The “Criminality From Face” Illusion

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Abstract—The automatic analysis of face images can generate predictions about a person’s gender, age, race, facial expression, body mass index, and various other indices and conditions. A few recent publications have claimed success in analyzing an image of a person’s face in order to predict the person’s status as Criminal / Non-Criminal. Predicting “criminality from face” may initially seem similar to other facial analytics, but we argue that attempts to create a criminality-from-face algorithm are necessarily doomed to fail, that apparently promising experimental results in recent publications are an illusion resulting from inadequate experimental design, and that there is potentially a large social cost to belief in the criminality from face illusion.

Index Terms—facial analytics, criminality prediction, computer vision, machine learning, artificial intelligence, technology ethics.

I. INTRODUCTION

Criminal or not? Is it possible to create an algorithm that analyzes an image of a persons face and accurately labels the person as Criminal or Non-Criminal? Recent research tackling this problem has reported accuracy as high as 97% [14] using convolutional neural networks (CNNs). In this paper, we explain why the concept of an algorithm to compute “criminality from face,” and the high accuracies reported in recent publications, are an illusion.

Facial analytics seek to infer something about an individual other than their identity. Facial analytics can predict, with some reasonable accuracy, things such as age [11], gender [7], race [10], facial expression / emotion [25], body mass index [6], and certain types of health conditions [29]. A few recent papers have attempted to extend facial analytics to infer criminality from face, where the task is to take a face image as input, and predict the status of the person as Criminal / Non-Criminal for output. This concept is illustrated in Figure 1.

One of these papers states that “As expected, the state-of-the-art CNN classifier performs the best, achieving 89.51% accuracy...These highly consistent results are evidences for the validity of automated face-induced inference on criminality, despite the historical controversy surrounding the topic” [40]. Another paper states that “the test accuracy of 97%, achieved by CNN, exceeds our expectations and is a clear indicator of the possibility to differentiate between criminals and non-criminals using their facial images” [14]. A press release about another paper titled A Deep Neural Network Model to Predict Criminality Using Image Processing stated that “With 80 percent accuracy and with no racial bias, the software can predict if someone is a criminal based solely on a picture of their face. The software is intended to help law enforcement prevent crime. The original press release generated so much controversy that it “was removed from the website at the request of the faculty involved and replaced by a statement meant to defuse the situation: “The faculty are updating the paper to address concerns raised [13].”

Section II of this paper explains why the concept of an algorithm to compute criminality from face is an illusion. A useful solution to any general version of the problem is impossible. Section III explains how the impressive reported accuracy levels are readily accounted for by inadequate experimental design that has extraneous factors confounded with the Criminal / Non-Criminal labeling of images. Learning incidental properties of datasets rather than the intended concept is a well-known problem in computer vision. Section IV explains how Psychology research on first impressions of a face image has been mis-interpreted as suggesting that it is possible to accurately characterize true qualities of a person. Lastly, Section V describes why the belief in the illusion of a criminality-from-face algorithm potentially has large, negative consequences for society.

II. AN ILLUSORY PROBLEM DEFINITION

Part of the criminality from face illusion is that the problem definition is simple to state and is similar in form to that of facial analytics with sound foundations. However, simple thought experiments reveal the impossibility of creating any general algorithm to correctly apply the label Criminal / Non-Criminal to a face.

Consider a person who to a given point in their life has never even thought of committing a crime. Assume Image A is their face from this period. (See Figure 2) One day this person is inspired by what they imagine to be the perfect crime. From the moment that idea enters their head and heart, they know that they will commit the crime. Image B is their face from this period. The fateful day arrives, the crime is committed, and life proceeds well for a while. Image C is their face from this period. But the day of arrest, trial and conviction...
comes, and the person begins to serve their sentence. Image D is their face from this period. The criminality-from-face algorithm developer now confronts the question: what is the ground-truth label for each of the images A, B, C and D?

