Mitigating health disparities in hospital readmissions

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Abstract

Background: The management of hyperglycemia in hospitalized patients has a significant impact on both morbidity and mortality. This study used a large clinical database to predict the need for diabetic patients to be hospitalized, which could lead to improvements in patient safety. These predictions, however, may be vulnerable to health disparities caused by social determinants such as race, age, and gender. These biases must be removed early in the data collection process, before they enter the system and are reinforced by model predictions, resulting in biases in the model's decisions. In this paper, we propose a machine learning pipeline capable of making predictions as well as detecting and mitigating biases. This pipeline analyses clinical data, determines whether biases exist, removes them, and then make predictions. We demonstrate the classification accuracy and fairness in model predictions using experiments.

Results: The results show that when we mitigate biases early in a model, we get fairer predictions. We also find that as we get better fairness, we sacrifice a certain level of accuracy, which is also validated in the previous studies.

Conclusion: We invite the research community to contribute to identifying additional factors that contribute to health disparities that can be addressed through this pipeline.

Keywords: Hyperglycemia; fairness; machine learning; accuracy; machine learning pipeline; biases; predictions.

1 Background

Hyperglycemia is the medical term for having high blood glucose levels (blood sugar) (1). Hemoglobin A1c (HbA1c) is a blood test that is used to help diagnose and monitor people with diabetes (2). When diabetic patients come to the emergency department, their HbA1c level should be determined. The outcome can then be used to assess the patient's current glycemic control and the urgency of needed follow-up (e.g., hospitalization).

The management of hyperglycemia in hospitalized patients has a significant impact on morbidity and mortality (3). Many hospitals have begun to adhere to formalized guidelines and set tight glucose targets for critical patients in their intensive care units (ICUs). However, the same protocols are not followed for most admissions due to health disparity.

A health disparity (4) is a difference or gap in health status or health care supply and access that is frequently associated with social, economic, and environmental adversity. Health inequalities impact groups of people who experience systematic barriers to receiving health care services due to health disparities (5).
According to research (1), examining historical patterns of diabetes care in hospitalized diabetic patients may lead to improvements in patient safety. Some studies (6) show that measuring (HbA1c) is also associated with lower readmission rates in hospitalized patients. We will continue this line of research (evaluating the effect of HbA1c testing on hospital readmission rates) to see if there are racial/ethnic disparities that may affect the hospitalization rate. The goal is of this research to reduce the disparities in readmission rates of diabetic patients based on gender/race/ethnicity.

The potential impact of big data in health science cannot be ignored. It is also quite evident now that machine learning (ML) algorithms developed from big data could worsen or perhaps create new forms of disparities (7). Bias in ML literature is usually defined in terms of the dataset or model—bias in labelling, sample selection, data retrieval, scaling and imputation, or model selection (8). These biases can be mitigated at three stages: early, mid, and late (8) of a software development life cycle. The early stage (pre-processing) would be to reduce bias by manipulating the training data before training the algorithm (9). The mid stage (in-processing) would be to de-bias the model itself (10), which is also framed as an optimization problem. The late stage (post-processing) refers to reducing the biases by manipulating the output predictions after training (11). Prior research (12,13) has shown that missing the chance to detect biases at an early stage can make it difficult for the ML pipeline to mitigate them later on.

A ML pipeline is composed of several steps that facilitate the automation of ML workflows (14). In this paper, we propose a fair ML pipeline that can take a large clinical data and de-bias it early on.

We summarize our contributions as:
1. We create a fair ML pipeline that can predict readmission rates for individuals with diabetes mellitus, while taking care to minimize health disparities among vulnerable population groups during predictions.
2. We build the fair ML pipeline according to the widely accepted data science pipeline structure (15), with the goal of making it easier for practitioners to use. This pipeline is intended to reduce health disparities; however, given another dataset, this design can be used to reduce biases in that domain; the only requirement is that the pipeline be trained on new data;
3. We conduct extensive experiments on a benchmark dataset to determine how predictions are impacted before and after de-biasing the data.

Appendix A contains some of the key terms used in this work.
2 Materials and Methods

2.1 Dataset
We use the “Diabetes 130-US hospitals Data Set for the years 1999-2008” (16) in this research. The data contains attributes, such as patient number, gender, age, race, admission type, time in hospital, medical specialty of admitting physician, HbA1c test result, diagnosis medications and so. All the electronic medical records are de-identified by the dataset providers (6) and consists of around 50 features that we also use. The details of dataset features used in this work are given in Appendix B.

