Model bias and its impact on computer-aided diagnosis: A data-centric approach



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Abstract

Machine learning and data-driven solutions open exciting opportunities in many disciplines including healthcare. The recent transition to this technology into real clinical settings brings new challenges. Such problems derive from several factors, including their dataset origin, composition and description, hampering their fairness and secure application. Considering the potential impact of incorrect predictions in applied-ML healthcare research is urgent.

Undetected bias induced by inappropriate use of datasets and improper consideration of confounders prevents the translation of prediction models into clinical practice. Therefore, in this work the use of available systematic tools to assess the risk of bias in models is employed as the first step to explore robust solutions for better dataset choice, dataset merge and design of the training and validation step during the ML development pipeline.

Introduction





- (a) Given a dataset with unidentified composition of the dataset population, there is a high risk of bias, i.e. a model is Systematically prejudiced to faulty assumptions.
- (b) For example in an extreme case almost all of the control cases form a special subpopulation of young age. With knowledge on the dataset age composition one is at least aware that any model developed with this dataset has a high risk of being biased by age (Model 1) or can even choose a model mitigating the age influence (Model 2).
- Biased models are very likely to lead to impaired performance in the target population hampering generalizability.

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Fig 3: Overview of the relationships of popular COVID-19 and related non-COVID-19 datasets. Datasets in green present enough documentation to asses potentials bias. From [2].



Fig 4: Temporal analysis of the datasets employed in the selected 78 peer-review papers. Top-left: Number of papers indexed in Pubmed that report a Machine Learning model for COVID-19 X-Ray imaging by month of their published date (from Pubmed database). Bottom-left: number of papers using a given dataset per month. Bottom-right: total number of papers using each dataset. Note that only one dataset among the classified as recommended were used (BIMCV), and only in one paper. The number of papers using exclusively Cohen/IEEE 8023 and UCSD-Guangzhou is 18, a particularly risky combination. More information [2].

Dataset bias and confounder assessment is generally not properly conducted. This is an essential step to produce good models that have safe,

[1] Vega, Carlos. "From Hume to Wuhan: an epistemological journey on the problem o induction in COVID-19 machine learning models and its impact upon medical research." IEEE Access (2021). [3] Gebru, Timnit, et al. "Datasheets for datasets." arXiv preprint arXiv:1803.09010 (2018). [4] Collins, Gary S., et al. "Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence." BMJ open 11.7 (2021): e048008.

review). * New version, still not public. - Garcia Santa Cruz, Beatriz, et at. Prognosis and Diagnosis models of Brain MRI using Artificial intelligence: General overview and future directions". (In preparation).



- To avoid risk of bias coming from dataset misuse is important that researchers follow transparent practices and adequate reporting
- The selected images from each dataset should be listed one by one (e.g. as supplementary material), including all the patients available information. The reasons behind the inclusion of subjects from these particular datasets and with these specific characteristics should be explained in the
- The strategy followed to mitigate the potential biases should be explained For example, datasets could be balanced or in terms of outcome prevalence for each of the key demographic variables.
- Ask oneself which population is represented by the datasets, i.e. which were the recruitment procedures, location and setting, the inclusion and exclusion criteria, and subjects demographics. They should also address how exactly the outcome was obtained and how is related with the disease and with the application.
- Explain how the model can be applied into clinical setting, what is the benefit for the patient or how it would help medical personal to take decisions.

References:

More information:

[2] Garcia Santa Cruz, Beatriz, et al. "Public Covid-19 X-ray datasets and their impact on model bias-a systematic review of a significant problem." (2021). (Under