Title

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Author
VENKATESH, Varish

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Varish Venkatesh
Electrical & Computer Engineering Department, University of California, Los Angeles

varishv06@ucla.edu

Abstract: Modern smartphone cameras rely on computational photography to overcome physical limitations. Using standpoint theory and Black feminist epistemology, this paper examines bias in camera processing pipelines and proposes community based approaches for equitable algorithm design.

INTRODUCTION:

Smartphone cameras over the years have become the most widely used photographic devices in the world, replacing traditional cameras. Most traditional cameras work by capturing a single untouched exposure image, often using the preset settings that a user configured. Unlike traditional cameras, modern phone cameras rely on computational photography which is a set of techniques that uses burst capture, frame alignment, denoising, tone mapping, and other software operations to build the final image from intermediate sensor data (Delbracio et al., 2021; Levoy, 2010). This technology allows smartphone cameras, which are limited in aperture and pixel density due to size constraints, to create photographs that are comparable or even more visually appealing when compared to a traditional camera. However this opens the argument that smartphone cameras produce images that do not accurately reflect the subject that it is capturing.

This argument becomes socially important when it comes to capturing a human body. The software present in the smartphone controls the camera systems which decides many variables including metering exposure, setting the white balance, mapping the skin tones, adding shadows, and more. An article for Google's Real Tone, a trademark technology present in Google Pixel Phones that promises to represent all skin tones in an accurate and appealing way, states that many camera sensors, processing algorithms, and editing tools were historically trained largely on datasets that had light skin as the baseline and that this bias persisted for decades before being addressed directly (Google, 2024). In other words, smartphone cameras have changed the way they approach post processing, varying between brand, time, trained datasets, and other factors. This information shows proof that analyzing the variance in smartphone cameras and reflecting its impact on bias and society would be an excellent case study to conduct. What makes this particularly troubling is that the people most harmed by these defaults, those with darker skin tones, had less seat at the table when the defaults were written.

This paper approaches this complicated and confusing topic of smartphone computational photography as both a literature review and a critical case study. It uses standpoint theory to prove that these imaging systems present in smartphones reflect the biases and injustices present in modern day society. It also uses Black feminist epistemology to argue that minorities who have been subject to inaccurate representation should have a greater authority when it comes to deciding what and how they should be represented in post processing algorithms. This work is in partial fulfillment of the ENGR184 course using the blueprint curriculum in Ref [1,2] and captured in a collection [3]

METHODS:

In this paper, I will use a qualitative literature review method centered around cultural texts on smartphone computational photography. The topics for these papers include but are not limited to computer vision, machine learning algorithms, history of photography, and feminist epistemology. Using the evidence presented in the paper and personal insight, two important questions will be answered. The first is how smartphone cameras actually construct the final appearance of human subjects. The second is what social assumptions become visible when those constructions benefit some people more than others.

The papers are grouped into three groups each supporting a key idea listed previously. The first group of papers defines exactly how computational photography works. Delbracio et al. (2021) describes mobile computational photography as a series of algorithmic advances that transform low resolution raw images captured by smartphones into professional photographs, comparable to ones shot in high quality cameras. This is done by utilizing burst photography, noise reduction, and super-resolution. Hasinoff et al. (2016) specifically talks about the burst image feature described earlier used to enhance image and color quality. They write that their pipeline "captures, aligns, and merges a burst of frames to reduce noise and increase dynamic range" (Hasinoff et al., 2016). Basically by stitching together multiple low quality images, cameras are able to use machine learning to fill up missing pixels resulting in a clear and vivid image. Levoy (2010) also goes into computational photography and describes how most smartphone cameras don't even allow users to see the intermediate steps or the raw sensor images and output only the final processed image. This opacity is not merely a design convenience. It is what allows representational bias to go unquestioned by the very people experiencing it.

The second group of sources examine the bias present in these post processing algorithms specifically when talking about analyzing the human face. The article that provides the most concrete proof of this bias is from Buolamwini and Gebru (2018). The study they conducted involved testing post processing algorithms on different skin colored persons. The study found that benchmark datasets for automated facial analysis were overwhelmingly composed of lighter-skinned subjects. They also found that classification errors were highest for individuals with a darker skin complexion. Grother et al. (2019) further supports this idea for bias by analyzing face recognition algorithms. While this study focused on specifically face recognition, it is safe to say that the data can be used for this paper, both relying on trained datasets and learned models. Through the NIST Face Recognition Vendor Test conducted by this study, it was found that accuracy was indeed correlated with racial demographics and more specifically skin color which supports the bias in training datasets for people with lighter skin color. The convergence of these two independent studies makes it difficult to dismiss the disparity as an anomaly.