![Fair ML pipeline for hospital readmissions](image)

Figure 1: Fair ML pipeline for hospital readmissions

2.2 Overall framework
We develop a fair ML pipeline to examine, report, and mitigate discrimination and biases in the hospital readmission of diabetic patients based on HbA1c measurement (6). We use the same classification strategy as in the original paper (6) to determine the likelihood of readmission (target variable) based on patient’s records (patient is readmitted within 30 days of discharge, HbA1c measurements, HbA1c > 8%, medication) to determine the outcome. However, our work contributes to determining whether the hospitalization readmissions are equitable for all groups based on gender, age and race. Our fair ML pipeline is shown in Figure 1.
As shown in Figure 1, we start with the raw data, which in this case is diabetic patient hospitalization data (6). The data is first given to the discrimination test unit, which determines whether certain privileged groups (e.g., white, male or such) are given a systematic advantage and certain unprivileged groups are given a systematic disadvantage. This applies to characteristics such as race, gender and age. If the discrimination test shows the existence of biases which we determine through fairness metrics (defined in Section 3.1), we use a pre-processing fairness algorithm to reduce or remove those biases. We manipulate the training data prior to training the algorithm to remove biases. If there are no biases, we use the standard ML pre-processing technique. After pre-processing (either bias removal or standard preprocessing), the data is separated into training and testing data. Then, we perform the classification task and make predictions. The test data is used to determine the accuracy of the classification. We repeat the discrimination test on the test data, which we assume is bias-free at this point. If the discrimination evaluation reveals no biases, we put the model into production for use. Otherwise, we reprocess the data to correct any biases that were missed during the bias pre-processing stage and send it back to the pipeline.

2.3 Binary classification and bias removal

Appendix C show the notation that we use here. Formally, we define the classification and bias removal problem as:

Given a dataset $D = (p, x, y)$ consisting of protected attributes $p$ (race, gender, age), remaining attributes $x$ (features other than $p$ in Appendix B), and binary class $y$ (patient is ‘readmitted’ or ‘not readmitted’), the goal is to have a transformed dataset $D' = (p, x', y)$ ($x'$ is modified set of attributes) that is guaranteed to be having no health disparities. The goal is to change only the remaining attributes $x$, leaving $y$ unchanged from the original data set to preserve predictions.

**Classification algorithm:** We use the Extreme Gradient Boosting (XGBoost), which is an implementation of the gradient boosted trees algorithm, for the classifier. We chose XGBoost over more recent deep neural networks, such as BERT (17), due to the numeric and categorical nature of our data.

**Fairness algorithm:** we use the Reweighing (RW) algorithm (9) that uses a weighing scheme for the examples in each (group, label) combination to ensure fairness prior to classification. Here by groups, we mean grouping based on protected attributes (gender, race, age).

We measure the health disparity between different groups in terms of a disparity impact (DI) ratio (18). We use DI ratio to define fairness in this (binary) classification setting. A ML model has DI when its performance changes across groups defined by protected attributes (19). We define DI as in equation 1:
\[
\frac{Pr(\hat{y} = 1 \mid g_1)}{Pr(\hat{y} = 1 \mid g_2)}
\]

This calculation measures the percentage of unprivileged group \((g_1)\) who received a favorable outcome is divided by the percentage of privileged groups \((g_2)\) who received a favorable outcome. DI has its origin in legal fairness considerations (20) that often use four-fifths rule (21), which means if the unprivileged group receives a positive outcome less than 80% of their proportion of the privileged group, this is a DI violation.

The purpose of this methodology is to guarantee that, given \(D\), any classification algorithm aiming to predict \(\hat{y}\), will not have DI. We are interested in the outcomes to ensure that protected attributes do not suffer from biases.

3 Results and Analysis

3.1 Evaluation strategy

First, we define the protected attributes: \{‘age’, ‘gender’, ‘race’\}. Then, we define privileged and unprivileged groups as:

- **Privileged groups**: \{‘age’: 1 (older than or equal to 25); ‘gender’: 1 (Male); ‘race’: 1 (‘non-Black’)\}
- **Unprivileged groups**: \{‘age’: 0 (younger or equal to 25); ‘gender’: 0 (Female); ‘race’: 0 (‘Black’)\}.

