On the Game Day Sideline: A Case Study of Web-based AI Color Correction for Social Media Content

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Abstract

Both sports brands and their fans value brand color accuracy across all mediums from jumbotron footage at a live event to social media content. ColorNet, a trio of color correction tools developed at Clemson University, addressed this concern. ColorNet 1.0 used a patented algorithm trained with paired datasets, ColorNet 2.0 addressed some weaknesses in ColorNet 1.0 and achieved similar results using machine learning segmentation, and ColorNet 3.0 was a combined hardware and software solution that allowed content creators to identify distortions in the color spectrum and apply appropriate targeted adjustments. This case study implemented ColorNet 1.5 as a web application intended for sideline, game day use by content creators to ensure brand color accuracy for social media content. Results show that content creators who participated in this study highly value and can identify brand color correctness and that increased processing speed would be a necessity for production-level implementation of this tool.

Introduction

Achieving consistent brand color is challenging in a fast-paced sports game day environment. When consumers look at branded content across many different devices and channels, they expect to see their favorite team with accurate brand color representation (eg. Budelmann et al., 2010; Chang & Lin, 2010). However, there are challenges at a live event. Content creators work in small teams on the sideline during the day trying to capture, edit, and post the most memorable moments through both photographs and video clips to multiple social media channels in as close to real time as possible. In the higher education environment, the social media content team often includes student interns with limited professional experience and content is created across several camera models from multiple manufacturers.

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For example, when this study began, a standard kit for Clemson Athletics included: Five different camera bodies: Sony A7III, Sony A7SII, Sony A7SIII, Canon 5D Mark IV, and Sony FX3 and three Sony lenses—24-70 mm, 70-200 mm, and 100-400 mm—and two Canon lenses—24-70 mm and 100-200 mm. Each iteration of these cameras and lenses produces different color representation in the resulting content (Golabkesh & Walker, E.B., 2022).

Previous studies conducted at Clemson University revealed that approximately half of the fans participating in the study recognized when brand colors are off specification on the jumbotron, and even more commented on the inaccuracies when they were asked specifically about the color representation (Conti & Walker, E.B., 2019). ColorNet is a patented artificial intelligence algorithm that is capable of addressing this issue by detecting and correcting a specified brand color pixel-by-pixel in a live video feed (eg. Walker, E.B., Smith, D.H., Lineberger, J.P., Mayer, M., Mayes, E., & Sanborne, A., 2020; Walker, E.B., Smith, D.H., Mayes, E., Lineberger, J.P., Mayer, M., & Sanborne, A., 2020).

A more recent study applied the ColorNet algorithm in a social media context to see if it could also improve color consistency on real-world social media content across channels, platforms, and content types. The study found a statistically relevant improvement in brand color representation after processing content from this context (Smith, D.H. & Walker, E.B., 2022). Analysis included both brand color and skin tones from content that had been posted on Twitter and Instagram across nineteen official accounts over the past ten years.

This study builds upon previous work to develop and implement a web-based ColorNet application that could be used in a real world, game day situation with Clemson Athletics content creators as a case study.

ColorNet: Version history

ColorNet has three current iterations, each developed to address brand color correctness on imagery in a unique way. Version 1.0 was based on a data-trained algorithm with the initial goal of ensuring brand color consistency for video displayed on a jumbotron at live sporting events. ColorNet 1.0 created an anticipated mask and applied it to the original, color-incorrect image in order to output a color-correct image, Figure 1. The advantage of ColorNet 1.0 was that it was a light, quick-running code base that proved effective in live alpha and beta tests running at 60 frames per second (fps) at 720p. The major weakness of this version was that each new color a user wants to target for correction requires a new, manually created dataset and time to retrain the algorithm and test the results.

