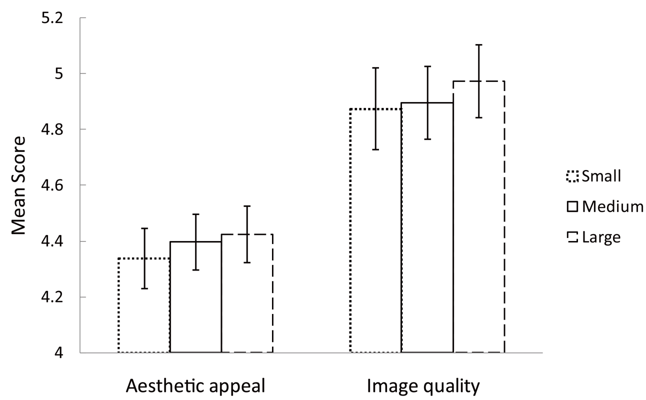

FIGURE 3. **The effects of depth of field on aesthetic appeal and image quality.**

2) RESULTS OF THE QUESTIONNAIRE

As mentioned in the last session, participants were required to answer the quesionnaire about their standard on aesthetic appeal and image quality. One participant's data were lost, hence Table 1 shows the results of 31 participants. In the table, percentage equals to the time that the term mentionded by the participants diveded by the number of particpants. We could see that the features of aesthetic appeal and image quality were similar whereas the significance of the features

TABLE 1. Subjective aesthetic appeal and image quality features.

AQ features	Percentage (n=31)	IQ features	Percentage (n=31)
Color	61.3%	Sharpness	51.6%
Composition	41.9%	Color	32.3%
Image Content	29%	Artifacts	25.8%
Main subject	22.6%	Focus	22.6%
Focus	16.1%	Luminance	19.4%

was different. For aesthetic appeal, colour and composition were regarded as the most important features while sharpness and colour played the most significant roles for image qaulity assessment. Cerosaletti and Loui also found that colour is the most important characteristics for aesthetic appeal [11].

In the questionnaire, we also asked participants how they would expect the results. 64.5% of the participants thought depth of field would influence aesthetic appeal. 19.3% were not sure about the results and the other participants thought depth of field was not a related factor for aesthetic appeal. For image quality, Fewer than half participants (41.9%) thought depth of field would influence image quality. The number of the participants who were not sure or held the opposite oppinion was increased.

3) COMPARISON BETWEEN PARTICIPANTS

Since depth of field was a popular technique in photography, we thought the participants who were experts in photography would have different criterions for aesthetic appeal and image quality. In the questionnaire, there were two questions to help us separate the participants into two groups, namely: experienced and naive. Then we got 15 experienced participants and 17 naive participants. Fig. 4 shows experienced and naive participants subjective assessment on aesthetic appeal and image quality. A repeated two-way ANOVA analysis (2 groups of participants * 3 levels of depth of field) revealed that naive participants scored both aesthetic appeal and image quality higher than experienced participants ($F(1, 632) = 30.2$, $p < 0.001$). The results suggest that experienced articipants may be more critical for the evaluation of aesthetic appeal and image quality.

