Fairness-aware Dataset generation using Crowd-sourcing platform for Face Detection applications.

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Scope of the Project

Fairness in AI is an advancing field that is dedicated towards making AI/ML solutions unbiased with respect to attributes of individuals that they cannot control. This is specifically important in the case of Face detection algorithm because their large-scale deployment can put minority groups at a disadvantage [5]. While there have been several proposed solutions – Custom dataset creation for training [1], GAN-based attribute removal, usage of custom loss functions [6], and attribute-based threshold tuning [3]. We believe that creation of a fairness aware dataset will help advance the field because we will be tackling the problem at its root. Previously, Fairness based dataset has been prepared with respect to race, age, and gender [1], but further detailing is rare. In this work, we define more attributes for every face and attempt to create a more detailed dataset. We also use crowd-sourcing platform as we want to test their feasibility for fairness-based application and want to gauge the cost associated with data collection of such scale.

Methods

To understand the methods to be used during the independent study, it is necessary to understand the work already accomplished by research laboratory.

Completed Phases of the project –

1. Dataset Selection for Attribute generation - CelebA
2. Crowdsourcing platform selection – Amazon Mechanical Turk
3. Definition of Framework for Data Collection.
4. Deployment of Assignment on Mechanical Turk
5. Data Cleaning
6. Training models to predict attributes with high probability for unseen images.

Phases to be completed and Techniques used –

1. Training models to predict attributes with high probability for unseen images.
    a. Object Localization, and
    b. Classification using CNN.
2. Using Trained models to predict attributes for all the images in CelebA dataset.
    a. Celeb Identity matching
    b. Prediction using the trained models
3. Definition of sampling techniques for this data for multiple applications.
    a. This is a rather open ended question as to how we can use the data in various ways so as to bring better performance for face detection algorithms and better gauge their fairness.
4. Use the dataset to compare the face detection algorithms in use today. - RetinaFace, and yolo-v5-face.

a. Here, I will prepare a script which will take inputs of face attributes (like Skin, lips etc.) and a face detection model (yolo-v5-face, RetinaFace).
b. We will use certain metrics to gauge fairness as outlines in [2], some of those are False Non-Match rate, false match rate, general accuracy of face detection segregated into different attributes.

Final Deliverables

The final deliverables of the project will be in the form of

A. a codebase comprising of the following –
   a. Trained models with reasonable test accuracy on unseen images (July 5th)
   b. A dataset where each image of CelebA dataset has defined attributes – Eyes, Nose, Hairs, Ears, Eyebrows, lips, chin etc.. (July 5th)
   c. A Script to use the dataset to compare the face detection algorithms for their bias given the attribute. (July 31th)
   d. The codebase will be properly documented with enough Readme files to understand all the operations. (July 31st)
B. A written report that contains the following –
   a. Results of the trained models on various attributes (Top k scores) (Aug 05)
   b. Discussion regarding sampling techniques (of Dataset) for various applications. (Aug 05)
   c. Results showing at least two face detection algorithm's bias with respect to three attributes. (Aug 05)

References

1. Yang, Yu, and Aayush Gupta. "Enhancing fairness in face detection in computer vision systems by demographic bias mitigation." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 36. No. 1. 2022.
2. H. F. Menezes, A. S. C. Ferreira, E. T. Pereira and H. M. Gomes, "Bias and Fairness in Face Detection," 2021 34th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI), Gramado, Rio Grande do Sul, Brazil, 2021, pp. 247-254, doi: 10.1109/SIBGRAPI54419.2021.00041.
3. Philipp Terhörst, Jan Niklas Kolf, Naser Damer, Florian Kirchbuchner, Arjan Kuijper, "Post-Comparison Mitigation of Demographic Bias in Face Recognition Using Fair Score Normalization ", arXiv:2002.03592
4. Shervin Minaee, Ping Luo, Zhe Lin, Kevin Bowyer, "Going Deeper into Face Detection: A Survey ", arXiv:2103.14983
5. Elijah Mayfield, Michael Madaio, Shrimai Prabhumoye, David Gerritsen, Brittany McLaughlin, Ezekiel Dixon-Román, and Alan W Black. 2019. Equity beyond bias in language technologies for education. In Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications. 444–460
6. Zeyu Wang, Klint Qinami, Ioannis Christos Karakozis, Kyle Genova, Prem Nair, Kenji Hata, and Olga Russakovsky. 2020. Towards fairness in visual recognition: Effective strategies for bias mitigation. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 8919–8928.