Bridging Human Intuition and AI in Colorful Food Assessment

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Abstract

The concept of "eating the rainbow" has emerged as a promising strategy for promoting healthy food choices. This study investigates the relationship between human and computer perceived colorfulness and healthiness in food images. We surveyed 25 diverse participants who rated the colorfulness and healthiness of 60 food images, and we applied a computational colorfulness metric to these images under three conditions: original image, masked food and dishware, and masked food only. Results revealed a weak but significant positive association between human-rated and computer-rated colorfulness, and a significant positive association between human-rated colorfulness and perceived healthiness, regardless of nutrition education background. However, we found no significant correlation between computer-analyzed colorfulness and human-perceived healthiness across all image types. This discrepancy highlights the complex relationship between food colorfulness and perceived healthiness, emphasizing the need for more sophisticated computational models that better align with human perception in AI-assisted dietary tools.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; • **Applied computing → Health informatics**; • **Computing methodologies → Computer vision**; • **Information systems →** *Multimedia information systems.*

Keywords

human-computer interaction, computational color analysis, colorfulness perception, food healthiness, dietary assessment, AI-assisted dietary tools, food image analysis

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1 Introduction

While numerous technologies and methods have been developed to assist people in food logging and dietary analysis, they often fall short of providing accurate, comprehensive, and beneficial guidance [5, 7, 9]. Problems range from user-related issues like inconsistent or inaccurate reporting to technological challenges such as the inherent difficulty of categorizing the infinite variety of foods people consume. Moreover, the prevalent focus on calorie counting in computer-based dietary tracking oversimplifies the nuances of nutritional quality and can potentially lead to counterproductive behaviors [13].

"Eating the rainbow" is an emerging nutritional concept that aims to simplify healthy eating by emphasizing color diversity in food choices and encouraging increased fruit and vegetable consumption [2, 11, 12, 16]. By focusing on easily observable characteristics like color variety, this method provides a more accessible and user-friendly approach to improving dietary habits. As we explore more effective tools for promoting healthy eating, incorporating the perception of colors in food as a complementary computer-based dietary tracking method could offer a more intuitive and user-friendly way to assess meal quality.

However, to effectively implement such color-based approaches in dietary tools, we need to understand how human perception of food colors aligns with computational analysis. This study seeks

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to investigate (RQ1) the relationship between human-perceived colorfulness and computer-rated colorfulness in food images, and (RQ2) the relationship between human-perceived healthiness and computer-rated colorfulness in food images. To address these questions, we conducted a survey with 25 diverse participants who rated the colorfulness and healthiness of 60 food images. We then applied a computational colorfulness metric to these images under three conditions: original image, masked image in which only food and dishware are visible, and masked image of food only. We performed statistical analysis to evaluate the associations between human-rated colorfulness, perceived healthiness, and computer-analyzed colorfulness. This study highlights the challenges in translating human perception into computational models, particularly regarding the correlations between colorfulness and perceived healthiness of food images.

2 Related Work

AI technologies have transformed dietary tracking, offering personalized, real-time insights through smartphone applications. Mobile apps are playing a major role in this shift, offering features like food identification from photos, nutritional tracking, and personalized meal planning [21].

For example, MyFitnessPal integrates Passio's Nutrition AI [18], which includes features like visual food detection, OCR scanning of nutrition labels, and barcode scanning for packaged products. It also supports voice logging for fast, easy entry of multiple foods. As another example, MyNetDiary uses image recognition and food analysis algorithms to scan and analyze meals, including toppings and sauces [23]. Both apps enable users to track micro and macronutrient intake and access personalized meal plans, making it easier to manage dietary goals with AI-driven tools.

However, when dietitians and nutritionists review food photos, they often find discrepancies between AI-estimated and actual calorie intake. These can be due to underreporting, misreporting, selection of inappropriate food items, omission of ingredients like cooking oils, or underestimation of portion sizes. While nutrition professionals can easily identify these errors, AI systems that only provide calorie estimates without additional context may fail to establish user trust. Moreover, AI virtual assistants are often found to fail in meeting participants' personalized goals and needs, and frequently misunderstand their requests [17]. Consequently, involving nutrition professionals in the development and evaluation of these systems is crucial to ensure accuracy, meet user requirements, and bridge the gap between AI capabilities and human expertise [4].