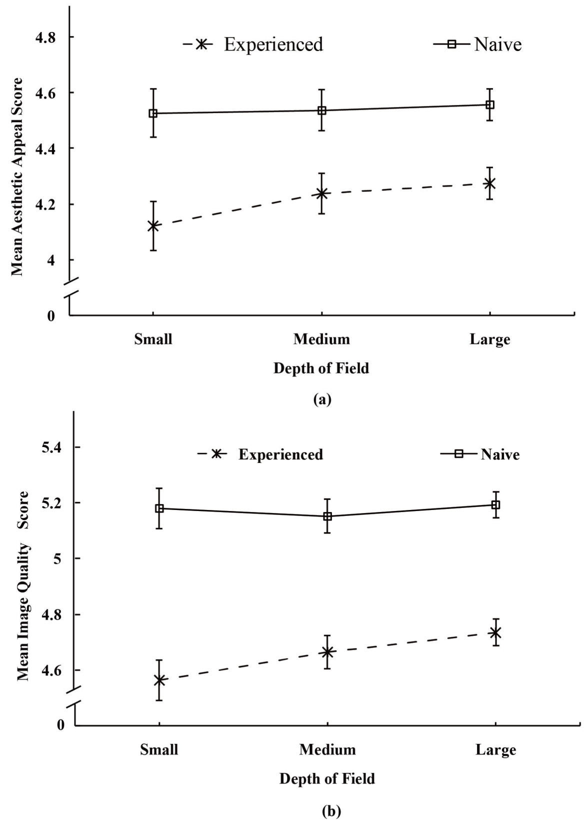

FIGURE 4. The effects of expertise on aesthetic appeal and image quality.

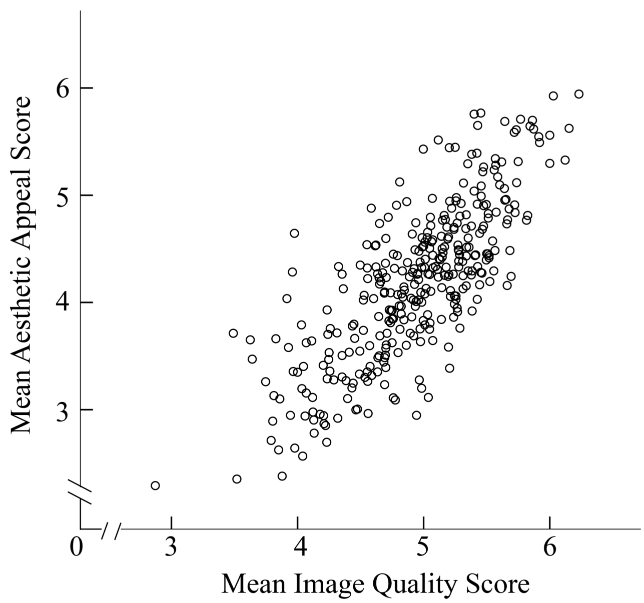

FIGURE 5. The scatter diagram of the subjective data.

III. MODELS BETWEEN AESTHETIC APPEAL AND IMAGE QUALITY

In the last session, we analyzd the effects of depth of field on subjective assessment of aesthetic appeal and image quality. Based on the current data we got, we would like to examine them to see whether we could predict aesthetic appeal through image quality data. We used two different methods to do the modelling.

A. LINEAR REGRESSION MODELLING

We first took a overall look at the data, and Fig 5 shows the scatter diagram. It can be seen that aesthetic appeal seems increase with increasing image quality. Hence, we tried to use a linear model to investigate the relationship between aesthetic appeal and image quality.

As mentioned in the subjective experiment session, there were 339 photographs in total which were classified into three categories according to the size of depth of field. We took 70% of the photographs (236) to train the model, and verified the model with the rest 103 photographs. We performed a

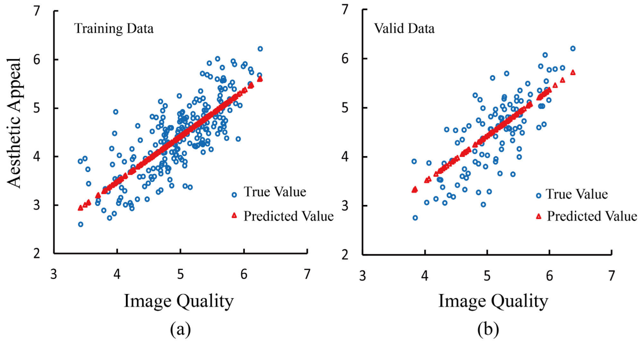

FIGURE 6. The linear regression model in (a) training dataset and (b) valid dataset.

linear model regressing "image quality (IQ)" on "aesthetic appeal (AQ)" in SPSS. We found that the predicted AQ could be calculated with the following equation (1):

$$AQ = 0.94 * IQ - 0.273 \tag{1}$$

The results show that the aesthetic appeal has a slope of 0.94 and it is statistically significant at a p-value of 0.001. We found that the R2 = 0.615 which means that the linear regression explains 61.5% of the variance in the data. Equation 2 shows how to calculate square R. In the equation, AQ_P represents the predicted aesthetic appeal, AQ_T is the true aesthetic appeal, and AQ is the mean aesthetic appeal across photographs.