Answering this question forces the algorithm developer to face up to (pun intended) the fact that there is no plausible foundation for the criminality-from-face problem definition. One possible answer is to assign all four images the label of Criminal. This requires the algorithm developer to believe in the “born criminal” concept and also to believe that there is something measurable from the face image that reveals this predestined condition of a person. There have been historical criminologists who subscribed to these beliefs; for example, Cesare Lombroso, who will be discussed later. But today these beliefs are regarded as having no scientific foundation. Another possible answer is that Image A should be labeled Non-Criminal and B, C and D should be labeled Criminal. This answer requires the algorithm developer to believe that the criminal intent entering the person’s head and heart causes a measurable change in their facial appearance. Still another possible answer is that Images A and B should be labeled Non-Criminal and C and D labeled Criminal. This answer requires the algorithm developer to believe that the act of committing a crime causes a measurable change in the person’s facial appearance. The last answer assigns Images A, B and C to Non-Criminal and Image D to Criminal. This answer requires the algorithm developer to believe that being convicted of the crime causes a measurable change in the person’s facial appearance. The last three possible answers are so untenable that we do not know of anyone who advocates for any of them. However, believing that a criminality-from-face algorithm can exist requires believing in one of the four answers.

A second thought experiment highlights additional difficulties in the criminality-from-face problem definition. Imagine that a person drives from Chicago to Detroit. As the person leaves Chicago, they begin to smoke marijuana as they drive. This person has a medical marijuana prescription and is careful to keep their tetrahydrocannabinol (THC) concentration below the Illinois legal limit. Image E is a face image from this portion of their trip. Continuing to drive, the person enters the state of Indiana. The person assumes that Indiana law is the same as Illinois law, but in fact Indiana has zero tolerance for drugged driving and no exception for medical use. Image F is a face image from the Indiana portion of the trip. The person later crosses into Michigan, where medical marijuana use trumps the state’s zero tolerance law for the presence of THC. Image G is a face image from the Michigan portion of the trip. The person is a careful driver and is never stopped by the police on the trip. The criminality-from-face algorithm developer again has to confront the question of assigning ground-truth labels to images. The person did commit a crime in Indiana, although they did not realize it, and the action that was illegal in Indiana was legal in Illinois and Michigan.

The problem highlighted in this thought experiment is that Criminality / Non-Criminality is a social construct that can vary with the location and over time. Instances involving more serious crimes than drug use include the killing of a person and the use of “stand your ground” laws in determining criminality, and the process of marital rape becoming a crime in the various states of the US between the mid-1970s and mid-1990s. Reflecting on these examples, there is nothing about conceiving, committing, or being convicted of a crime that causes any distinctive change in facial appearance. There is no distinctive feature of facial appearance that predestines a person to become a criminal or to be unable to become a criminal. Whether or not a given action is sufficient to allow a person to be convicted of a crime can depend on the time and location where the action is committed. What, then, should be made of reports that algorithms have achieved impressive levels of accuracy in labeling images as Criminal / Non-Criminal? Nothing more than a basic flaw in experimental method is required to explain the apparently impressive accuracy results.

### III. Illusory Experimental Results

The reasoning that criminality-from-face is just an extension of existing, sound facial analytics leads to flawed experimental designs. In predicting age from a facial image, there are known, identifiable features that correlate with increased age (e.g., lines on the face), and a person’s age is the same regardless of their geographic location. Similarly, in predicting a person’s emotional state from a facial image, there are known configurations of facial features that correspond to particular emotions, and no expectation that an emotion detected in one image reveals a permanent condition of a person’s life. Criminality-from-face algorithms do not share any of the firm foundational elements of other, sound facial analytics.