Instead of trying to perform complex analytics like calorie counting, an alternative is to build technologies that encourage people to reflect on the diversity of foods that they eat. One common heuristic offered by nutritionists is to eat colorful foods, which encourages diversity of foods and food groups.

Color plays a significant role in shaping human perception and emotional responses. Studies have shown that color photos were rated as more pleasant than grayscale photos when the image valence was positive, and more unpleasant when the image valence was negative [14], demonstrating the impact of color on our emotional interpretation of visual stimuli. However, human perspectives on color are subjective and influenced by factors including cultural background, personal experiences, and psychological states [6]. These individual and cultural differences in color perception can lead to varying interpretations and responses to colored stimuli. Even seemingly simple tasks like assigning color labels (e.g., blue, red, yellow) to samples from the color spectrum can result in varying levels of disagreement among human annotators [3]. For instance, one study showed high consistency for colors like green but less agreement for others such as white [24]. In the context of food, plate colors have been shown to influence food intake. More research is needed to understand the contrast interaction between the colors of the plate and the served food [1].

This subjectivity and variation in how people see color presents a major difficulty in computational models of color and colorfulness. Digital camera sensors typically capture three observations per pixel corresponding to red, green, and blue (RGB) portions of the visual spectrum. While RGB space is convenient for recording and display color, other perceptually-uniform spaces such as CIELAB [20] and CIEDE2000 [15] have been developed to better represent perceived differences between colors [22]. Building on this, S-CIELAB [26] incorporated spatial context and texture to preprocess images before applying the standard CIELAB [20] color formula, further refining color perception models. Hasler and Süsstrunk [8] proposed a colorfulness metric that correlates well with human perception of colorfulness in natural images. They found that their metric correlated with 95.3% of their human-annotated data. This colorfulness metric has been widely adopted in various applications, including image quality assessment [25], aesthetic evaluation [19], and other subjective perceptions of images like enjoyment [14].

3 Methods

To answer the question of the relationship between human and computational perceived colorfulness and healthiness in food images, we collected a dataset of exemplar food images. Nine members of our lab with diverse cultural backgrounds (i.e., East Asian, South Asian, Latino, White; born within or outside the USA) photographed their meals using a customized app made with Glide over 14.4 weeks. A total of 372 food images were taken, and we randomly selected 60 for this study. Photos were collected this way using personal smartphones to capture a more practical and accurate representation of food as it appears in everyday situations. Real-life food images have imperfect framing and composition, as well as diverse backgrounds and settings.

3.1 Human-rated colorfulness and perceived healthiness

We recruited twenty-five US adult participants using Prolific to complete a survey that we hosted on Qualtrics. Each participant was shown the 60 food images, one-by-one. For each image, participants rated two attributes, colorfulness and healthiness, on a scale from 0-100 (i.e., 101-point scale used in perception studies [10]), with 0 being least colorful or least healthy, and 100 being most colorful or most healthy. Following the image rating task, participants answered additional questions designed to gather information on their visual perception (frequency of difficulty distinguishing between similar color shades, reliance on visual cues for food quality, freshness, and portion size), use of technology for dietary tracking, nutrition-related experiences (consulting dietitian, nutrition classes/workshops) and relevant demographic data to contextualize the responses.

Questions on color perception and visual cues in food assessment used a 5-point Likert scale ranging from "Never" to "Always." Questions about nutrition education and expert consultation were presented as yes/no items. For questions about adherence to specific diets, dietary tracking app usage, and AI assistant usage, participants were allowed to select multiple applicable options from the provided lists. Each participant was compensated $6 for 30 minutes of their time, and the study was approved by our institution's IRB.

3.2 Computer-rated colorfulness

We generated computational estimates of colorfulness on the same 60 photos that we presented to the humans. We used a web interface from Labelbox, Inc. to manually annotate the boundaries of food and dishware leveraging the pen tool. Using the annotations, we generated three versions of each food photo (see Figure 3): (A) the original image, (B) a masked image in which only food and dishware are visible (with the rest blacked out), and (C) a masked image of food only. These three versions of food images correspond to three different models of colorfulness assessment: (A) colorfulness of a food image depends on all visual information in the image, (B) colorfulness of a food image is restricted to the food and the dishware, and (C) colorfulness of a food image is restricted to only the food region.