$$R^2 = \frac{\sum(AQ_P - AQ)^2}{\sum(AQ_T - AQ)^2} \tag{2}$$

With these models, we also calculated the accuracy of the predicted values. The subjective assessed mean aesthetic appeal score across participants for each photographs was regarded as the true value and the calculated value using equation 1 was regarded as the predicted value. If the difference between true value and predicted value was smaller than 1, we classified the predicted value as correct. The accuracy was 96.6%. We tested the model on the valid dataset. We got the accuracy at 95.1% and R2 is 0.45. Fig. 6 shows the predicted values and the true values in both training data set and valid data set.

Using the same method, we investigated whether depth of field had effects on the model. For dataset across depth of field, the linear regression models are as follows:

$$AQ = 0.743 * IQ + 0.723 \tag{3}$$
$$AQ = 0.794 * IQ + 0.476 \tag{4}$$
$$AQ = 0.877 * IQ + 0.022 \tag{5}$$

All of the three models are quite similar, and the p-values of the three models are all smaller than 0.001, which means that the three models have a significant meaning to predict the aesthetic appeal from image quality.

There are two "Accuracy" in Table 2, "d<1" means that the difference between the predicted aesthetic appeal score and the true aesthetic appeal score is smaller than 1. "d<0.5" means the difference is smaller than 0.5. From the table, we could see that linear regression model can work to predict subjective aesthetic appeal from subjective image quality assessment. However, for the photographs with medium depth of field, the model does not work as well as it for the small or large depth of field.

TABLE 2. Correlation coefficient R^2 and predicted accuracy of the models across depth of field.

Dataset	R^2	Accuracy(d<1)	Accuracy(d<0.5)
Small DOF Training Data	0.593	100%	78.3%
Small DOF Valid Data	0.462	100%	76.2%
Medium DOF Training Data	0.621	100%	79.1%
Medium DOF Valid Data	0.343	86.2%	44.8%
Large DOF Training Data	0.57	95.4%	71.6%
Large DOF Valid Data	0.502	97.9%	74.5%
ALL DOF Training Data	0.615	96.6%	72.5%
ALL Valid Data	0.45	95.1%	72%

TABLE 3. Shared parameters.

Parameter	Value
Learning rate	1e-3
Network type	Full connected layers
Layer1	80 units
Layer2	100 units
Layer3	80 units
Activation	relu
Batchnormalize	True

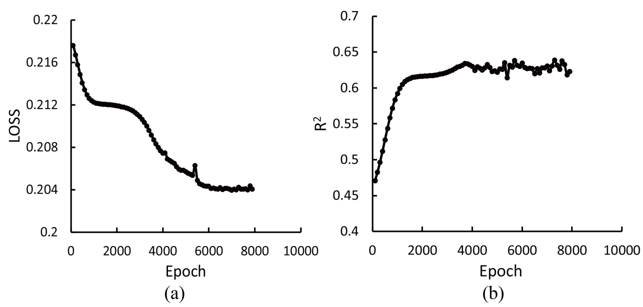

FIGURE 7. (a) The relationship between Loss and Epoch;(b) The relationship between R^2 and Epoch.

B. DEEP NEURAL NETWORKS (DNN) MODELLING

It can be seen in last section that linear regression could work for predicting aesthetic appeal from image quality. However, the linear regression could only explain around 50% of the variance in the data. Hence, we tried to use the Deep Neural Networks (DNN) to improve the models. We used the same dataset as in the linear regression model to train the DNN models. The parameters of the model are shown in Table 3.