To better understand what goes wrong in these cases, let’s begin with a close look at the data and experiments for the criminality-from-face algorithm from the paper by Hashemi and Hall [14]. This paper is important to discuss because: (1) the authors recognize the potential for controversy, as they state “…this study’s scope is limited to the technical and analytical aspects of this topic, while its social implications require more scrutiny and its practical applications demand even higher levels of caution and suspicion”; (2) remarkably high accuracy is reported, with the authors declaring that “the test accuracy of 97%, achieved by CNN, exceeds our expectations and is a clear indicator of the possibility to differentiate between criminals and non-criminals using their facial images”; and (3) the paper appears in a peer-reviewed journal owned by a well-regarded publisher, so we can assume that the reviewers and editor, as well as the authors, believed in the validity of the work.
Experimental work on criminality-from-face algorithms naturally requires a dataset of face images, some of which are labeled Criminal and some Non-Criminal. An algorithm is trained on a subset of this data and the accuracy of the resulting algorithm should be estimated on a different subset of the data. It is of course essential to avoid possible sources of bias in the data. There should be no extraneous differences between images in the Criminal and the Non-Criminal categories. As a trivial example, if all persons in images labeled Criminal wore black hats and all persons in images labeled Non-Criminal wore white hats, the algorithm might learn the difference in color of hats, and 100% accuracy might be reported, when in fact the algorithm is useless at detecting criminals. Meticulous attention to the details of the experimental dataset is essential, even more so when training deep neural networks than it is when using “hand-crafted” features. Deep neural networks will by their nature pick up on any consistent difference between images in the two categories.

The face images for the Criminal category are described as follows [14]. “A total of 8401 gray-scale mugshot images of arrested individuals are obtained from National Institute of Standards and Technology (NIST) Special Database. Images are all in png format...Cropping the facial rectangle from the rest of the image prevents the classifier from being affected by peripheral or background effects surrounding the face...The result contains 5000 front view face images of 4796 male and 204 female individuals and of variable sizes, ranging from 238 × 238 up to 813 × 813 pixels. Since neural networks receive inputs of the same size, all images are resized to 128 × 128.”

The web page for NIST Special Database 18 [19] states that it contains “...3248 segmented 8-bit gray scale mugshot images (varying sizes) of 1573 individuals”. The source of the discrepancy in number of persons and images in the Criminal category in [14] and in the NIST dataset [19] is not known to us. An additional detail is that the User’s Guide for NIST Special Database 18 [38] states that a Kodak MegaPixel1 camera was used to digitize printed mugshot photos.

The face images for the Non-Criminal category are described as follows [14]. “A total of 39,713 RGB facial images are obtained from five sources (Face Recognition Database, FEI Face Database, Georgia Tech face database, Face Place, Face Detection Data Set and Benchmark Home)...The images are then converted to gray-scale, again to be compatible with mugshots in the criminal dataset. The result contains 5000 front view face images of 3727 male and 1273 female individuals and of variable size, ranging from 87 × 87 up to 799 × 799 pixels. Images are resized to 128 × 128.”

The images in the Criminal and the Non-Criminal category are all size 128×128, all grayscale, all nominally frontal pose and neutral expression. These factors may make it seem that differences between the images in the two categories are controlled. However, based on the descriptions of the data, there are also multiple extraneous factors that have 100% correlation with the two categories of images.

- All images for the Criminal category come from the NIST dataset, and all images for the Non-Criminal category come from a set of five datasets from other sources.
- All of the images labeled Criminal are photographs of printed images and are taken in a controlled manner with the same camera model, and all of the images labeled Non-Criminal are photographs of live persons taken by various cameras.
- All of the images labeled Criminal were in (lossless) PNG format, and all of the images labeled Non-Criminal were in (lossy) JPG format.
- All of the images labeled Criminal started out as grayscale; all of the images labeled Non-Criminal were converted from color to grayscale by the investigators.

Rather than the CNN learning to distinguish between Criminal and Non-Criminal faces, it could have learned to distinguish between (a) images converted to grayscale using the tool the investigators used, and grayscale images from some other source, (b) images originally in PNG and images originally in JPG, (c) images of printed pictures of persons versus images of live persons, or some other property also completely unrelated to the Criminal / Non-Criminal categorization.

