On the Bias, Fairness and Bias Mitigation of a Wearable-based Artificial Intelligence Model for Detecting Freezing-of-Gait

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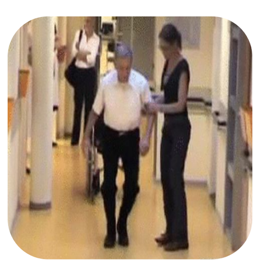
INTRODUCTION

- **Freezing-of-Gait (FOG)** is a debilitating Parkinson's disease (PD) symptom related to **increase** in **fall risk** and **injuries** [1].
- Despite progress in wearable and machine learning (ML) research for FOG detection, studies assessing **bias** and **fairness** of FOG detection models are **sparse**.
- Our study evaluated the bias and fairness of a **state-of-art** FOG detection model using standard **group fairness metrics** from four FOG wearable sensor datasets **and** evaluated the effectiveness of **multi-site transfer learning** as a **bias mitigation approach**.

CLINICAL SIGNIFICANCE

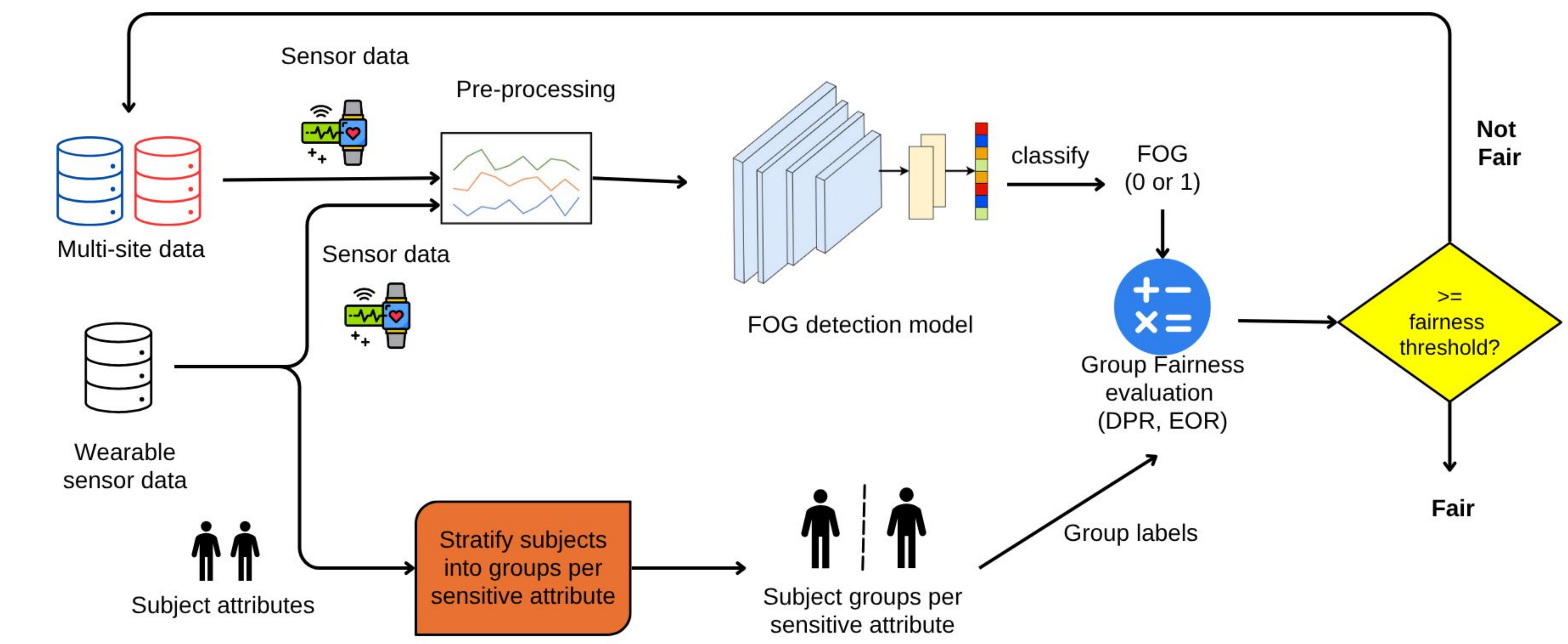


- Existing research has highlighted biases in PD diagnosis and care such as **delayed diagnosis** in **women** and significant **underdiagnosis** in **black patients** [2,3].
- Low-cost wearable-based FOG detection systems can **expand PD care access** through **continuous monitoring**, particularly for **underserved populations**, enable **personalized intervention plans**, and support development of **new therapeutic approaches** in clinical trials [4].

METHODS

- Four publicly available wearable sensor datasets: **DeFOG** (N=38) from **home** environments and **tDCS FOG** (N=62), **Daphnet** (N=10), **De Souza *et al.*** (N=35) from **clinical** settings [5, 6, 7].
- Subject attributes evaluated included **demographic attributes** such as **Age** and **Sex** and **clinical variables** such as **FOG type** and **Disease Duration** (years) [5].
- For **FOG type**, freezing episodes (FOG=1) were classified as **tremulous** or **akinetic** after analyzing the total power in the **locomotion band** (0-3Hz) and **freeze band** (3-8 Hz) [8].
- Trained a **Deep Convolutional and LSTM** (**DeepConvLSTM**) model known for its effectiveness in capturing complex FOG movements [9]. **Random Forest** and a **transformer-based models** [10] were also trained for comparison.
- Group fairness metrics used in evaluation: **Demographic Parity Ratio** (**DPR**) and **Equalized Odds Ratio** (**EOR**) [11].
- Applied transfer learning approaches i.e. pretraining using multi-site data (**multi-site transfer**) and from large scale pretrained human activity recognition models [12,13] (**generic activity feature transfer**) as bias mitigation methods. Conventional bias mitigation approaches such as **adversarial debiasing** [14] were applied for comparison .