We also examine the initial training data for biases, mitigate them, and recheck. Our evaluation strategy is two-fold: ‘Before bias mitigation on original test data’ and ‘After bias mitigation on transformed test data’.

3.2 Evaluation metrics

We use the following evaluation metrics for fairness and accuracy.

- **Disparate Impact (DI)** evaluates if a data or model is unbiased or biased. To keep the value of DI under 1, we use \(|1 - \text{disparate impact}|\) (22), its value should be close to zero for model to be fair.
- **Average odds difference (avg_odd)** (23) is the average of difference in false positive rates and true positive rates between unprivileged and privileged groups. A value of 0 implies both groups have equal benefit.
- **Equal opportunity difference (eq_opp)** (23) is the difference in true positive rates between unprivileged and privileged groups. A value of 0 implies both groups have equal benefit.
- **Balanced accuracy (acc)** evaluates the accuracy of a classifier, a value close to 1 is a good value.

The DI, avg_odd and eq_opp are fairness metrics while the acc is accuracy metric.
3.3 Baseline methods

We use Logistic Regression (LG) (24), Random Forest (RF) (25), Gradient Boosting Machine (GBM) as baselines models for the classification. We use the Adversarial Debiasing (AD) (26) as in-processing model. We also use Calibrated Equalized Odds Postprocessing (CEOD) [21] as the post-processing method.

|           | Original  | Transformed |
|-----------|-----------|-------------|
| acc       | 0.7201    | 0.6857      |
| DI        | 0.4498    | 0.3006      |
| avg_odd   | -0.2018   | -0.1884     |
| eq_opp    | -0.1982   | -0.1752     |
| acc       | 0.7412    | 0.6923      |
| DI        | 0.4498    | 0.2672      |
| avg_odd   | -0.1939   | -0.1198     |
| eq_opp    | -0.1836   | -0.0933     |
| acc       | 0.7302    | 0.6888      |
| DI        | 0.4498    | 0.2906      |
| avg_odd   | -0.1968   | -0.1284     |
| eq_opp    | -0.1945   | -0.1792     |
| acc       | 0.7510    | 0.7031      |
| DI        | 0.4498    | 0.2472      |
| avg_odd   | -0.1832   | -0.1081     |
| eq_opp    | -0.1732   | -0.0712     |

Table 2: Fairness and classification results

3.4 Results

Results before and after de-biasing: Results are shown in Table 2 and discussed next:

The classifier trained with the original dataset (before de-biasing) has a DI score 0.4498 which indicates biases in the data. When the classifier is trained with the transformed dataset (after de-biasing), the DI value is 0.3006 for LG, 0.2672 for RF, 0.2906 for GBM and 0.2472 for XGBoost (these DI values are taken by calculating |1-DI|), which indicates less bias after de-biasing. This demonstrates that transforming the data to remove the DI improves the fairness of the classifier. The values of avg_odd and eq_opp have also increased from their initial negative values close to 0 after transformation, which is indicator of fairness.

Comparison among different fairness methods: We also compare RW (pre-processing with best-performing XGBoost classifier) with the AD (in-processing) and CEOD (post-processing) fairness methods to see which model gives us the best results. Unlike pre-processing fairness algorithms, in-processing and post-processing have their own classifiers. In Figure 2, we show
the accuracy and fairness (DI) performance after bias mitigation using these methods' default classification settings.

The results in Figure 2 shows that RW outperforms the AD and CEOD methods. This shows that if we mitigate biases early on in a ML pipeline, those biases are not replicated in the predictions. As expected, the RW method achieves the highest classification accuracy with XGBoost. XGBoost is well-suited for this type of numeric and categorical dataset. Additionally, we see that the fairness of the pre-processing technique is optimal, as evidenced by the DI value's lower score.

Overall, these results also indicate that there is a tradeoff between accuracy and fairness. Usually, when one goes high, the other metric value goes down, as evidenced in research also (23,27). A good model is one that can achieve fairness without losing much accuracy.

4 Discussion and conclusion

One of the overarching goals of Healthy People 2030 (28) is to eradicate health disparities and develop health literacy among populations, which is also a motivation for this research. According to a review of studies (29,30), ethnic minorities are disproportionately affected by the majority of diabetes complications. In this research, we try to find if the outcome (readmission to hospitalization) is favorable or unfavorable for different groups.