Also, as detailed in the User’s Guide for the NIST dataset, the mugshots for all “criminal” face images were initially printed photographs that were digitized using an identical process and camera. There are several studies in automated forensic analysis that exploit unique photoresponse non-uniformity (PRNU) noise characteristics embedded in images to enable camera identification (i.e., device fingerprinting) [4]. The conventional methods have evolved to include CNN based architectures [5]. Thus, the experiment in [14] may simply show an ability to detect printed mugshot images digitized using the Kodak MegaPixel1 camera.

To be fair, Hashemi and Hall note the existence of confounding factors, before dismissing the possibility that this had a significant effect on the results [13]. “It is noteworthy that the criminal mugshots are coming from a different source than non-criminal face shots. That means the conditions under which the criminal images are taken are different than those of non-criminal images. These different conditions refer to the

![Example Images](image-url)
camera, illumination, angle, distance, background, resolution, etc. Such disparities which are not related to facial structure, though negligible in majority of cases, might have slightly contributed in training the classifier and helping the classifier to distinguish between the two categories. Therefore, it would be too ambitious to claim that this accuracy is easily generalizable” (italics added). However, given the number of obvious disparities between the two categories, there is no good reason to believe that the CNN was able to learn a model of Criminal / Non-Criminal facial structure. We believe that it is infinitely more likely that the “disparities not related to facial structure” are the only thing that the CNN is using to separate the two categories of images.

The experimental dataset used by Wu and Zhang [40] has similar problems. The Non-Criminal images for that work are described as follows. “Subset $S_n$ contains ID photos of 1126 non-criminals that are acquired from Internet using the web spider tool; they are from a wide gamut of professions and social status, including waiters, construction workers, taxi and truck drivers, real estate agents, doctors, lawyers and professors; roughly half of the individuals in subset $S_n$ have university degrees. But the Criminal images come from specialized sources. “Subset $S_c$ contains ID photos of 730 criminals, of which 330 are published as wanted suspects by the ministry of public security of China and by the departments of public security for the provinces of Guangdong, Jiangsu, Liaoning, etc.; the others are provided by a city police department in China under a confidentiality agreement. We stress that the criminal face images in $S_c$ are normal ID photos not police mugshots. Out of the 730 criminals 235 committed violent crimes including murder, rape, assault, kidnap and robbery; the remaining 536 are convicted of non-violent crimes, such as theft, fraud, abuse of trust (corruption), forgery and racketeering.” The essential point is that if there is anything at all different about ID photos acquired from the Internet versus ID photos supplied by a police department, this difference is 100% correlated with the Criminal / Non-Criminal labels and will be used by the trained CNN to classify the images. So, just as with the experiments in [14], there is no good reason to believe that the CNN in the experiments in [40] was able to learn a model of Criminal / Non-Criminal facial structure.

Beyond the problem of extraneous factors that are 100% correlated with the image categories labeled Criminal and Non-Criminal, there is the problem that the image categories do not in fact have the suggested mapping to the real world. In contrast to data used by Wu and Zhang [40], experiments conducted by Hashemi and Hall [14] have exclusively labeled mugshot face images as “criminal.” This is significant because in the United States (which appears to be the source of the mugshots) a mugshot does not indicate that a person has been convicted of a crime. A mugshot is taken when a person is arrested and arrives at a booking station. Searching for “criminal,” “convicted,” or “guilty” in the README file for NIST Special Database 18 [38] yields no hits. This labeling is also problematic because roughly 95% of convictions in the US are based on a defendant’s acceptance of a plea deal. It is reported that “…15 percent of all exonerees people convicted of crimes later proved to be innocent — originally pleaded guilty. That share rises to 49 percent for people exonerated of manslaughter and 66 percent for those exonerated of drug crimes” [28]. So even mugshot subjects who are subsequently convicted of a crime, may in fact be innocent. Just as images in the Criminal category may in fact not represent persons who have committed a crime, in both studies [14], [40], there is no way to verify that every image in the Non-Criminal category represents a person who has never committed a crime.