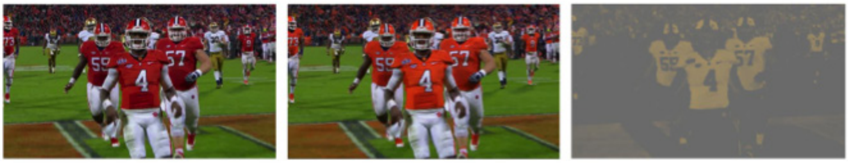

Figure 1: *ColorNet 1.0 used a trained algorithm to create masks (far right) which are applied to the color-incorrect image (far left) to produce a corrected image (middle). The output of the algorithm was the mask.*

In order to address the necessity of manually creating datasets for each additional color, ColorNet 2.0 used a convolutional neural network to output segmentation masks, Figure 2. Segmentation is typically used to identify objects but in our case we wanted it to identify specified parts of the color range. This version selected pixels near a specified color in the spectrum and masked them for correction, ignoring all pixels not identified as the target color. This model worked with color in the HSL (hue, saturation, and lightness) color space rather than in RGB (red, green, and blue) which helps target a brand color whether it was found in highlight or in shadow. The advantage of ColorNet 2.0 was that no training data was needed and adding new target colors was quick. Disadvantages included a slower model and an increase in target artifacts resulting in less "clean" corrections.

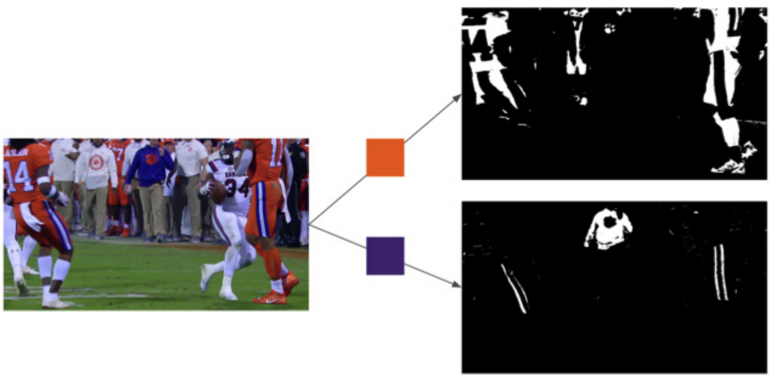

Figure 2. *ColorNet 2.0 used segmentation to select a portion of the color spectrum in each frame, eliminating the need for manually created datasets.*

ColorNet 3.0 was a non-machine learning approach that focused on identifying the "distortions" present in the color rendering seen on screen, Figure 3. This combined hardware/software solution applied a targeted, adjustable distortion to incorrectly colored images to reveal the "true" brand colors. The strengths of ColorNet 3.0 was that it was computationally efficient, it does not require any training data to target additional colors, and multiple colors can be selected and the distortion adjusted individually by the production team for each event using the provided hardware device. The disadvantage was that the production team needs to manually determine the target colors and level of anticipated distortion which may require initial training. The development team plans to provide a set of preprogrammed, commonly used settings to reduce this impact.

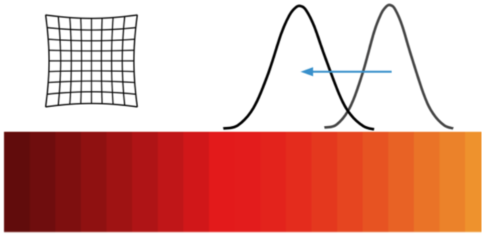

__Figure 3.__ ColorNet 3.0 used a combined hardware and software solution to select a color range that appears incorrect and apply/adjust a corresponding distortion to that area of the image to counteract the color incorrectness.

Experimental Procedure

This study consisted of three parts: a pre-survey, a sideline implementation, and a post-survey. Participants were recruited through contacts with the athletics and university-level content creation teams.

Pre-survey. The pre-survey investigated the level of tolerance for brand color accuracy to understand a baseline of visual preferences at the creator level. This survey also determined the need to continue pursuing this development based on whether the content creators recognized and desired to fix brand color inaccuracies. Section one of the survey covered basic demographics and asked if the respondents had been previously tested and/or diagnosed with any visual color deficiencies. In the second part of the survey, each participant received seven of fourteen randomized photos pulled from social media and were asked the following question: “How close is this to being ready to post?”, Figure 4. Finally, we asked if brand color accuracy was important in their personal and team workflow.