Computer-rated colorfulness was calculated using the method of Hasler and Süsstrunk [8]. For each pixel p in an image, they compute the difference between the red and green channels, $\text{rg}_p = R_p - G_p$, and the difference between the blue channel and the average of the red and green channels, $\text{yb}_p = 0.5(R_p+G_p)-B_p$. They then compute the mean μ and standard deviation σ of these variables, and then compute a colorfulness score for the image, Colorfulness = $\sigma_{\text{rgyb}} + 0.3 \times \mu_{\text{rgyb}}$, where $\sigma_{\text{rgyb}} = \sqrt{\sigma_{\text{rg}}^2 + \sigma_{\text{yb}}^2}$, and $\mu_{\text{rgyb}} = \sqrt{\mu_{\text{rg}}^2 + \mu_{\text{yb}}^2}$. We calculated colorfulness for all three versions of food images. For masked images, colorfulness was calculated only in the visible regions containing food and dishware (if present).

3.3 Statistical analysis

Mean and standard deviations of human-rated and computer-rated colorfulness, and human-rated healthiness ratings were computed using Python with the pandas library (version 2.2.2). Linear regression was performed using GraphPad Prism version 10.4.1 (GraphPad Software Inc, San Diego, California, USA) to determine the relationship between human-rated colorfulness and human-rated healthiness, and computer-rated colorfulness and human-rated healthiness in scatter plots. p-values < 0.05 were considered statistically significant.

4 Results

Twenty-five participants (18-84 years old, 28% male, see Table 1) completed the survey in an average of approximately 17.5 minutes. The study participants represented a diverse racial and ethnic background (Table 1). The majority of participants identified as White or Caucasian (n = 15, 60%). The second largest group was Black or African American participants (n = 6, 24%), followed by Asian participants (n = 4, 16%). The smallest group was Hispanic, Latino, or of Spanish origin (n = 1, 4%).

Table 1: Demographics and Diets of Study Participants (n=25).

	Respondents	
	#	%
Gender		
Female	18	72%
Male	7	28%
Age		
18-24	7	28%
25-34	8	32%
35-44	3	12%
45-54	4	16%
55 and above	3	12%
Race and Ethnicity		
Asian	4	16%
Black or African American	6	24%
Hispanic, Latino, or of Spanish origin	1	4%
White or Caucasian	15	60%
Diet Type		
No specific diet	15	55.6%
Vegetarian	6	22.2%
Low-carb	3	11.1%
Gluten-free	1	3.7%
Low-fat	1	3.7%
Vegan	1	3.7%

Analysis of participants' dietary preferences revealed diverse eating habits within the sample (Table 1). Twelve (48%) participants had some form of nutrition education, either through classes, workshops, or interactions with health experts (e.g., dietitians). The majority of participants (55.6%, n=15) reported following no specific diet. Among those adhering to specific diets, vegetarianism was the most prevalent (22.2%, n=6), followed by low-carbohydrate diets (11.1%, n=3). Other dietary patterns, including gluten-free, low-fat, and vegan diets, were each reported by a single participant (3.7% each).

Fifteen (60%) participants had not used any dietary tracking apps. Among the 10 (40%) who did, 9 used MyFitnessPal, some in combination with other apps such as Loseit!, Noom, Cronometer, Fooducate, Lifesum, and FatSecret. Thirteen (52%) participants had not used AI chatbots or virtual assistants for nutrition-related purposes. Among the 12 (48%) who did, common uses included meal planning, nutritional information lookup, diet advice, recipe ideas, and motivation for healthy eating habits.

Twenty (80%) participants never experienced difficulty distinguishing similar color shades (e.g., blue and purple, or red and green), while 5 (20%) participants rarely did. A majority of participants (56%, n = 14) often or always relied on visual cues to assess food quality and freshness, 8 (32%) participants sometimes did, while 3 (12%) participants rarely or never did. Participants were nearly evenly split between never/rarely (44%, n = 11) and often/always (36% n = 9) when using visual cues (e.g., comparing to everyday objects) to estimate portion sizes, with 5 (20%) participants indicating they sometimes did.

