Development of a Novel and Racially Unbiased Deep Learning Algorithm to Predict Preterm Birth in Hypertensive Parturients: A Pragmatic Approach to De-biasing

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Introduction: Hypertensive disorders of pregnancy affect 2-8% of all pregnancies and contribute to 15% of preterm births worldwide[1]. Complications from preterm births are responsible for 35.5% of neonatal deaths[2] and, in those who survive, the subsequent neurodevelopmental, gastrointestinal and pulmonary disorders result in significant healthcare resource utilization. In addition, there are substantial racial disparities in care, and black women have 50% higher rates for preterm birth than white or Hispanic women[3]. High-risk patients should be transferred to tertiary care hospitals, equipped with neonatal ICU (NICU), however, there are no predictive tools to aid physicians in timely risk prediction. Moreover, recent research has raised awareness about the potential for algorithms to perpetuate bias, including racial bias[4,5]. Thus, we sought to develop a fair, racially agnostic algorithm predicting the risk of preterm birth in patients with hypertensive disorders of pregnancy.

Methods: Using ICD 9/10 codes, under approved IRB protocol, we identified patients with hypertensive disorders of pregnancy who delivered in our tertiary care center over the period 1991-2019. We selected 14 features for each patient in the dataset, and trained a 6 layer fully connected deep neural network (FCDNN). The network used sigmoid activations with a final softmax layer and dropout every other layer and was optimized with an Adam optimizer according to a binary cross-entropy loss function. Subsequently, we balanced the dataset with equal weighting of white, black, and Hispanic patients and then removed race as a model input before training. The models were trained for 20 epochs on the data with an 80-20 split between the training and the test set. We compared the performance of the unbalanced and balanced model.

Results: We identified 35,955 patients in our dataset; of those, 7,263 (20%) had preterm birth. Of the total patient cohort, 20,401(56.74%) were white non-Hispanic, 6,530 (18.16%) were black and 3,937(10.95%) were Hispanic. In the initial model, we used all predictors, including race. The model had area under the receiver operating characteristic curve (AUC) of 0.723, accuracy - 74.3% and weighted F1 score-0.84. This model had unequal performance amongst racial groups of up to 10% difference in accuracy. After rebalancing and weighting white non-Hispanic, black, and Hispanic patients equally and removing race as a predictor, the subsequent model had equal performance across all races with no overfitting as well as slightly improved overall predictive performance. The AUC increased to 0.787, the accuracy – to 82.0%, and the weighted F1 score – to 0.86. We propose this approach (Fig. 1) as a quality control step to evaluate for bias during model development.

Conclusion: We report the development of a novel, racially agnostic preterm birth predictive tool in patients with hypertensive disorders of pregnancy using deep learning. This tool can be used to support clinicians in patient transfer decisions and NICU bed planning. We propose the adoption of this pragmatic method to evaluate, detect and resolve bias in model performance. This approach can be applied to achieve un-biased decision-making in models on any robust dataset.

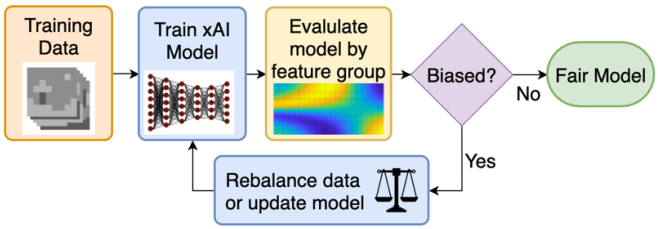

Fig. 1 Workflow to detect and resolve model bias.

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