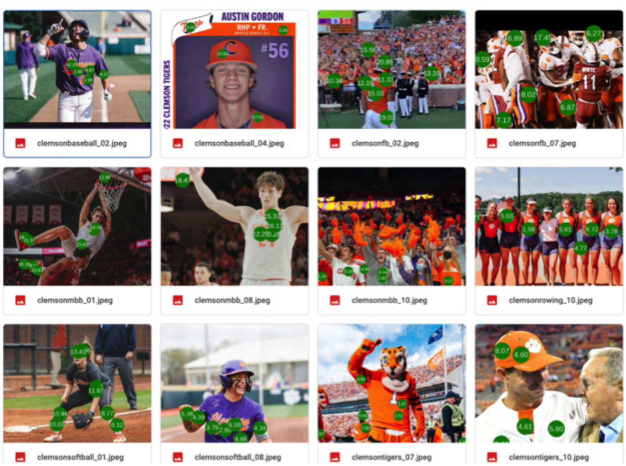

__Figure 4.__ Each survey respondent received seven of fourteen randomized images pulled from previous social media posts across seven official channels and asked “How close is this to being ready to post?” The green circles indicate the measured ΔE value relative to Clemson brand orange used in the quantitative post-survey analysis and were not shown in the survey.

Case study. The case study examined a five day-period where users implemented the web application. The web application design stack was React-Flask-Python. PyTorch was used to train the machine learning (ML) model used to correct the uploaded images. The application was hosted on an IBM Cloud compute instance.

Each participant confirmed that they were attending an athletic event during the specified time period where they would collect and upload photographs capturing brand color content in the scenes. A PDF detailing the instructions on how to use the web application was provided via email, Figure 5. The developer was also available through email to address any questions or issues that arose during the specified dates.

Each photograph was uploaded by the participant to our servers, automatically labeled based on a provided user name, processed through ColorNet 1.5, and then available for download to the content creator. After the case study, the research team had access to both the original, uploaded photograph and the resulting processed image. From these matched pairs, we were able to make Delta E-based, pixel-level comparisons to each users' images to confirm the efficacy of the color correction.

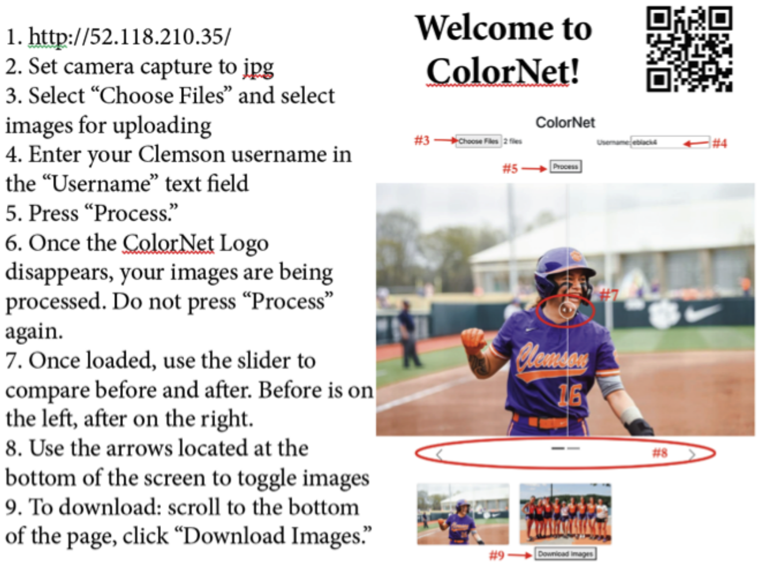

Figure 5. *Each participant in the case study was provided with a set of visual and written instructions via email.*

Post-survey. Feedback regarding the experience using the web app was provided via a post-survey and by examining the paired original and post-ColorNet-corrected photographs uploaded by users. The post-survey asked users about their specific camera and workflow on the day they uploaded images to ColorNet followed by a set of four questions focused on the user experience of the application.

Mixed methods analysis used qualitative and quantitative individual feedback from content creators before and after using the app in their process as well as analysis of the brand color consistency across the resulting pre/post image pairs to measure the resulting ColorNet adjustments. The image pairs were analyzed based on pixels identified as brand color content in “neutral” lighting in each of the fourteen images in the survey were identified using LabelBox, an online tool for image analysis. Any areas of the image that displayed brand color is extreme highlight or shadow or looked noticeably faded (i.e. seatbacks in the stadium that sit in full sun year around) were not identified or factored in to avoid skewing the data.