We found a positive association between human-rated colorfulness and perceived healthiness for all 60 food images ($p < 0.001$, $R^2 = 0.47$) (Figure 1A). Positive associations between human-rated colorfulness and perceived healthiness were also found for both participants who had some form of nutrition education ($n = 12$, $p < 0.001$, $R^2 = 0.30$; Figure 1B) and those without ($n = 13$, $p < 0.001$, $R^2 = 0.58$; Figure 1C). We also found a statistically significant but weak positive association between human-rated colorfulness and computer-rated colorfulness for original food images ($p = 0.0098$, $R^2 = 0.11$) (Figure 2A), masked images in which only food and dishware are visible ($p = 0.023$, $R^2 = 0.085$; Figure 2B), and masked images of food only ($p = 0.027$, $R^2 = 0.081$; Figure 2C). However, there is no significant association between computer-rated colorfulness and human-rated healthiness in any of the three types: original food image ($p = 0.46$, $R^2 = 0.0095$; Figure 3A), masked images in which only food and dishware are visible ($p = 0.62$, $R^2 = 0.0042$; Figure 3B), and masked images of food only ($p = 0.82$, $R^2 = 0.00087$; Figure 3C).

Figure 4 presents a visual comparison of food images rated lowest in colorfulness by humans and computers. The top row displays four images that received the lowest human-rated colorfulness scores, while the bottom row shows four images with the lowest computer-rated colorfulness scores. Figure 5 presents a similar visual comparison but for the images with the highest human- and computer-rated colorfulness scores.

5 Discussion

Current dietary tracking computer technology methods have limitations, and finding ways to provide users with useful and actionable information is a challenge. Most dietary apps focus on calorie counting, which may be useful to some users but harmful to others. Here, we suggest an additional computer-based dietary tracking method that could be complementary to calorie counting: food colors.

As rated by 25 participants ($p < 0.001$, $R^2 = 0.47$) in our study, there is a positive association between human-rated colorfulness and perceived healthiness for all 60 food images (Figure 1A). A similar trend was observed when the data was divided into participants who had some form of nutrition education ($n = 12$, $p < 0.001$, $R^2 = 0.30$; Figure 1B) and those without ($n = 13$, $p < 0.001$, $R^2 = 0.58$; Figure 1C). Indeed, this aligns with the well-established concept of 'eating the rainbow' in nutrition science and public health promotion, which encourages consuming a variety of fruits and vegetables to ensure a diverse intake of nutrients. Interestingly, the association was stronger for participants without nutrition education, as indicated by the higher R^2 value. This unexpected result may imply that formal nutrition education introduces additional factors in health perception beyond meal colorfulness, potentially leading to a more nuanced evaluation of food healthiness. Regardless of education on nutrition, eating the rainbow could provide the potential for enhanced information in nutrient-related tracking efforts, and dietary tracking algorithms could measure easy-to-understand metrics such as colorfulness in order to help.

However, identifying the correlation between color and healthiness could be difficult for computers. In our study, for example, when we asked for computer-analyzed colorfulness of these three types of images, we found no statistically significant association with perceived healthiness. This discrepancy highlights a challenge in human-computer interaction within the context of food image analysis. This gap between human perception and computer analysis shows the need for more refined computational models to better mimic human perception of food colorfulness and its association with healthiness.

Moreover, our results from the three types of images– (A) the original image, (B) a masked image in which only food and dishware are visible, and (C) masked image of food only– showed a weak but statistically significant positive association between human-rated colorfulness and computer-rated colorfulness ($p < 0.05$, R^2 ranging from 0.081 to 0.11 across different image types). Specifically, these three types of images create three different models: (A) colorfulness of a food image depends on all visual information in the image, (B) colorfulness of a food image is restricted to the food and the dishware, and (C) colorfulness of a food image is restricted to only the food region. Despite the variety of models, the association is still considered weak. The weak correlation contrasts with the strong positive association Hasler and Süsstrunk found with natural images [8]. The weaker correlation in food images might indicate that human perception of colorfulness in food is more complex or nuanced than in general natural scenes.

The complexity was also reflected in our participants' visual cues for assessing food. While most participants (80%) reported no difficulty distinguishing similar color shades, there was considerable variation in how they used visual cues for assessing food. The majority relied on visual cues for assessing food quality and freshness, but were more divided on using visual cues for portion size estimation. This discrepancy suggests that while color perception is generally not an issue, translating this perception into practical dietary decisions may be more challenging.

