

# Understanding the Relation Between User Engagement and the Color Emotions from Images



Lea Mae Cruzat<sup>1</sup>, Dr. Benito Mendoza<sup>1</sup>, Marcelo Sztainberg<sup>2</sup>, Dr. Nancy Wrinkle<sup>2</sup>  
 New York City College of Technology<sup>1</sup> Northeastern Illinois University<sup>2</sup>



## Abstract

Food insecurity is a critical problem in the USA; 38 million people live in conditions of limited or uncertain access to adequate food, according to the USDA. This problem has a harder impact on minority groups, such as Hispanics. Several organizations across the country have different efforts and programs to tackle this problem. For example, the USDA distributes about 88,000 meals a day. Programs like these help a good part of the population in need. These programs use different information channels such as websites, mobile apps, social media, and even text messages to reach communities in need. However, some communities remain disconnected; they do not take advantage of these opportunities. There is a lack of cultural and emotional connection between the organizations and the communities. The work presented here is part of a bigger project that aims to identify the cultural and structural factors that hinder the Hispanic community from engaging with food security organizations' programs. Our goal is to study the correlation between color emotions from images on social media posts and user engagement. We will use the extracted color emotions from the images on the post and analyze the user engagement of the post. We aim to create a machine learning model that can predict user engagement of social media posts using color emotions.

## Introduction

Many Americans, especially minorities such as Hispanics, struggle with food insecurity—inadequate access to food. According to Feeding America, in an article called “The Impact of Coronavirus on Food Insecurity in 2020 & 2021”, around 42 million people experienced food insecurity in 2021. Governmental and private organizations are making enormous efforts to help those suffering from food insecurity. Despite the rise of technology and social media usage to reach out to the communities in need, there is a disconnection between organizations and the targeted audience; many are not taking advantage of the resources. Understanding the emotions that drive those communities could increase their engagement. We are studying the relation between color emotions and user engagement.

## Background

Colors can affect our emotions in various ways. Certain brightness, shade, and tone can affect our feelings. Emphasizing specific colors or denoising them changes the effect of color on emotion. There are a couple of models for representing emotions from images. Our work is based on the Kang approach [1], which advances the model from Kobayashi [2]. Kang developed a database of 50 emotion labels, each represented by a three-color combination. Kang's model was used to find emotions in paintings.

## Methodology

- The we selected Facebook post by these organizations:

Table1. Organizations and Followers

Organization	Type	Followers
Food Bank for New York City	Charity Organization	36k
Greater Chicago Food Depository	Charity Organization	40k

- We stored elements of the posts, such as images, reactions, and shares.
- The images are first filtered using the denoising filter to filter out random brightness on the image.
- We construct Kang's color emotions database (emotionsDB) from [1], along with a Hue & Tone 130 color system (hueDB).
- Extracting color emotions from images:**
  - Image Filtering** (Smoothing): We use a bilateral filter
  - Image Normalization.** We implemented a method to match each color in the original image to the colors in the hueDB.
  - Spectrum Analysis.** The spectrum shows the ratio of pixels for each color in an image.
  - Match emotions to spectrum.** We calculate the similarity to each emotion in the emotionsDB to the spectrum of an image.
- Similarity between one color and the spectrum.** For a color c, its similarity to the spectrum S is the sum of the normalized distance to each color Si weighted by the ratio of Si in the spectrum.
- Similarity between emotions and spectrum.** The similarity of an emotion e to the spectrum S, is the sum of the similarity of the three colors of e to S.