The concern that unintentional bias in experimental datasets in computer vision can lead to impressive but illusory results is very familiar to researchers. Torralba and Efros explored the pervasive nature of the problem a decade ago in a well-known paper [56]. They showed that standard classifiers could often achieve surprisingly high accuracy at categorizing the dataset an image belongs to. They pose a “fundamental question” that is highly appropriate in the current context [56]: “However, there is a more fundamental question: are the datasets measuring the right thing, that is, the expected performance on some real-world task? Unlike datasets in machine learning, where the dataset is the world, computer vision datasets are supposed to be a representation of the world.”

Bias in experimental datasets is not specific to research in assessing criminality from face. Another instance of the problem was recently recognized in “kinship detection research. The kinship problem is to analyze two face images and detect if the persons have a relation such as parent-child or sibling. The KinFaceW-II dataset was assembled and distributed to support research in this area, and has 250 pairs of images for each of Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S) and Mother-Daughter. The dataset has been used in research publications by various researchers. But Lopez et al. [18] pointed out that, for each kinship pair, the two face images have been cropped from the same original image, and that two face images cropped from the same larger image share similarity that has nothing to do with the faces. To make the point, they presented results comparing image pairs purely on the chrominance distance between images (no facial analysis at all) showing that chrominance distance actually scored higher in kinship detection than a number of published algorithms. Based on these results, they state, “we strongly recommend that these data sets are no longer used in kinship verification research”.

Dataset bias in this area led to apparently impressive accuracy that has nothing to do with the phenomenon of interest, and similar bias can readily account for the results in criminality from face research.

A relatively simple principle for evaluating experimental results in facial analytics research is suggested as a reasonable safeguard: no paper that claims to use machine learning to predict labels for the content of images, in this case Criminal and Non-Criminal for face images, should be accepted for publication if its experimental data for the different labels is 100% correlated to different sources. This would capture kinship results in which all true kin image pairs are cropped from a single source image, and criminality from face research in which all Criminal images come from one source and all Non-Criminal images come from a different source.

Some researchers may not accept our argument that pursuit
of a criminality-from-face algorithm is doomed from first principles to failure. Rhetorically, for them, what would be a more convincing experimental design for their research? Images of pairs of monozygotic twins in which one twin had a criminal record and one did not might make a more convincing experimental design. Images of pairs of persons, cropped from the same group photo, where one person has a criminal record and the second person, with no criminal record, is selected as the most similar person in the photo might also be compelling. This sort of dataset might be assembled from photos of sports teams, musical groups, political groups, or other sources.

IV. Confusion with Models of “First Impressions”

Wu and Zhang cite the work of Princeton psychologist Alexander Todorov as a justification for the plausibility of modeling criminality from faces [35], [32], [34]. However, this justification is based on a mistaken assumption that by modeling the first impressions of subjects viewing a face as Todorov does, one can discern something true about the underlying personality traits for that face’s identity. Todorov’s research is limited to the social perception of faces, and models his laboratory has published make predictions about what the average person would likely say about a particular face image [24], [31]. These predictions represent a consensus of sorts for various attribute judgements (e.g., trustworthiness, dominance). In Wu and Zhang’s words, the existence of consensus judgements for certain attributes allows them to explore the “diagnostic merit of face-induced inferences on an individual’s social attributes” [40]. In other words, the extent to which physiognomic cues predict personality traits, which they believe Todorov’s work hints at.

But the existence of a consensus attribute judgement for a particular person’s appearance does not mean that it holds any truth about their personality. Much to the contrary of Wu and Zhang’s claims, Todorov writes in his preface to the book *Face Value: the Irresistible Influence of First Impressions* [30] that “Psychologists in the early twentieth century found little evidence for the accuracy of first impressions, but the past decade has seen a resurgence of physiognomic claims in scientific journals. We are told that it is possible to discern a person’s political leanings, religious affiliation, sexual orientation, and even criminal inclinations from images of their face...A closer look at the modern studies shows that the claims of the new physiognomy are almost as exaggerated as those in the eighteenth and nineteenth centuries.” Given the work Todorov has published within social psychology, it is not surprising to learn that he is sharply critical of the idea that one can determine criminality solely by looking at faces.

