Globalizing Fairness Attributes in Machine Learning: A Case Study on Health in Africa

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Summary

African-contextualized fairness attributes along the ML pipeline

There are several Africa-specific barriers to the development of fair machine learning for health (ML4H) in Africa. For each data modality, we identify these barriers and discuss the fairness attributes that need to be considered by fairness-aware methods.

● Medical imaging: race, skin tone, NIL.
● Medical speech: language, ethnicity, literacy, education
● Survey data: socio-economic attributes, gender, sexual orientation, ethnicity
● Unstructured written health notes: language, gender, ethnicity, race
● Optical sensor devices: Race, skin tone
● Omics: Country of origin, phenotype, genetics, race, gender
● Lab-values: NIL, rural-urban divide

African-contextualized barriers to ML4H by health modality

Whether training from scratch or finetuning a pretrained model, it is crucial to understand how African-contextualized fairness attributes affect each step of the ML development pipeline. We highlight important considerations for health-specific applications in Africa.

➔ Contextualize the fairness criteria to ensure that fairness definitions are aligned with local laws and cultural beliefs
➔ Align incentives between stakeholders, researchers and practitioners during problem selection to address contextually relevant problems
➔ Caution around using pretrained models given there is no guarantees that fairness properties will transfer under distribution shifts.

Global Responsible Machine Learning for Health Practices

The field of Algorithmic Fairness had been majoritarily contextualized to Western context, raising the question of the meaning of fairness in the Global South.

To develop fair machine learning models, one needs first to understand what the fairness attributes of a given context are and where to apply them.

We identify axes of disparities for fairness between African and non-African countries, as well as provide a contextual understanding of globally applicable fairness attributes such as race and religion.

We underline different limitations to the development of machine learning for health tools in Africa and delineate where fairness attributes need to be considered.

Finally, we highlight important open challenges to developing fairness-aware methods in Africa including representative data collection and mitigating distribution shifts.

Implications for machine learning

Global axes in the African context

Social attributes
Race
Ethnicity
Skin tone
Religion
Language
Gender
Sexual orientation

Socio-economic attributes
Literacy and education
Rural-urban divide
Family income
Disability

Health attributes
Phenotype
Genetics
Pre-existing conditions
Co-existing conditions

Remote sensing
Imaging
CT scans
Spectroscopy

Lab values
Blood
Urinalysis
Pathology

Omic data
DNA
RNA
Protein

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