## Result/Discussion

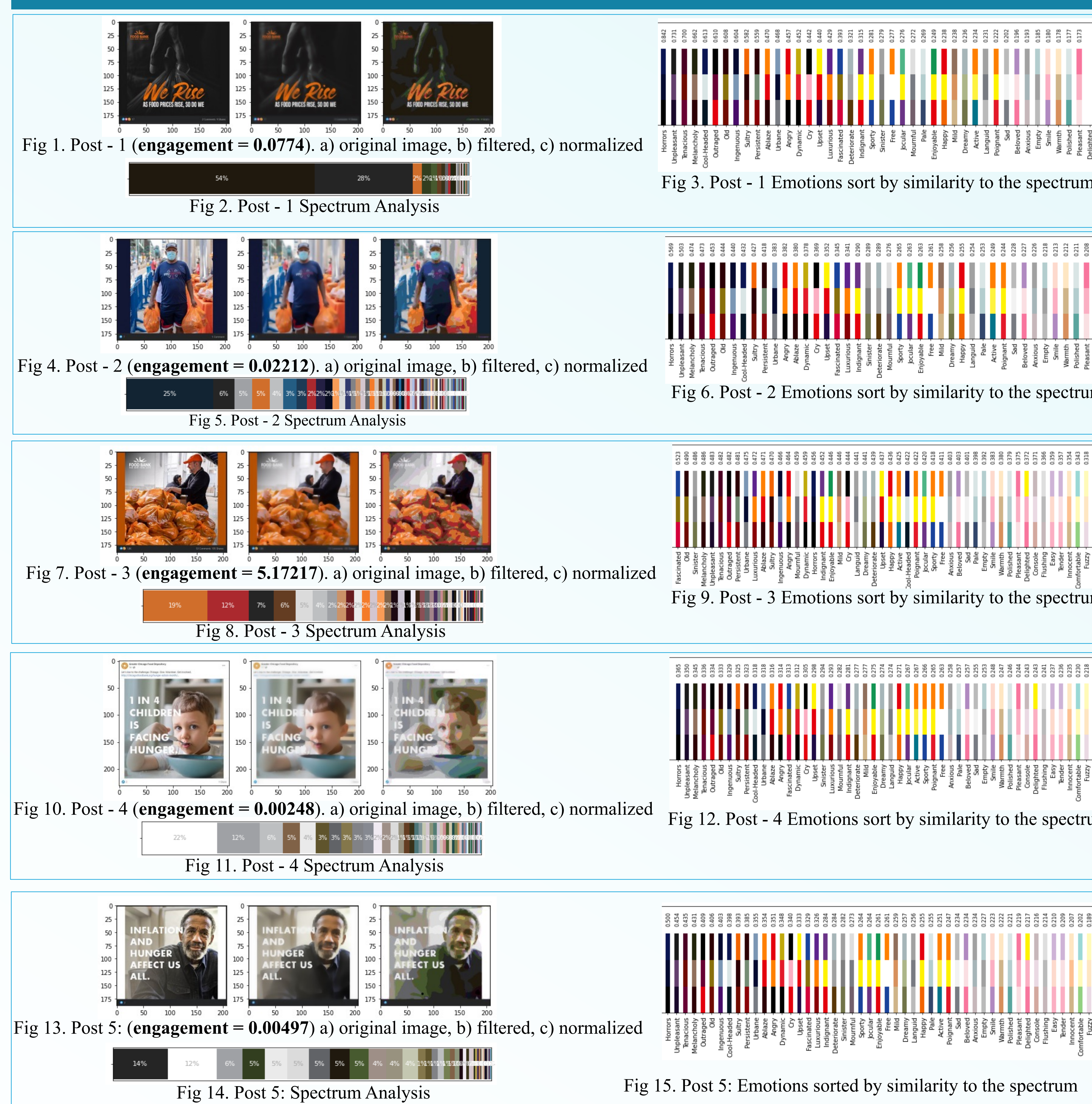


Table 2. Organizations and User Engagement

Post No.	Organization	Comment	Reaction	Share	Engagement Rate
1	Food Bank for New York City	2	17	9	0.077444337
2	Food Bank for New York City	1	7	0	0.022126953
3	Food Bank for New York City	53	1712	105	5.172175356
4	Greater Chicago Food Depository	0	0	1	0.002489792
5	Greater Chicago Food Depository	0	2	0	0.004979584

## Methodology

- As a distance metric, we use the L2 (Euclidean) distance.
- To avoid device dependency, the operations are done in the Lab color system, which is very similar to a Hue & Tone 130 color system.
- Images are converted from RGB to Lab.
- The engagement rate of a post is calculated as **Facebook Engagement Rate = ((Reactions/ Total Posts) ÷ Total Reach) \* 100**

## Conclusion

From an empirical and shallow analysis, there are certain indications that color emotions do affect user engagement. It is shown that most of the images with high similarity with the emotion “horror” had a low engagement rate. Comparing it to the image that has the highest similarities with the emotion “fascinated,” the engagement rate is significantly higher than those that had high similarities with negative emotion. With more data to collect and a further understanding of color emotions and user engagement and sentiment, we aim to develop a machine learning model that includes color emotions to predict user engagement and sentiment.

## Future Work

- Using a large dataset of posts and images to further analyze the relationship between color emotion and user engagement.
- Analyze the relationship between sentiment (positive, negative, neutral) and color emotion

## References

[1] Kang, D., Shim, H. & Yoon, K. A method for extracting emotion using colors comprise the painting image. *Multimed Tools Appl* 77, 4985–5002 (2018). <https://doi.org/10.1007/s11042-017-4667-0>

[2] Kobayashi, Shigenobu. "Color image scale." [http://www.ncd-ri.co.jp/english/main\\_0104.html](http://www.ncd-ri.co.jp/english/main_0104.html) (2009).

[3] Solli M, Lenz R. Color Emotions for image classification and retrieval. Proceedings IS&Ts 4th European Conference on Colour in Graphics, Imaging, and Vision. Springfield, VA: IS&T; 2008. p 367–371.

[4] Kaya, G. A. (2021). Sentiment Analysis of Users' Reactions to Deadly Disasters Posts in Turkey: Facebook Data. *International Journal of Multidisciplinary Studies and Innovative Technologies*, 5(2), 167–172.

[5] LaMorte, W. W. (2021, April 21). PH717 module 9 - correlation and regression. The Correlation Coefficient (r). Retrieved September 23, 2022, from <https://sphweb.bumc.bu.edu/otlt/MPH-Modules/PH717-QuantCore/PH717-Module9-Correlation-Regression/PH717-Module9-Correlation-Regression4.html>

## Acknowledgment

This material is based upon work supported by the National Science Foundation under Grants numbers 2131291. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Thanks to CAHSI for sponsoring the student's trip to GMIS 2022.