Wu and Zhang are not the only researchers that have considered Todorov’s work in the context of predicting criminality from faces. Valla et al. conducted behavioral studies on the accuracy of people for this task, remarkably finding that groups of subjects were able to discriminate between criminals and non-criminals in some cases [37]. (Wu and Zhang confirmed to us that this is the Cornell University study that they reference in their response to the critiques levied against their paper [41].) Similar to Wu and Zhang, Valla et al. also believe that Todorov’s work on first impressions demonstrates a link between social behavior and innate traits. In order to argue this point, they allege that Todorov has a tendency to “shy away from the possibility of accurate impressions” based on physiognomic cues out of “concern that it harkens back to the stigmas associated with social Darwinism.” Thus, according to Valla et al., Todorov’s findings can be used as a justification for criminality-from-face studies — he simply isn’t drawing a strong enough conclusion from his data. Of course, this line of argumentation only makes sense if first impressions can be shown to be reliable predictors of innate behavioral traits. As for Valla et al.’s remarkable finding — they combined mug shots of arrested people with photographs of innocent students on campus in their study, such that the task performed by the subjects was really just dataset discrimination [33].

A more recent study on the convictability of faces, also from Cornell, does make use of photos from the same source to show low, but above chance, accuracy for human subjects on this task [23]. But it ultimately concludes that non-face context is likely a significant driver of decisions, and warns off using the results in a criminal justice context other than attempting to understand how faces are viewed in a social context (in the manner of Todorov).

The sound work that has been done on how humans form subjective first impressions from a face image does not imply that the first impression is actually true. The work that has explored whether humans can accurately determine Criminal / Non-Criminal from a face image runs into the same dataset bias pitfall as work on automated facial analytics for predicting Criminal / Non-Criminal. A persuasive experiment for the alleged phenomenon of humans being able to accurately perceive the criminality of persons from their face image has yet to emerge.

V. Social Implications of this Technology

Society at large should be very concerned if physiognomy makes a serious resurgence through computer vision. Algorithms that attempt to determine criminality from face images reinforce mistaken beliefs about biology and add a deceitful instrument to the ever growing digital surveillance toolkit. Such technology is rooted in the Positivist School of criminology, which has long argued that criminals are born, not made [16]. Indeed, Hashemi and Hall directly acknowledge Cesare Lombroso, the 19th century sociologist who founded the Positivist School, as the motivation for their work [14]. Inspired by the newly introduced theories of Charles Darwin, Lombroso popularized the technique of facial measurement for predicting criminal tendencies, arguing that heritable flaws manifested themselves in both anatomy and behavior [17]. Lombroso’s research was eventually discredited on the grounds that it did not make use of valid control groups [39], but Positivist notions persist in contemporary thinking about criminality [8].

And it is not difficult to understand why this idea is still attractive. Since the dawn of the genetic revolution in biology, the general public has developed a commonly held belief that genes code for complex behaviors (think of the
expression “it’s in my genes”). Thus it is not a stretch to imagine criminal behaviors having some genetic basis under this regime. But such a simplistic belief is problematic in that it skips several levels of abstraction, ignoring the essential role of learning in human development [15], as well as the interplay between the environment and a nervous system defined by a genetic profile [27]. While there may be some correlation between genes and complex behaviors, the mechanisms are not currently understood, and no evidence of a direct genetic link to criminal behavior exists [21]. A further confound surfaces when behavioral traits must be coupled with some physical manifestation to diagnose criminality. To justify the plausibility of this, one could point to conditions such as the fetal alcohol spectrum disorders, which present with abnormal facial features and anti-social behavioral traits [26]. But the vast majority of criminals in any country do not suffer from such syndromes [20]. Given the variety of mental disorders that do not present with any obvious physical abnormality (e.g., mood disorders, schizophrenia), there can be no expectation that a physical marker associated with criminality will be present even in cases where there is some indirect genetic basis to the behavior that led to a crime.