ML PIPELINE



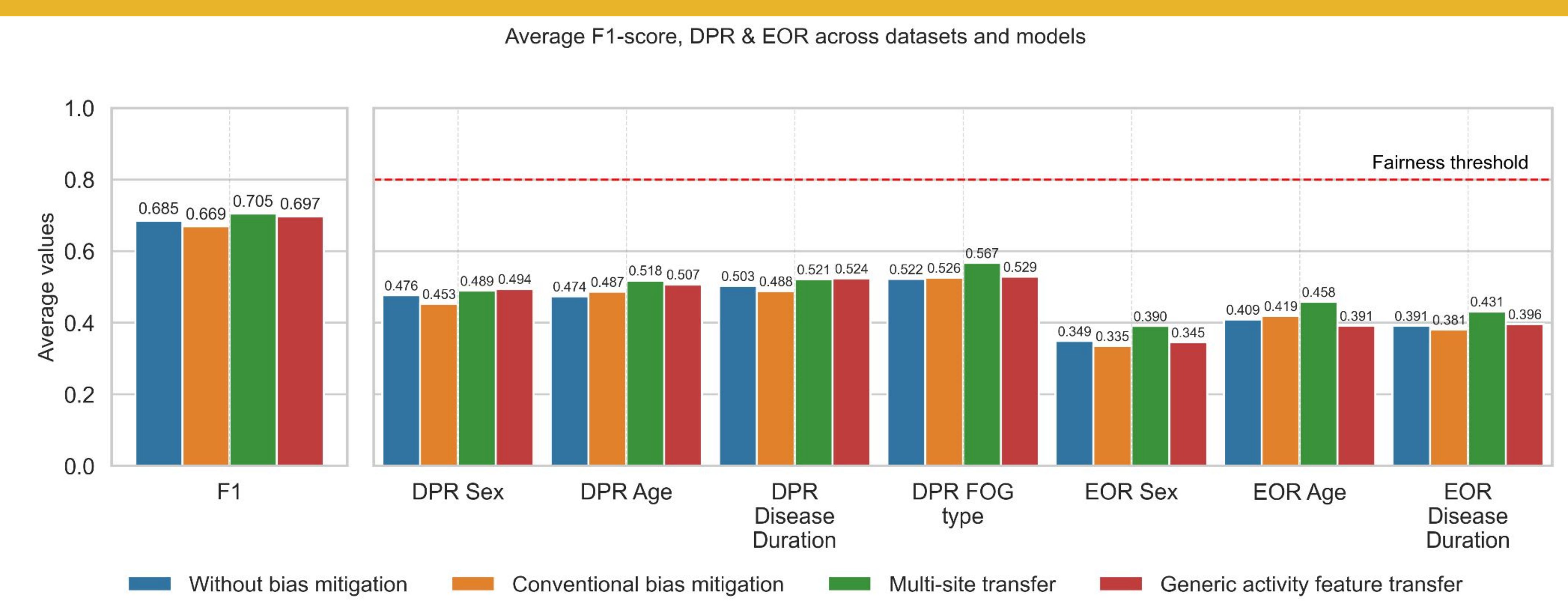
Following the standard human activity recognition pipeline [15], we applied the **sliding window** approach to segment the data into 3-second windows for DeFOG, tDCS FOG, and De Souza *et al.* and 4.5 second windows for Daphnet. For fairness analysis, self-reported sex, FOG type and median split groups for age (69: DeFOG/tDCS FOG/De Souza, 66:Daphnet) and disease duration (De Souza=7, tDCS FOG=9 , DeFOG=13, Daphnet=12.5 years) were used.

80% Applied the **four-fifths** rule (threshold = 0.8) as the **fairness threshold**, where DPR=1 & EOR=1 indicate perfect fairness.

We hypothesized that transfer learning across datasets exposes the model to **increased** and **more diverse** data thus improving its overall **model generalizability** and **reducing bias** with respect to the subject attributes in the target dataset.

With **multi-site transfer**, the model was pretrained on source/pretrain datasets and fine tuned on a target dataset with similar on-body sensor locations such as lower back and ankle.

RESULTS



- No single attribute was found to achieve the fairness threshold with the **sex** attributes showing the **lowest values** for DPR and EOR across all datasets. This was due to the **significant underrepresentation** of **females** in all four datasets.
- The transfer learning-based bias mitigation approaches consistently **increased** the DPR and EOR of the **sex** attribute.
- These transfer learning-based bias mitigation methods i.e multi-site transfer and generic activity feature transfer **increased** the **performance** (average change in F1-score of **+0.026** and **+0.018**, respectively) and **reduced** the **bias** (average change in DPR of **+0.027** and **+0.039**, respectively) across datasets and attributes.

CONCLUSION

- **No single attribute** is **fair** across both datasets. This implies the inconsistency of model performance across different subject groups (e.g., longer disease duration) can result in care disparities.
- Our results show empirically that transfer learning through multi-site datasets can **improve overall model performance** and **reduce biases**. Future work may include datasets with race attributes and conducting intersectional analysis to investigate how protected attributes interact to influence predictions.

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