Fig. 7 shows how the Loss and R^2 of the DNN model change with epoch. Loss represents the difference between the predicted value and the true value, shown in equation 6. In the equation, ${y_p}^i$ is the predicted aesthetic appeal score and ${y_t}^i$ is the true value. It can be seen in the figure that the Loss decreases quickly with increasing epoch. Here, epoch means

TABLE 4. Correlation coefficient R^2 and predicted accuracy of the models across depth of field of DNN models.

Dataset	R^2	Accuracy(d<1)	Accuracy(d<0.5)
Small DOF Training Data	0.984	95.7%	82.6%
Small DOF Valid Data	0.767	100%	85.7%
Medium DOF Training Data	0.906	97%	83.6%
Medium DOF Valid Data	0.549	86.2%	48.3%
Large DOF Training Data	0.702	94.5%	75.2%
Large DOF Valid Data	0.521	97.9%	74.5%
ALL DOF Training Data	0.633	97.5%	73.7%
ALL Valid Data	0.565	93.2%	68.9%

the time that the dataset was trained. With the increasing epoch, R^2 is also increasing. Hence, the DNN model is getting better with increasing with epoch.

$$Loss = \sum (y_p i - y_t i)^2 \tag{6}$$

The results of the DNN model are shown in Table 4. We compare the performance of DNN model against the linear regression model. We can see that R^2 of the DNN model is much higher than the linear regression model, which means that DNN model can better explain the variance of the predicted aesthetic appeal scores. The accuracy ($d < 1$) of the predicted value is quite similar for the both models. If we make the accurate standard more critical, the accuracy ($d < 0.5$) of the DNN model is higher than the linear regression model.

IV. DISCUSSIONS

In this paper, we investigated the effects of depth of field on subjective evaluation of aesthetic appeal and image quality. With the subjective scores, we proposed two different models to predict aesthetic appeal scores from image quality scores.

A. THE SUBJECTIVE EVALUATION OF AESTHETIC APPEAL AND OVERALL QUALITY

In the current study, we found that depth of field was a significant main factor on both aesthetic appeal and image quality. Large depth of field was considered yielding both higher aesthetic appeal and higher image quality in photographs. Obviously, our results did not support the researchers who claimed small depth of field could increase the aesthetic appeal of photographs [8], [10]. In addition, our results seem to contradict a previous study that considered sharpness as a less important photographic feature in the evaluation of aesthetic appeal compared to other features such as semantics and clutter [11]. There could be several reasons for our different findings. First, the small level of depth of field we used might have created too much blur, making many details missing. Observers might have evaluated the less informative photographs as less beautiful. Second, the small depth of field made the objects in the photographs be perceived closer [14], [19], [30], which might have a negative effect on the aesthetic appeal of the photographs. Though small depth of field was believed to be able to introduce many advantages, we concluded that a larger depth of field was inclined to lead to more beautiful photographs.

For image quality, depth of field was also a significant main factor. Generally, participants gave the photographs with large depth of field (i.e., almost sharp everywhere) a high score in image quality. The resutls are surprising because people do like using small depth of field effects in taking photographs in daily life. It seems that when people are asked to evaluate image quality they consider depth of field blur as image degradation just like motion blur. It is difficuly to explain the reasons. Maybe the size of the depth of field was not controlled properly, and the areas where participants wanted to get more information were blurred. On the other hand, it was not likely that a majority of the photographs we selected had a sub-optimal depth of field. The results are helpful when designing blur quality metrics or de-blurring algorithms. According to the results, sharpness is one of the most important features that affect the subjective evaluation of image quality. It is important for these metrics to distingwish depth of field blur from distortion blur or motion blur [11].

B. COMPARISON BETWEEN EXPERIENCED AND NAIVE PARTICIPANTS

The results showed that the experienced participants were more critical than naive participants when judging the aesthetic appeal and image quality. For experienced participants, the aesthetic appeal scores increased with increasing depth of field. The reason could be that the experienced participants considered sharpness as the most important visual feature that makes a photograph more beautiful, which proves previous work [8], [43]. For naive participants, depth of field did not influence their evaluation of aesthetic appeal, which goes against the conclusion that a small depth of field could make a photograph more beautiful [8], [10]. We can conclude that experienced and naive participants have different opinions on depth of field, and their judgements on aesthetic appeal and image quality are different. For image quality, the results are similar to what we found for aesthetic appeal, but less pronounced.