These misunderstandings about biology have a problematic social implication when Positivist ideas are coupled to systems of mass surveillance. Contemporary theories of criminal control are wrapped in scientific language in order to gain legitimacy within the academy and dodge scrutiny from policy makers [9]. Thus it is convenient to talk about the biology of criminality when one needs to justify the use of a controversial technology. As we have already pointed out, there is a logical disconnect between legal definitions of criminality and the body. Nonetheless, the rise of the surveillance state in the 20th century and surveillance capitalism in the 21st was predicated on the distortion of scientific findings. Here we discuss three particularly troubling scenarios where artificial intelligence (AI) has already been used in a manner that erodes human rights and social trust, which could be further exacerbated by the deployment of ineffective criminality from face algorithms.

The first scenario is the nation-scale use of this technology by a government which mistakenly believes that it works as advertised. There is growing interest in facial analytics for surveillance purposes, and algorithms that assess visual facial attributes have been added to that repertoire [1]. The existing technologies that do actually work have already proven to be controversial. In 2019, marketing material for a smart camera system with an automatic ethnicity detector from the Chinese technology company Hikvision surfaced [22]. In particular, this product was advertised as being able to tell the difference between Han Chinese, the ethnic majority in China, and Uyghurs, an ethnic minority involved in a long-standing conflict with the central government in Beijing. Because Uyghurs do indeed look different than Han Chinese, they can be detected and tracked via automated means. Under similar reasoning, if the same is true of criminals and innocents, then profiling with facial analytics is also possible in that case. It is extremely troubling when facial analytics are used to discriminate against an out-group. But it is outright reckless for a technology that cannot possibly work to be used as if it did. Such a scenario will lead to innocent people being inconvenienced at best, and a senseless loss of life at worst.

Related to the first scenario is the second, which is the use of this technology in data driven predictive policing. Instead of widespread deployment, cameras equipped to detect criminals could be installed in more localized “hot spots” to study their movements so that the police would know where to look for criminal activity in the future. There is already a lucrative market for law enforcement products of this nature [2]. While the ability to monitor the activities of potential lawbreakers is tantalizing, problematic racial biases have been found in facial recognition technologies that match surveillance photos to mugshots [12]. Those same racial biases are likely to become manifest in any machine learning-based system using that data, given that they are an artifact of the data itself. It is not hard to imagine criminality-from-face algorithms being trained with the same databases that are currently used for other predictive policing applications. Thus the best these algorithms can do is reproduce available biases as their decisions, leading to a strongly misleading picture of the criminal presence in an area.

We also find similar problems in the commercial world. One example is the application of personality attribute prediction for job candidate assessment. Machine learning-based personality profiling is now being used as a first-round screening process at some companies [3]. Given the uptick in interest in AI automation, this practice will only spread. In particular, one would expect to see such technology being deployed extensively in the service industry to reduce hiring costs. With more concern in service-oriented businesses about the risk of criminal behavior on the job, there will inevitably be interest in a capability to predict criminality from face. As with the government surveillance and predictive policing scenarios, the risk of this directly leading to discriminatory practices is high.

VI. CONCLUSIONS

In spite of the assumption that criminality-from-face is similar to other facial analytics, there is no coherent definition on which to base development of an algorithm. Seemingly promising experimental results in criminality-from-face are easily accounted for by simple dataset bias. The concept that a criminality-from-face algorithm can exist is an illusion, and belief in the illusion is dangerous.

The most innocuous danger of the criminality-from-face illusion is that good researchers will waste effort that could otherwise create solutions that truly would benefit humanity. A larger danger is that government and industry will believe the illusion and expend precious resources on an effort that cannot succeed. The most ominous danger is that belief in the illusion will result in applications being fielded that arbitrarily sort human beings that “fit the description” into the categories Criminal and Non-Criminal — with potentially grievous consequences.

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