AI

IBM Research Releases ‘Diversity in Faces’ Dataset to Advance Study of Fairness in Facial Recognition Systems

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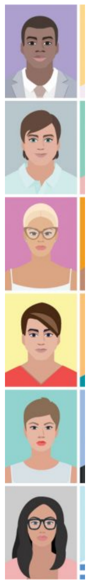


Have you ever been treated unfairly? How did it make you feel? Probably not too good. Most people generally agree that a fairer world is a better world, and our AI researchers couldn’t agree more. That’s why we are harnessing the power of science to create AI systems that are more fair and accurate.

Many of our recent advances in AI have produced remarkable capabilities for computers to accomplish increasingly sophisticated and important tasks, like translating speech across languages to bridge communications across cultures, improving complex interactions between people and machines, and automatically recognizing contents of video to assist in safety applications.

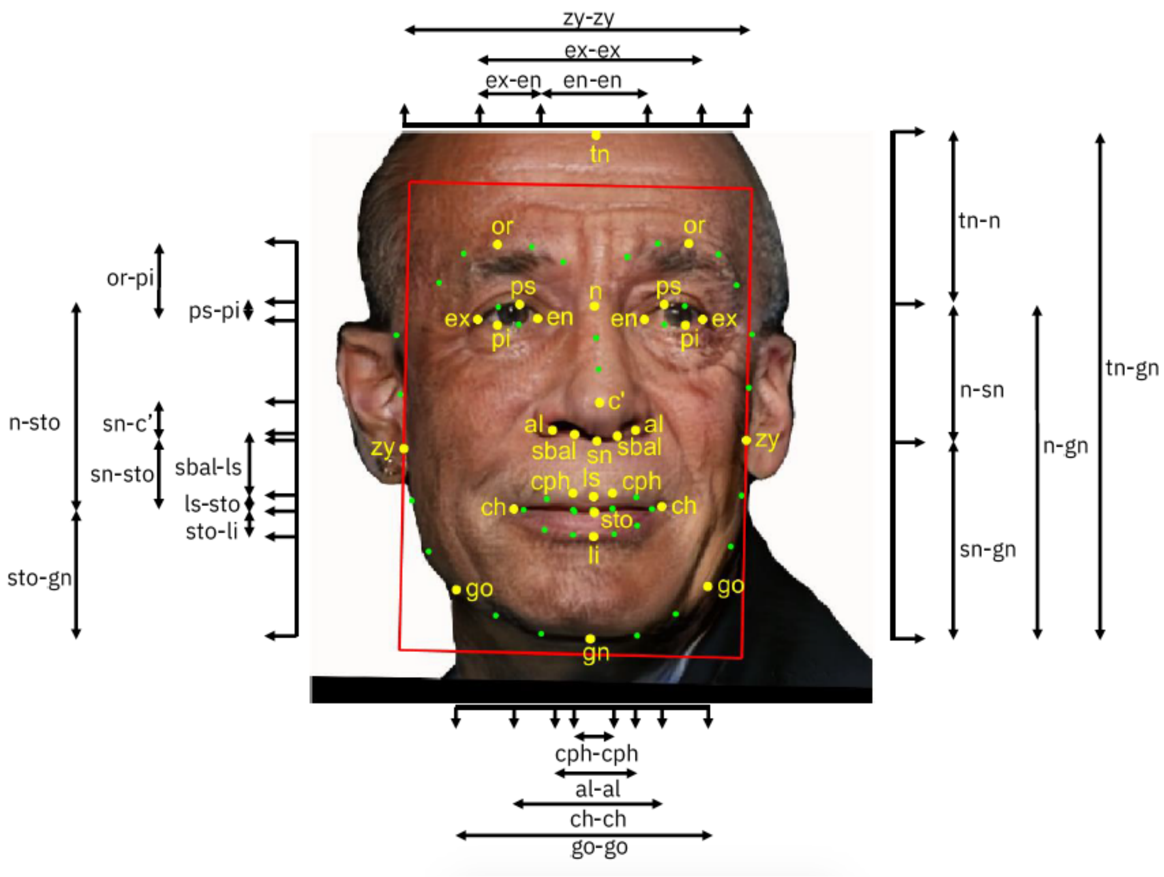
Much of the power of AI today comes from the use of data-driven deep learning to train increasingly accurate models by using growing amounts of data. However, the strength of these techniques can also be a weakness. The AI systems learn what they're taught, and if they ar datasets, accuracy and fairness could be at risk. For that reason, IBM, along with AI developers an be thoughtful about what data we use for training. IBM remains committed to developing AI syster

The challenge in training AI is manifested in a very apparent and profound way with facial recognit difficulties in making facial recognition systems that meet fairness expectations. As shown by Joy *Gender Shades* in 2018, facial recognition systems in commercial use performed better for lighter darker females [1]. The heart of the problem is not with the AI technology itself, per se, but with ho recognition systems are trained. For the facial recognition systems to perform as desired – and the accurate – training data must be diverse and offer a breadth of coverage, as shown in our prior wo data sets must be large enough and different enough that the technology learns all the ways in wh recognize those differences in a variety of situations. The images must reflect the distribution of fe

How do we measure and ensure diversity for human faces? On one hand, we are familiar with how tone, and how different faces can vary across some of these dimensions. Much of the focus on faci on how well it performs within these attributes. But, as prior studies have shown, these attributes not entirely adequate for characterizing the full diversity of human faces. Dimensions like face sym face is in, the length or width of the face's attributes (eyes, nose, forehead, etc.) are also importan

Today, IBM Research is releasing a new large and diverse dataset called Diversity in Faces (DiF) to accuracy in facial recognition technology. The first of its kind available to the global research comn annotations of 1 million human facial images. Using publicly available images from the YFCC-100M annotated the faces using 10 well-established and independent coding schemes from the scientifi schemes principally include objective measures of human faces, such as craniofacial features, as v such as human-labeled predictions of age and gender. We believe by extracting and releasing thes on a large dataset of 1 million images of faces, we will accelerate the study of diversity and covera systems to ensure more fair and accurate AI systems. Today's release is simply the first step.

We believe the DiF dataset and its 10 coding schemes offer a jumping-off point for researchers arc recognition technology. The 10 facial coding methods include craniofacial (e.g., head length, nose ratios (symmetry), visual attributes (age, gender), and pose and resolution, among others. These s identified by the scientific literature, building a solid foundation to our collective knowledge.



Our initial analysis has shown that the DiF dataset provides a more balanced distribution and broa compared to previous datasets. Furthermore, the insights obtained from the statistical analysis of DiF dataset has furthered our own understanding of what is important for characterizing human fa important research into ways to improve facial recognition technology.

To learn more about DiF, read our paper, "Diversity in Faces."

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