Results and Discussion

Pre-survey. Fifteen participants responded to the pre-survey with an age range of 20 - 48 and a mean age of 26.5 years old. Professional experience in athletic content creation ranged from six months to over ten years, with a mean of 4.6 years of experience in an equivalent industry. Of the respondents, nine identified as male and six as female. Seven were students, including representatives across four different majors. Eight out of fifteen had previously taken a color vision test and of those eight, none had received a diagnosed color deficiency.

Images were analyzed based on pixels that were identified as Clemson brand orange using the online tool LabelBox. Each image had between four and twelve pixels that were identified as brand color in neutral lighting. The RGB values of each pixel were compared to the brand specification provided by Clemson University using the Delta E 2000 formula and an overall “grade” was determined for how far off the image was from appropriate brand color. This grade was then aligned with user responses regarding how close an image was to ready to be posted in regards to color accuracy. For example an overall high Delta E (ΔE) value across all the specified pixels indicated an image that should require additional color correction before being ready to post on the official social media channels.

Hypothesis 1: Images with higher ΔE values would lead to users responding that higher levels of color-based correction were needed. Findings indicated that there is a significant positive relationship between the likelihood of saying an image needs major correction and worsening color accuracy in the images. The conclusion we draw is that this audience is sensitive to major color errors, at least in this brand color. In fact, holding all things equal, if our audience sees a ΔE of 10, they are 4.86x more likely to say it needs major correction than an image with a 4.35 ΔE.

Hypothesis 2: Individuals who said that color accuracy is “very important” would respond that higher levels of correction were needed when compared with respondents who say “somewhat important.” All of this audience thought it was somewhat or very important. Therefore, there was not a significant difference between those two responses and how much they felt an image needed adjusting.

Case study. Six participants engaged in usability testing of the web application. They uploaded a variety of different images from a range of different events and environments. There were four participants who identified as male and two as female with an age range of 20 - 34 and a mean age of 25.5 years old. Professional experience in athletic content creation ranged from six months to over ten years with a mean of 4.6 years of experience. Job titles include various content creation and directorial roles such as "Content Creator" and "Associate Director of Creative Solutions."

The participants used the web application in different environments: three used the application at a live event, one during an athletic practice, and one from an office setting. Four participants captured their images with both a mirrorless camera and their smartphone and one participant exclusively used a smartphone for image capture. Additionally, participants utilized the web application at different points in their workflow with three using the application after the images were processed through an Adobe Lightroom profile and two using only the provided application for image processing. Two participants even went on to post the images processed by the web application to social media. Three participants had questions while testing the application and received direct assistance from the developer.

The web application's usability testing revealed some issues with the color correction algorithm. Images that had four instead of three color channels would break the algorithm (eg. RGBA images) and images that were very large (4k+ pixels) were also problematic. Once we were aware of these use cases, these issues were addressed by the second day of testing, allowing for all of the remaining participant's images to be processed. One major flaw of the web application was that all the color correction was processed on the web server itself, meaning that the images had to be uploaded, processed, and then downloaded back onto the participant's device. While this process was entirely automatic, there was a significant amount of latency introduced when many images were uploaded simultaneously or when the participant had poor internet connection speed.

We measured the color accuracy of the uploaded images before and after color correction to understand the impact of ColorNet on Clemson's brand color consistency. Locations that should represent brand orange (jerseys, helmets, etc.) were manually selected for each image, again using LabelBox to identify and output specific pixel values. Using the RGB values at these locations, the ΔE value was measured relative to Clemson brand orange (Pantone 165). The effect of ColorNet on brand color accuracy was then evaluated by comparing the ΔE values before and after color correction. User 5 uploaded 34 photos, which was skewing the ΔE analysis so instead 3 photos were selected from that user to have a more consistent data set across participants.