C. PREDICTING AESTHETIC APPEAL FROM IMAGE QUALITY

In this work, we used two methods to predict aesthetic appeal from image quality: linear regression model and DNN model. The results proved that aesthetic appeal indeed can be predicted by image quality. The linear regression model can work but not as good as DNN model. We found that the linear regression model could only explain fewer than the half valid dataset. However, the accuracy of the predicted aesthetic appeal is high and the model could explain more than half valid dataset. Hence we conclude that aesthetic appeal can be well predicted by image quality with a proper DNN model. Moreover, depth of field does not influence the performance of the DNN model while the slope and intercept of the linear regression model slightly changes. It suggests that we can easily get the aesthetic appeal of any photograph with a good no-reference image quality metric.

D. LIMITATIONS TO OUR RESEARCH

In the current research, we evaluated the effects of depth of field on aesthetic appeal and image quality, not only for a large set of commonly available photographs from the internet and from personal collections, but we also added 24 photographs that we made under very well controlled conditions of depth of field. Obviously, the level of depth of field was not very precisely determined for the photographs taken from the internet and from personal collections. In that sense, the amount of photographs with a well-defined and clearly distinct depth of field may be considered limited, and could be extended with other content in future research. On the other hand, we used photographs that were very diverse in type of content, and nonetheless were able to draw general conclusions. Still, it might be useful to investigate the interaction of depth of field with image content, although probably not all content is commonly taken with all levels of depth of field.

V. CONCLUSION

In summary, we conclude that depth of field is a significant feature that can affect a photograph's aesthetic appeal and image quality. People who have more experience in photography are always more critical than other people when judging the aesthetic appeal and image quality of photographs. In addition, we conclude that aesthetic appeal is highly correlated with image quality. Linear regression model and DNN model both can be used to predict aesthetic appeal from image quality.

REFERENCES

[1] M. A. Webster, M. A. Georgeson, and S. M. Webster, "Neural adjustments to image blur," *Nature Neurosci.*, vol. 5, no. 9, pp. 839–840, Sep. 2002.

[2] K. N. Ogle and J. T. Schwartz, "Depth of focus of the human eye," *J. Opt. Soc. Amer.*, vol. 49, no. 3, pp. 273–280, 1959.

[3] F. Crete-Roffet, T. Dolmiere, P. Ladret, and M. Nicolas, "The blur effect: Perception and estimation with a new no-reference perceptual blur metric," *Proc. SPIE, Int. Soc. Opt. Eng.*, vol. 6492, Feb. 2007, Art. no. 64920I.

[4] H. De Ridder, "Cognitive issues in image quality measurement," *J. Electron. Imag.*, vol. 10, no. 1, p. 47, 2001.

[5] J. A. J. Roufs, "Brightness contrast and sharpness, interactive factors in perceptual image quality," *Proc. SPIE*, vol. 1077, pp. 66–72, Aug. 1989.

[6] R. Ferzli and L. Karam, "A no-reference objective image sharpness metric based on the notion of just noticeable blur (JNB)," *IEEE Trans. Image Process.*, vol. 18, no. 4, pp. 717–728, Apr. 2009.

[7] Y. Rivenson, Z. Göröcs, H. Günaydin, Y. Zhang, H. Wang, and A. Ozcan, "Deep learning microscopy: Enhancing resolution, field-of-view and depth-of-field of optical microscopy images using neural networks," in *Proc. CLEO, Appl. Technol.*, May 2018, pp. 1–2.

[8] R. Datta, D. Joshi, J. Li, and J. Z. Wang, "Studying aesthetics in photographic images using a computational approach," in *Proc. Eur. Conf. Comput. Vis.*, 2006.

[9] G. Mather and D. R. Smith, "Depth cue integration: Stereopsis and image blur," *Vis. Res.*, vol. 40, no. 25, pp. 3501–3506, Jan. 2000.