The third group of sources interpret this topic in a historical context. These sources show the correlation between the change in societal bias over time and how they correlate with phone processing. The first example of these types of sources is Roth (2009) which shows that photographic printing was historically calibrated against reference images centered on white women. Technology, despite advancing throughout the course of history, has still failed to improve in certain post processing categories. One example of this is Cronin et al. (2023) which demonstrates that even in contemporary smartphone photography, factors such as camera distance and angle can significantly influence photographed skin appearance, making certain skin colors appear darker or lighter. However, as time passed there has been more effort to recognise this problem. Google's Real Tone project, mentioned earlier, now recognizes skin tone representation as a design problem rather than an edge case (Google, 2024).

In order to interpret these three sets of literature, standpoint theory and Black feminist epistemology will be applied. In this paper, feminist epistemology will be defined as done in Anderson's Stanford Encyclopedia, which is how social position influences knowledge and inquiry. This is supported by Collins (2000) who argues that Black feminist thought emerges from lived experience and should be taken seriously, just like a field of knowledge. She states that it should not be excluded by dominant institutional standards. These frameworks are used here to ask not only whether phone cameras work, but whose standards define what "working" means

RESULTS AND INTERPRETATION

Based on the various studies covered, it is apparent that smartphone photography is not a neutral recording process. It is a sequence of computational judgements trained using bias data. Delbracio et al. (2021) argue that advances in mobile computational photography "have changed the rules of photography" (p. 571). This is a very important quote because it demonstrates that camera photography is not objective. Post processing essentially creates a set of rules which must be followed to create an image that is appealing to the human eye. And these rules change over time aligning with societal standards.

Hasinoff et al. (2016) make this especially clear in their description of HDR+ for mobile imaging. Camera systems on smartphones no longer wait for new technology to emerge to produce cleaner or shaper images. By capturing multiple frames, merging them to reduce noise, and post processing the image to create an image that is viewed as ideal for the majority of society, there is no need for camera upgrades. However there it is important to realize the importance of the image being ideal for the majority. For an image to be ideal for a majority, it must compromise some part of being ideal for the minority. In practice, this means that questions of fairness and representation cannot be separated from engineering design.

The articles which show the research on visual algorithms shows why this matters for faces. Buolamwini and Gebru (2018) in their study found that "darker-skinned females are the most misclassified group" (p. 77). In this study they also found that the commercial gender classification systems they studied had 34.7% error, compared with a maximum error rate of 0.8% for lighter-skinned males when using a smartphone camera. While this study can not be applied to every single smartphone, it does highlight how apparent racial bias is when it comes to smartphone training. This study also brings up the question on how this could affect other parts of the smartphone experience such as facial recognition. Is the smartphone experience objectively different based on the skin color of the consumer?

This question is further investigated through the NIST demographics effects report. Grother et al. (2019) writes, "We found empirical evidence for the existence of demographic differentials in the majority of contemporary face recognition algorithms that we evaluated" (p. 8). This study also finds false positive rates that are varied by an order of one to two magnitudes across the groups that were tested. Once again, while this is not directly smartphone photography, it challenges a popular STEM assumption that more computation automatically yields more objectivity. In fact these studies can actually prove the opposite as more variables, especially when it comes to machine learning training, can cause images to skew or cater to a specific skin color.

Historical photography research shows that this was an apparent problem for a long period of history. Roth (2009) explains that photographic industries have long used Shirley cards and other related bias standards to calibrate color balance. She also shows that these standards centered whiteness in a way that was treated as the ordinary rather than being politically meaningful. In one of the most meaningful sections of the text, Roth writes that cultural decisions have become "embedded in technologies that are presented to the public as 'neutral'" (p. 131). This is a very important excerpt for this case study because it proves that societal bias is engraved in post processing technology in smartphones and that they have been apparent throughout the course of history. While there have been counters to this such as Google's Real Tone project, which will be further explored next a majority of companies are still choosing to ignore this problem and view it as an engineering issue rather than a societal one that is based on the country's roots.

