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A Survey of Fairness in Medical Image Analysis: Concepts, Algorithms, Evaluations, and Challenges

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ABSTRACT

Fairness, a criterion focuses on evaluating algorithm performance on different demographic groups, has gained attention in natural language processing, recommendation system and facial recognition. Since there are plenty of demographic attributes in medical image samples, it is important to understand the concepts of fairness, be acquainted with unfairness mitigation techniques, evaluate fairness degree of an algorithm and recognize challenges in fairness issues in medical image analysis (MedIA). In this paper, we first give a comprehensive and precise definition of fairness, following by introducing currently used techniques in fairness issues in MedIA. After that, we list public medical image datasets that contain demographic attributes for facilitating the fairness research and summarize current algorithms concerning fairness in MedIA. To help achieve a better understanding of fairness, and call attention to fairness related issues in MedIA, experiments are conducted comparing the difference between fairness and data imbalance, verifying the existence of unfairness in various MedIA tasks, especially in classification, segmentation and detection, and evaluating the effectiveness of unfairness mitigation algorithms. Finally, we conclude with opportunities and challenges in fairness in MedIA.

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1. Introduction

1.1. Background

The past years have witnessed a surge in deep learning (DL) methods, for their prevalence performance in computer vision (CV) and natural language processing (NLP) tasks. DL has become an integral part in systems like automatic driving, facial recognition and healthcare analysis. Specifically, DL is maturing at a fast pace in medical research and applications, from low-level tasks, like image reconstruction, denoising and enhancement, to high level tasks including classification, segmentation and detection (Zhou et al., 2021a).

While current research is mostly concerned about deriving higher performance throughout the evolution of DL algorithms, such as the prediction accuracy on classification tasks, the Dice similarity score on segmentation tasks, etc., there is a growing interest in going beyond mere performance metrics by addressing, say, the interpretability, explainability and trustworthiness aspects of DL methods. The eXplainable Artificial Intelligence (XAI) methods concentrate on explaining their rationale, characterizing their relative merits, and conveying an understanding of how they will behave in the future. In general, XAI focuses on explaining algorithm, including trustworthy, interpretability, fairness, causality, reproducibility, etc. (Saeed and Omlin, 2021). In the FUTURE-AI initiative toward trustworthy MedIA (Lekadir et al., 2021), six guiding principles are presented:

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Fairness, Universality, Traceability, Usability, Robustness and Explainability. Fairness, as the first and the fundamental principle, calls upon the importance of considering fairness when designing algorithms in medical applications.

Concerns on the fairness of DL model are derived from a prominent debate between Yann Lecun and Timnit Gebru in 2020. It all started from a super resolution algorithm PULSE (Menon et al., 2020), which was accused of 'racism'. PULSE is designed to improve the image resolution, and generate a rich detailed and high fidelity image. Surprisingly, people found that a portrait image of Barack Hussein Obama got a clearer output image with a white man's face, after processed by PULSE. Although the reason may be the imbalance distribution of training data, this still caused an extensive concern on the bias and fairness issues in DL models.

As is widely recognized, fairness presupposes that all people have the same right and should be treated equally, which means DL models should not be discriminatory on factors like race, colour, sex, language, religion, politics, nationality, property or birth. The issue of fairness brings longstanding discussions on AI transparency and algorithmic non-discrimination in company promotion (D'Amour et al., 2020), university entrance evaluation (Wightman, 1998), music recommendation (Celma, 2010), etc.

There is a consensus in the research of fairness that the meaning of fairness is not analytically well-defined, and several definitions are even orthogonal (Li et al., 2022c). For example, different fairness criteria require different constraints on the model's performance (Barocas et al., 2017). Among all these fairness definitions, two commonly used definitions are individual fairness (Ilvento, 2019) and group fairness (Binns, 2020). Individual fairness requires that similar individuals should be treated equally and thus have similar predictions. For example, a model should have comparable diagnosis on two similar X-Ray images (the concept 'similar' is defined using some similarity measurements including cosine-similarity (Dwork et al., 2012). While group fairness requires equal performance on the groups divided based on sensitive attributes (e.g., race, sex, and age) first. In image processing area, group fairness is more frequently used than individual fairness, and in this survey we also focus on group fairness.

Recently, researchers are paying increasely more attention to fairness issues in medical applications. Comparing with former areas, fairness in MedIA is more valuable and important, because the relationship between algorithm and human is closer due to the widespread use of medical images in clinical decision making.