[10] S. Dhar, V. Ordonez, and T. L. Berg, "High level describable attributes for predicting aesthetics and interestingness," in *Proc. CVPR*, Jun. 2011, pp. 1657–1664.

[11] C. D. Cerosaletti and A. C. Loui, "Measuring the perceived aesthetic quality of photographic images," in *Proc. Int. Workshop Qual. Multimedia Exper.*, Jul. 2009.

[12] Y. Luo and X. Tang, "Photo and video quality evaluation: Focusing on the subject," in *Proc. Eur. Conf. Comput. Vis.*, 2008.

[13] A. P. Pentland, "A new sense for depth of field," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI–9, no. 4, pp. 523–531, Jul. 1987.

[14] D. Vishwanath and E. Blaser, "Retinal blur and the perception of egocentric distance," *J. Vis.*, vol. 10, no. 10, p. 26, Aug. 2010.

[15] T. Zhang, H. T. Nefs, and I. Heynderickx, "Human discrimination of depth of field in stereoscopic and nonstereoscopic photographs," *Perception*, vol. 43, no. 5, pp. 368–380, May 2014.

[16] H. T. Nefs, "Depth of field affects perceived depth-width ratios in photographs of natural scenes," *Seeing Perceiving*, vol. 25, no. 6, pp. 577–595, 2012.

[17] S. Hillaire, A. Lecuyer, R. Cozot, and G. Casiez, "Depth-of-field blur effects for first-person navigation in virtual environments," *IEEE Comput. Graph. Appl.*, vol. 28, no. 6, pp. 47–55, Nov. 2008.

[18] D. Vishwanath, "Is focal blur an absolute cue to depth?" *J. Vis.*, vol. 7, no. 9, p. 845, Mar. 2010.

[19] R. T. Held, E. A. Cooper, J. F. O'Brien, and M. S. Banks, "Using blur to affect perceived distance and size," *ACM Trans. Graph. (TOG)*, vol. 29, no. 2, pp. 1–16, Mar. 2010.

[20] A. Loui, M. D. Wood, A. Scalise, and J. Birkelund, "Multidimensional image value assessment and rating for automated albuming and retrieval," in *Proc. 15th IEEE Int. Conf. Image Process.*, Oct. 2008.

[21] E. A. Fedorovskaya, "Perceived overall contrast and quality of the tone scale rendering for natural images," *Proc. SPIE*, vol. 4662, pp. 119–128, May 2002.

[22] A. W. Ijsselsteijn, H. D. Ridder, and J. Vliegen, "Effects of stereoscopic filming parameters and display duration on the subjective assessment of eye strain," *Proc. SPIE*, vol. 3957, pp. 12–22, May 2000.

[23] M. Mauderer, S. Conte, M. A. Nacenta, and D. Vishwanath, "Depth perception with gaze-contingent depth of field," in *Proc. 32nd Annu. ACM Conf. Hum. Factors Comput. Syst.-CHI*, 2014, pp. 217–226.

[24] H. de Ridder, "Psychophysical evaluation of image quality: From judgment to impression," *Proc. SPIE*, vol. 3299, pp. 252–263, Jul. 1998.

[25] P. Marziliano, F. Dufaux, S. Winkler, and T. Ebrahimi, "Perceptual blur and ringing metrics: Application to JPEG2000," *Signal Process., Image Commun.*, vol. 19, no. 2, pp. 163–172, Feb. 2004.

[26] L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, "Image deblurring with blurred/noisy image pairs," *ACM Trans. Graph. (TOG)*, vol. 26, no. 3, p. 1, Jul. 2007.

[27] J. Biemond, R. Lagendijk, and R. Mersereau, "Iterative methods for image deblurring," *Proc. IEEE*, vol. 78, no. 5, pp. 856–883, May 1990.

[28] P. Marziliano, F. Dufaux, S. Winkler, and T. Ebrahimi, "A no-reference perceptual blur metric," in *Proc. Int. Conf. Image Process.*, vol. 3, Jun. 2003, p. 3.