The type of food present might affect perceived colorfulness. For instance, a salad might be expected to be more colorful than a soup, influencing how people rate its colorfulness. Individual and cultural associations with certain foods might also influence how their colorfulness is perceived. Additionally, in food images, colorfulness might be judged not just on the intensity of colors, but also on the combination of colors present. All these challenges could be opportunities for computing researchers and food-tracking app developers to consider.

Our findings on the use of dietary tracking apps and AI assistants for nutrition purposes highlight a significant gap in adopting these technologies. With 60% of participants not using any dietary tracking apps and 52% not utilizing AI chatbots or virtual assistants for nutrition-related purposes, there is considerable potential for growth in this area. The varied uses reported by those who do use these technologies – from meal planning to motivation for healthy eating habits – suggest diverse needs that future AI-assisted tools could address.

6 Limitations and future work

This study did not fully address how humans perceive colorfulness in food or the heuristics behind their decisions. Future work could include designing studies to understand if the presence of specific

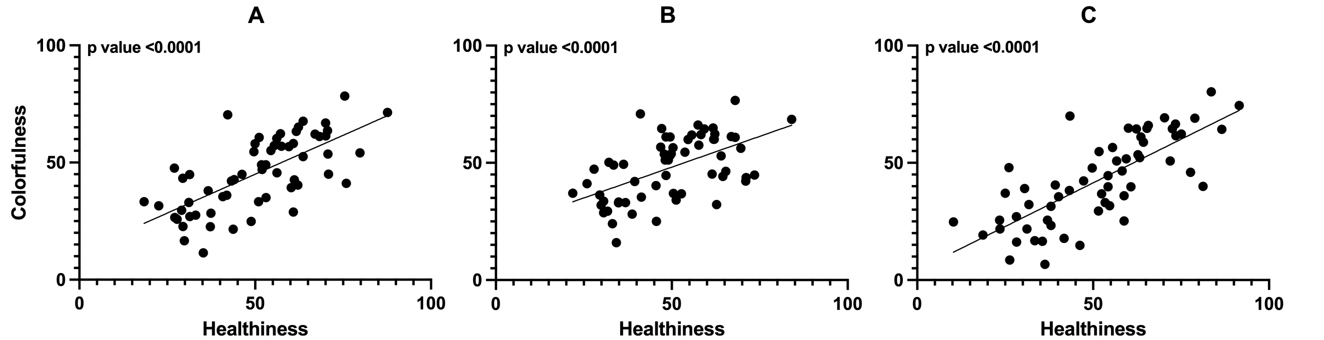

Figure 1: Scatter plots of human-rated colorfulness and perceived healthiness of 60 food images, for (A) all participants (n=25), (B) participants with some nutrition education (n=12), and (C) participants without nutrition education (n=13).

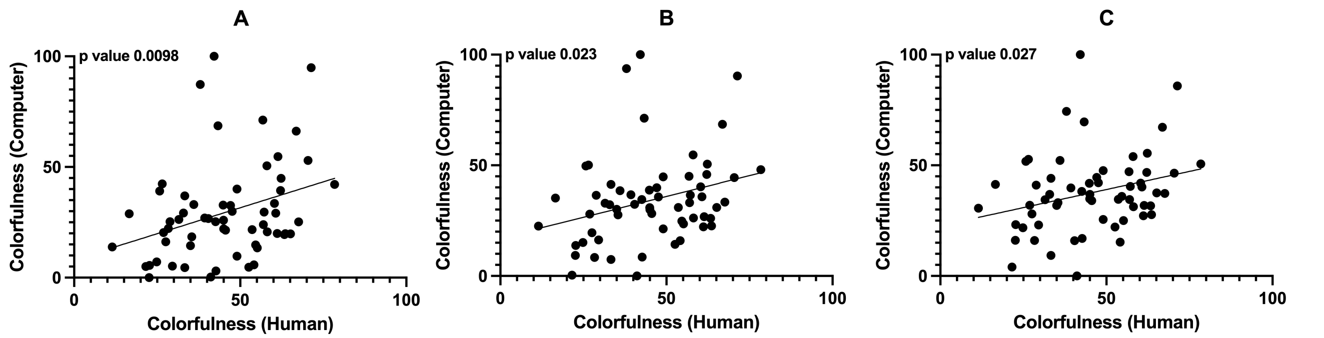

Figure 2: Comparison of human-rated and computer-rated colorfulness for 60 food images for: (A) Original food images, (B) Masked image in which only food and dishware are visible, (C) Masked images of food only. Each point represents one food image, with human-rated colorfulness on the x-axis and computer-rated colorfulness on the y-axis.