Google's Real Tone initiative shows that the industry now is starting to recognise this as a design problem rather than a side effect that can not be fixed. Google (2024) states that earlier camera technologies were largely developed with light skin as the baseline as mentioned before. This describes subsequent changes across exposure, color, tone-mapping, face detection, and white balance made by this initiative to eliminate bias present in their cameras. This article also mentions that tools are built the best when they are "built with the community" (Google, 2024). This matters because it moves this issue beyond discussion and turns it into actual intervention and initiative. This also proves representation can be improved through redesign and bias is not an unavoidable technical side effect. Google's smartphone cameras have been consistently rated as one of the best across multiple polls and public census. This once again highlights that this is an engineering problem as ideal processing across multiple skin colors is possible and there does not seem to be a requirement to satisfy only one type.

The redesign that is needed can be explained by standpoint theory. Anderson (2020) explains that feminist epistemology emphasizes the social situatedness of inquiry and the ways dominant practices of knowledge attribution disadvantage subordinated groups. Applied to this study, the argument is the following: camera teams do not optimize from nothing. They start the process by choosing datasets, define the quality metrics, label outputs as natural or pleasing, and decide which failure cases deserve attention. A homogenous design environment can likely make the mistake by confusing the visual performances with the perceived universal truth. In that regard it is safe to say that standpoint theory directly challenges the tendency, in the engineering side at least, to talk about the user as if all users no matter their race and background encounter the same system and the same conditions. The solution, then, is not simply to diversify the dataset. Instead it is to diversify who is in the room when the definition of quality is written.

Black feminist epistemology can also be applied for this study. It makes the critique sharper by changing who counts as an authority on the system. Collins (2000) argues that Black feminist thought should be understood as a knowledge tradition grounded in lived experience and that it should be concerned with empowerment under intersecting forms of oppression. In regards to smartphone imaging , this means that people most often misrepresented by the post processing of cameras should not be just treated as data points. In other words, it should not be treated in a profit minded way. Rather, they should be treated as evaluators on whether the system is working justly. This changes the meaning of image quality. While an image can be super sharp, it might now represent quality as it might not accurately interpret a person's skin color to their ideal.

The authority must translate to structural action. One concrete method of doing this is a stakeholder policy memo directed at smartphone manufacturers, platform developers, and device certification bodies such as the FCC. Such a memo would document the demographic performance gaps identified by Buolamwini and Gebru (2018) and Grother et al. (2019), present Cronin et al. 's (2023) findings on skin tone variability and bias as an unresolved engineering liability. It would also be ideal to formally demand three requirements be met on this topic. The first would be a mandatory benchmark that shows images processed for various skin tones and elected representatives validating the idealness of the images before releasing them. The next would be open sourcing the post processing model so that it can be standardized between brands and can be classified into various categories which can be presented to the customers. The third would be to require all smartphones to have the option to view the raw image before any post processing is done.

This proposal also challenges a foundational STEM assumption which is that improving a system's performance metrics is equivalent to improving the system. A smartphone camera pipeline can score higher on sharpness, dynamic range, and noise benchmarks but at the same time, it can render dark skin tones poorly because it was not trained for it. This raised a provocative question which is not whether bias can be reduced, but whether the metrics by which prediction is measured are themselves trustworthy. These changes listed above would produce better epistemology by making the standards by which imaging systems are judged answerable to the full range of people those systems are meant to serve.

CONCLUSIONS

The various literatures reviewed in this study show that smartphone cameras are not neutral and objective tools, rather are computational systems that construct images through burst capture, tone mapping, and face related processing. What the literature collectively reveals is that every step in that pipeline, from dataset curation to quality benchmarking, is engraved in a social choice. Obscuring those choices behind technical language does not eliminate their consequences.

This case study shows that representational bias in these smartphone cameras is not a modern glitch, rather a historical repetition of bias. Contemporary face analysis systems still show large demographic disparities and current companies now openly acknowledge the need for more equitable skin-tone representation. Standpoint theory and Black feminist epistemology together suggest that improving requires more than just better code, rather it requires rethinking who defines image quality, who participates in evaluation, and whose lived experience counts as evidence when the system fails.

Future work should be conducted in this area to further fix this issue in addition to the proposed stakeholder policy memo discussed. Treating community engagement as part of the technical process rather than data points would move computational photography toward more equitable design.

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