When to Use Demographic Data in Healthcare Models: A Bias-Responsible Approach

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***Abstract*—Given AI's increasing role in healthcare, it is vital to ensure that created models neither perpetuate nor introduce new biases. One of the naive approaches to mitigating bias is omitting demographic data features during model training. However, in healthcare, this method might not yield the best-performing models as these features may contain crucial care-related information. This paper explores the trade-offs between optimal performance and algorithm bias linked to using demographic data. We demonstrate the approach using a healthcare model that predicts ICU readmission risk of patients.**

***Index Terms*—Healthcare, Fairness, Machine Learning, Artificial Intelligence, ICU Readmission Risk**

I. Introduction

AI systems such as machine learning (ML) models are transforming various industries, and healthcare is no exception. In every context these systems are used, including healthcare, they raise the concern of bias against different demographic subgroups. In healthcare, ML models have been utilized for diagnosing various diseases, such as cancer [2], and most recently COVID-19 [1]. They have also been used for prediction, including patients' Intensive Care Unit (ICU) readmission risk, mortality, and ICU length of stay [4], [6]. As the use of ML in healthcare increases so does the concern to ensure that the developed models do not perpetuate existing biases or create new ones [3], [5]. In this paper, we examine the bias connected to using demographic data in ML for healthcare by evaluating the impact on model performance and fairness of including or withholding demographic data.

One naive approach to mitigate ML biases is to exclude features that might aid in identifying an individual, such as race, gender, and insurance type, from the training data, ensuring the model doesn't explicitly use such features for predictions [7]. However, this approach may not consistently yield the best performance and can be ineffective in preventing bias as these features may provide valuable information, particularly in healthcare. Lin et al. [4] demonstrated that incorporating all demographic information enhanced predictive models performance for ICU readmission risk. In contrast, including such demographic features might introduce additional bias. To understand this trade-off between performance and bias, we developed a framework for deciding when to use demographic data as input using Lin et al.'s model for demonstration [4]. Specifically, the paper explores the models presented by Lin et al. [4] to investigate whether the increased performance after using demographic data is consistent across all patients. We systematically explored the trade-off for each demographic variable and their combinations by comparing two identical models that differ only in whether they used particualr demographic information.

II. Method

In the work done by Lin et al., the authors used supervised machine learning models to predict ICU readmission risk using patients' clinical data. They tested several models, including the Long Short Term Memory (LSTM), Convolutional Neural Network (CNN), and a hybrid combination of the two. For input data, they tested different time series windows of the medical data, finding that the last 48 hours(L-48) before transfer/discharge data resulted in the best-performing models. Additionally, they evaluated whether adding demographic information boosted the performance of the model, finding positive results. [4]

For our analysis, we took two LSTM models with the L-48 data from the work done by Lin et al. [4] as base models where the only difference between the two is the incorporation of demographic data. The base model was the most explored and showed the third highest performance improvement with the inclusion of demographic data in the original work. We refer to the model with demographic information as `WD` and the one without it as `WOD`.

The original model by Lin et al. [4] utilizes True Positive Rates (TPR) for reporting results, and we adopt the same metric to examine performance and bias for two primary reasons. First, it is used to maintain consistency with the original work because it allows us to measure disparity using the originally intended metric. Second, assuming that a true positive prediction gets the benefit of extended care due to the high risk of readmission, TPR allows us to gauge the classification effectiveness of the models and assess whether the inclusion of demographic data has increased or decreased the disparity of such benefit.