[29] H. Liu, J. Wang, J. Redi, P. Le Callet, and I. Heynderickx, "An efficient no-reference metric for perceived blur," in *Proc. 3rd Eur. Workshop Vis. Inf. Process.*, Jul. 2011, pp. 174–179.

[30] D. Vishwanath, "Toward a new theory of stereopsis," *Psychol. Rev.*, vol. 121, no. 2, p. 151, 2014.

[31] A. Kuijsters, W. A. Ijsselsteijn, M. T. M. Lambooij, and I. E. J. Heynderickx, "Influence of chroma variations on naturalness and image quality of stereoscopic images," *Proc. SPIE*, vol. 7240, Feb. 2009, Art. no. 72401E.

[32] P. Seuntiens, L. Meesters, and W. Ijsselsteijn, "Perceived quality of compressed stereoscopic images: Effects of symmetric and asymmetric jpeg coding and camera separation," *ACM Trans. Appl. Perception (TAP)*, vol. 3, no. 2, pp. 95–109, 2006.

[33] R. G. Kaptein and A. Kuijsters, "Performance evaluation of 3D-TV systems," *Proc. SPIE* vol. 6808, Jan. 2008, Art. no. 680819.

[34] L. E. Szechter and L. S. Liben, "Children's aesthetic understanding of photographic art and the quality of art-related parent? Child interactions," *Child Develop.*, vol. 78, no. 3, pp. 879–894, May 2007.

[35] O. Axelsson, "Towards a psychology of photography: Dimensions underlying aesthetic appeal of photographs," *Perceptual Motor Skills*, vol. 105, no. 6, p. 411, 2007.

[36] W. Zhang and H. Liu, "Learning picture quality from visual distraction: Psychophysical studies and computational models," *Neurocomputing*, vol. 247, pp. 183–191, Jul. 2017.

[37] H. Liu, J. Redi, H. Alers, R. Zunino, and I. Heynderickx, "No-reference image quality assessment based on localized gradient statistics: Application to JPEG and JPEG2000," *Proc. SPIE*, vol. 7527, Feb. 2010, Art. no. 75271F.

[38] H. Liu, N. Klomp, and I. Heynderickx, "A no-reference metric for perceived ringing artifacts in images," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 20, no. 4, pp. 529–539, Apr. 2010.

[39] F. Gao, J. Yu, S. Zhu, Q. Huang, and Q. Tian, ''Blind image quality prediction by exploiting multi-level deep representations,'' *Pattern Recognit.*, vol. 81, pp. 432–442, Sep. 2018.

[40] A. M. Belfi, E. A. Vessel, and G. G. Starr, ''Individual ratings of vividness predict aesthetic appeal in poetry,'' *Psychol. Aesthetics, Creativity, Arts*, vol. 12, no. 3, pp. 341–350, Nov. 2017.

[41] E. A. Vessel, A. I. Isik, A. M. Belfi, J. L. Stahl, and G. G. Starr, ''The default-mode network represents aesthetic appeal that generalizes across visual domains,'' *Proc. Nat. Acad. Sci. USA*, vol. 116, no. 38, pp. 19155–19164, Sep. 2019.

[42] W.-H. Kim, J.-H. Choi, and J.-S. Lee, ''Objectivity and subjectivity in aesthetic quality assessment of digital photographs,'' *IEEE Trans. Affect. Comput.*, early access, 2019, doi: 10.1109/TAFFC.2018.2809752.

[43] P. P. Tinio, H. Leder, and M. Strasser, ''Image quality and the aesthetic judgment of photographs: Contrast, sharpness, and grain teased apart and put together,'' *Psychol. Aesthetics, Creativity, Arts*, vol. 5, no. 2, p. 165, 2011.

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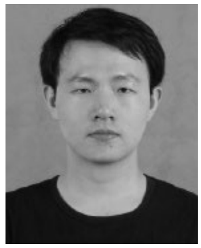

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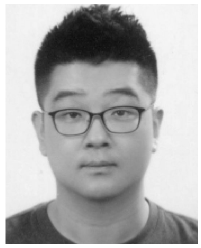

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