colors and combinations influences how colorful a food image is rated, and if context and environmental cues affect the perceived colorfulness of a food image. Such investigations could inform the development of more sophisticated computational models for assessing food images. Additionally, exploring the impact of cultural backgrounds, dietary preferences, and nutrition knowledge on color perception in food could provide valuable insights. These studies would not only enhance our understanding of human perception but also contribute to the creation of more accurate and culturally sensitive AI-assisted dietary tools.

In conclusion, while our study demonstrates the association between perceived colorfulness and perceived healthiness in food images, it also reveals the complexity of this relationship and the challenges in translating it into computational models. As we move towards more AI-assisted dietary tools, it will be crucial to develop systems that can bridge the gap between human perception and computational analysis of food imagery.

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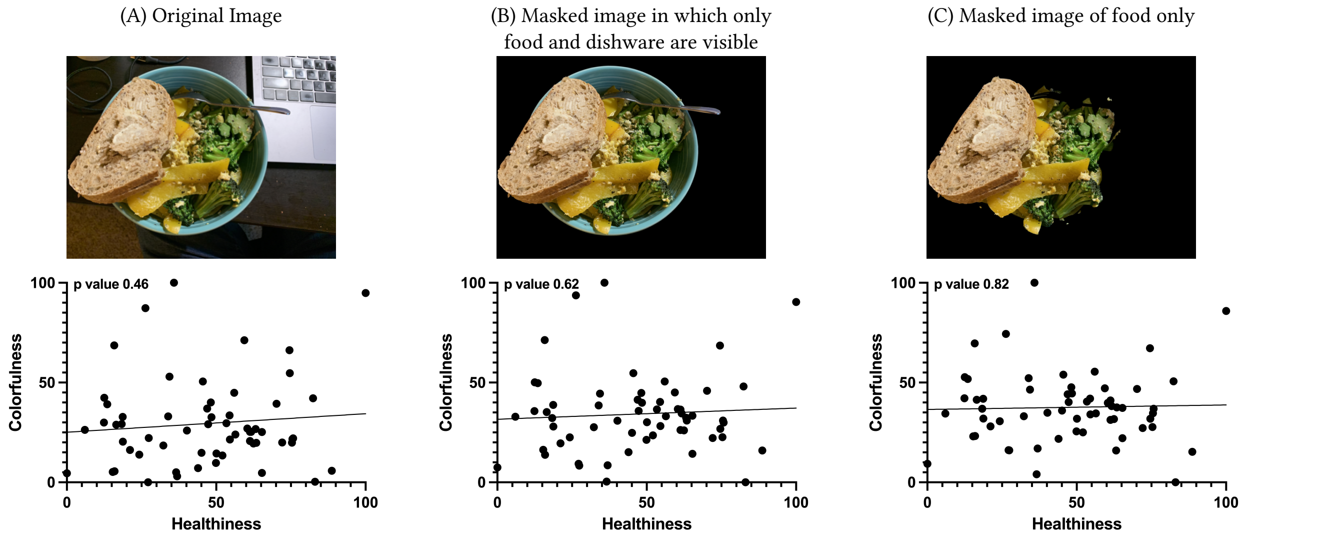

Figure 3: Computer-rated colorfulness on three types of food images: (A) original images, (B) masked images in which only food and dishware are visible, (C) masked images of food only.

A. Four food images with the lowest human-rated colorfulness scores.

B. Four food images with the lowest computer-rated colorfulness scores computed on original images.

Figure 4: Comparison of food images with lowest colorfulness scores, as judged by (A) humans and (b) computer.

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A. Four food images with the highest human-rated colorfulness scores.

B. Four food images with the highest computer-rated colorfulness scores computed on original images.

Figure 5: Comparison of food images with highest colorfulness scores, as judged by (A) humans and (B) computer.

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