To examine introduced bias resulting from the use of demographic data, the TPR of model `WOD` is computed for different demographic subgroups, and compared to the TPR of model `WD` for the same groups. The TPR for each model is derived by averaging the TPR values obtained through a 5-fold cross-validation. The difference of these TPRs between model `WOD` and `WD` is then used to measure the disparity of

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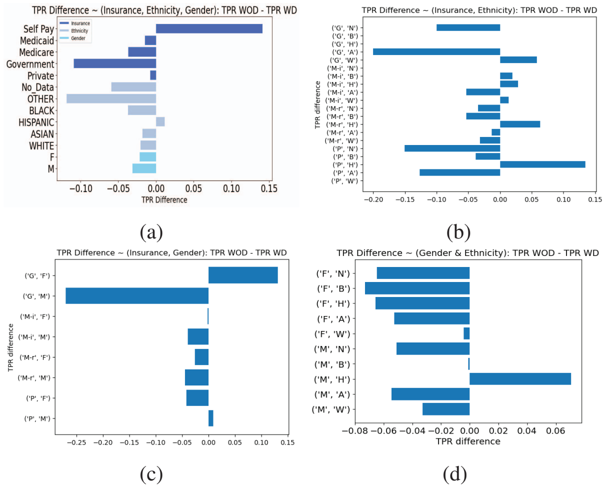

(a) (b) (c) (d)

Fig. 1: TPR differences of model WOD and WD: 1a for gender, ethnicity, and Insurance separately; 1b, 1c, and 1d for intersectional groups (Insurance, Ethnicity), (Insurance, Gender), and (Gender, Ethnicity), respectively, where F: Female, M: Male, G: Government, M-i: Medicaid, M-r: Medicare, P: Private are different insurance groups and N: No Data, B: Black, H: Hispanic, A: Asian, W: White are different ethnicity groups

benefit for each demographic group that happens as a result of using demographic data.

To explore further, we extend our analysis to include intersectional demographic groups. This entails repeating the same analysis for patients who belong to different categories of demographic groups, simultaneously. For example, we evaluate how model WOD performs for female patients with Medicaid insurance and compare it to how model WD performs for the same group of patients.

III. Results

When observing the results, bias could be noticed in two ways. First, when the TPR difference is negative for some demographic groups and positive for others, it implies varying benefits from the use of demographic information. Second, when there is a noticeable gap in the magnitude of the TPR difference among different groups, it suggests that the magnitude of benefit from the use of demographic information varies across such groups.

Fig. 1a to Fig. 1d present the TPR difference for individual subgroups and their intersection. Each figure is centered at 0 with positive WOD minus WD to the right and negative WOD − WD to the left of the center. The magnitudes of the bars show the extent to which demographic information contributed to the improvement. Figure 1a shows the TPR difference for all subgroups across gender, ethnicity, and insurance. Additionally, Figure 1b, 1c and 1d show the difference for all the intersectional groups.

Figure 1a shows that the addition of demographics data increased the benefit of all subgroups except for patients with self-pay and Hispanic patients compared to the model WOD. It can also be seen that there is a magnitude difference among both the positive and negative bars. All of the figures illustrate both kinds of biases discussed above. For example, figure 1c's first type of bias is noticeable when observing the performance bar for female patients with government insurance, where the bar is to the right of the center axis. It can be inferred that the addition didn't help this demographic group, resulting in an average performance decrease of approximately 13 percent. For the second bias, the noticeable comparison is the big difference between females and males with government insurance, where there is a benefit disparity of roughly 40 percent, although more disparities can be observed. Such inference can be made about all the other figures as well, but it is important to note that as the number of patients decreases in the group, the fluctuations in benefit could be higher and that needs to be kept in mind when making decisions.

IV. Discussion and Conclusion

As shown throughout this paper, depending solely on a single metric for reporting can obscure nuanced information, especially in the area of algorithmic fairness. For an increased overall performance of roughly 2 percent TPR, the figures above show the kind of benefit disparity that could be introduced. Such disparity could be attributed to inherent historical biases, systemic biases, or algorithmic biases, prompting the need for additional research to distinguish between these factors. Depending on the application, the acceptable trade-off and bias could differ, but these kinds of analyses allow us to understand such trade-offs before making decisions.

This paper presented the result of an analysis that looked to examine the trade-offs between optimal performance and algorithm bias linked to using demographic data. It is important to understand that the use of demographic information does not always increase benefits for all protected groups uniformly. This analysis is key to assessing the trade-off between performance and bias and can be used to decide whether or not to use demographic information.

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