ColorNet shifted the distribution of ΔE values toward zero, implying an overall improvement in color accuracy, Figure 6. However, this shift was not experienced equally by all users with some receiving no significant benefit (eg. user 2), and others experiencing large benefits (eg. user 4), Figure 7. We speculate that this resulted from differences in camera equipment, base camera settings (eg. JPG vs RAW and in-camera picture profiles), and post-processing methods used across participants.

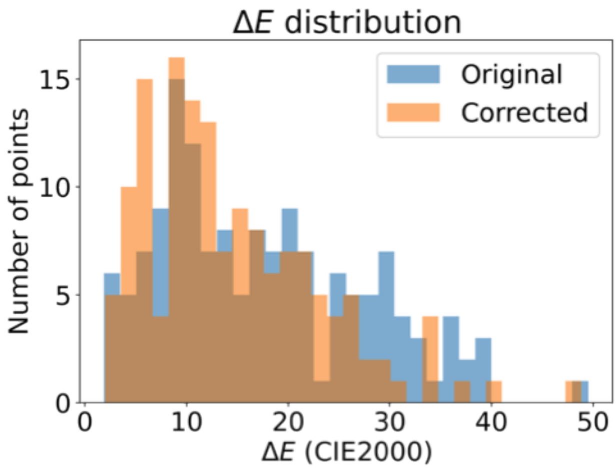

Figure 6. *Visualization of overall ΔE distribution individual data points from across all photographs.*

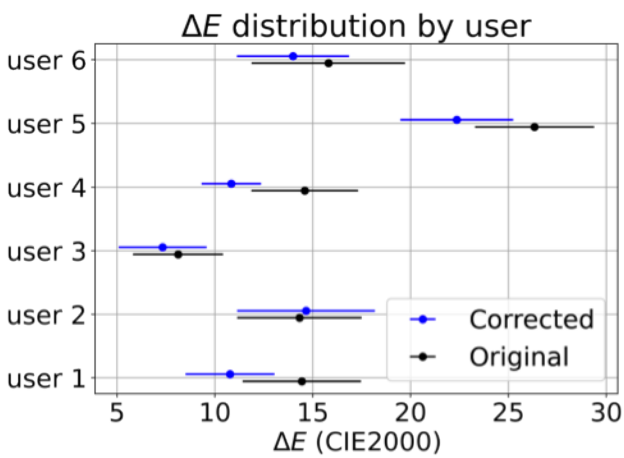

Figure 7. *Visualization of ΔE distribution for each user, showing the range of values and the average (dot in center) for both original and corrected images.*

Post-survey. Five users filled out the post-survey after using the web application during the case study. When asked how accurate the users felt ColorNet was for correcting brand color, three responded that it was somewhat accurate and two responded that it was very accurate. When considering how fast using the ColorNet app was, the result was a bimodal distribution. This was likely due to challenges with the internet connection during live sporting events or when a user submitted a high number of photographs simultaneously and the retrieval of the corrected images after processing was noticeably slow.

Users found the app to be reasonably intuitive. We can start to see a possible normal distribution with this question with one user responding that it was not very usable and four responding that it was either moderately or very usable. The final question asked if users would consider employing the ColorNet application in their workflow again. To this question, one respondent said not very likely and one said very likely, with the other three saying they would be somewhat likely.

This analysis is limited by the relatively small number of participating users. Across all of these questions, more user input following another round of development would be necessary to have a better feel for the usability, speed, accuracy, and projected likelihood of using the app in the future.

Conclusion

In conclusion, implementing an in-development web application in the field presented challenges but it also led to valuable information to guide future efforts in further development and improvements to processing speed. Although the color correction provided by ColorNet 1.5 was accurate enough in practice, the primary bottleneck in the system was the time cost of uploading and downloading the images over the internet. This is especially true in the fast-paced environment common to our target participants. A mobile application, versus a web application, would provide benefits in this area by moving the image processing from an external server to the user's device. This change would allow for much faster processing times and not be limited by unreliable internet connections. Additionally, the current ColorNet implementation could offer improved processing speeds by adding more computing horsepower to the host server. When considering usability, we would like to improve the clarity of what is happening on the app during wait times (eg. when images are uploaded and downloaded). In addition, users requested that we include the option to fully toggle between uncorrected and corrected final images within the app, providing a more clear visual of the pre- and post-corrected image.

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