Through a pre-processing fairness approach, we mitigate biases and demonstrate fairness through extensive experiments. We find that prediction accuracy decreases during de-biasing process. We compare our method with other fairness techniques (post-processing and in-processing) and find that pre-processing methods give us more fairer predictions, which is validated through different fairness measures. We also get good accuracy when we de-bias the data prior to model training.

A few limitations and future directions are:
1. There is no universally accepted definition of what constitutes bias and fairness (31). As a future direction, we must first investigate different definitions of biases, especially, in health domain to determine the fairness of data and algorithms.

2. We consider a small number of biases, we understand that there are many other types of health disparities, such as food, safety, health coverage and recently related to COVID-19, which may be overlooked in the research.

3. One of the research's limitations is the scarcity of labelled biased health-related data. So far, we have used a benchmark dataset to assist us in detecting and mitigating bias. However, we would like to acquire more labelled data in the future to show how to mitigate biases on a broader dataset.

There is much work to do toward achieving fairness in health domain, and we hope that others in the research community will contribute to this research.

Data availability: The data is available at https://archive.ics.uci.edu/ml/datasets/Diabetes+130-US+hospitals+for+years+1999-2008#

Code Availability: The code will be available after review upon request.

Declarations Ethics Approval: No human participants, their data, or biological material was used in this perspective’s pieces. Therefore, ethics approval is not applicable in this case.

Consent to Participate: Does not apply as no human subjects were involved.

Consent for Publication Does not apply as no human subjects were involved.

Conflicts of Interest The authors declare no competing interests.

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Appendices

Appendix A: Key terms used in fairness
- **Bias** is a type of systemic error.
- A **protected attribute** divides a population into groups, for example, race, gender, caste, and religion.
- A **privileged** value of a protected attribute denotes a group that historically has a systematic advantage, for example, male gender, white race.
- An **underprivileged** group faces prejudice based on systematic biases such as gender, race, age, disability, and so on.
- **Group fairness** means that the protected attribute receives similar treatments or outcomes.
- **Individual fairness** means that similar individuals receive similar treatments or outcomes.
- **Equalized odds** is a statistical notion of fairness that ensures classification algorithms do not discriminate against protected groups.
- **Fairness or fair** is a broad term used in ML and generally refers to the process of undoing the effects of various biases in the data and algorithms.

Appendix B: Dataset features used in this study

| Feature                  | Type      | Description and values                                                                 |
|-------------------------|-----------|----------------------------------------------------------------------------------------|
| Patient number          | Numeric   | Unique identifier of a patient                                                         |
| Race                    | Nominal   | Caucasian, Asian, African American, Hispanic, and other                                |
| Gender                  | Nominal   | Male, female                                                                           |
| Age                     | Nominal   | Grouped in 10-year intervals: [0, 10), [10, 20), ..., (90, 100)                        |
| Weight                  | Numeric   | Weight in pounds.                                                                     |
| Admission type          | Nominal   | Emergency, urgent, elective, newborn, and not available                                |
| Discharge disposition   | Nominal   | Discharged to home, expired, and not available                                         |
| Admission source        | Nominal   | Physician referral, emergency room, and transfer from a hospital                      |
| Time in hospital        | Numeric   | Days between admission & discharge                                                    |
| Number of lab procedures| Numeric   | Number of lab tests performed during the encounter                                    |
| Glucose serum test result| Nominal | Indicates the range of the result or if the test was not taken. Values: "">200," "">300," "normal," and "none" if not measured |
| A1c test result         | Nominal   | was greater than 8%, "">7" if the result was greater than 7% but less than 8%, "normal" if the result was less than 7%, and "none" if not measured, |
| Diabetes medications    | Nominal   | Indicates if there was any diabetic medication prescribed. Values: "yes" and "no"     |
| Readmitted              | Nominal   | 30 days, "">30" if the patient was readmitted in more than 30 days, and "No" for no record of readmission |

Appendix C: Notations used in Section 2.3

| Symbol   | Description                                                                 |
|----------|-----------------------------------------------------------------------------|
| y ∈ 0,1 | Actual value or outcome                                                     |
| ŷ ∈ 0,1 | Predicted value or outcome                                                  |
| Pr(ŷᵢ = 1) | Probability of (ŷᵢ = 1) for observation i                                    |
| gᵢ, gⱼ | Identifier for groups based on protected attribute. A group is either privileged or unprivileged. |