It is clear that the evaluation of fairness of deep learning algorithms is, and will continue to be, a common scenario and an inevitable issue in training deep learning models. Hence, the concepts of fairness, the relationship between fair MedIA and fairness issues in other fields, current research in MedIA and potential research directions and challenges are highly desired. However, there is a lack of systematic review of fairness in MedIA. In this paper, we attempt to bridge this gap.

1.2. Aims and scope

We first provide a precise and detailed definition of group fairness and compare it with similar concepts. We then review the methods proposed in facial recognition, most of which have not been widely applied in MedIA. After that, we introduce the collection of medical image datasets that can be used in fairness analysis in medical applications, including the modality and sensitive attributes. Then, we present our experiments on several datasets, where we investigate the importance and necessity of fairness evaluation and mitigation in medical applications, and assess the effectiveness of fairness mitigation methods. Finally, we propose the ongoing difficulties and challenges in fair medical analysis and point out several potential research directions in this area.

The structure of this paper is as follows: Chapter 2 introduces basic concepts of fairness and compares fairness with other related concepts; Chapter 3 surveys current research in fairness in MedIA; Chapter 4 evaluates the value and necessity of fairness evaluation in area of MedIA by several experiments; and Chapter 5 offers the opportunities and challenges in fair MedIA and concludes the whole survey. Fig. 1 provides a summary of paper organization.

2. Concepts

In order to analyze fairness, we need to have a clear and precise definition of fairness. "Fairness" remains a complex and controversial concept in machine learning and deep learning area until Narayanan *et al.* (Narayanan, 2018) give a systematic and formulaic definition.

Unlike other evaluation metrics of DL algorithms, fairness criterion is a metric that focuses on the relationship between algorithm performance and human factors. Take a simple classification task as an example, the information of patients can be separated as task-related information (medical images, denoted as X), e.g., MRI images and X-ray images, and task-irrelevant information that is inherent, which is called *sensitive attributes*, A, such as age, gender, race, etc. These sensitive attributes can separate patients into several groups, like male / female, Asian / African / American. We need to emphasize here that, although in some scenarios, sensitive attributes are related to target task, we still regard these attributes as task-irrelevant and do not expect to categorize the classification task via this information, because due to the distribution of dataset, algorithms prefer to use the easiest criterion to classify the samples, which is also known as shortcut learning (for example, classify all female patients as with illness A and all male patients as with illness B). Besides, we temporarily suppose that the medical images do not include any information of sensitive attributes (in fact, sensitive attributes like gender can be extracted from medical images like (Li et al., 2022a). Therefore, we can use a casual graph to describe this classification task as in Fig. 3a.

In order to achieve algorithmic fairness, we want to break the connection between sensitive attributes A and target task output T (see right subfigure in Fig. 3a). In other words, absolute fairness means that algorithm has the same performance on different groups of patients, regardless of their different sensitive attributes.

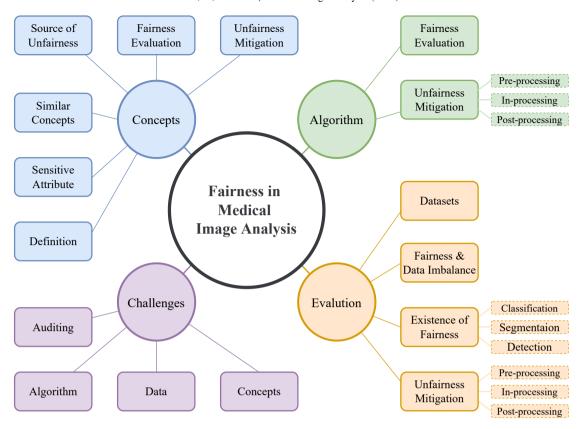


Fig. 1: An illustration of paper organization.

2.1. Definition of fairness

Suppose we have a dataset D with N samples $d_1, d_2, ..., d_N$, the i-th sample d_i consists of medical image data X_i , sensitive attributes A_i and target task ground truth label Y_i . i.e. $d_i = \{X_i, A_i, Y_i\}$. A medical image X is an arbitrary-dimensional array depending on specific task, sensitive attributes $A = \{A^1, A^2, ..., A^L\}$ contain L elements, with each sensitive attribute A^l representing a discrete variable (e.g., gender) or a continuous variable (e.g., age). For processing convenience, we discretize a continuous sensitive attribute. For a discrete variable A^l , we denote the number of possible values by C_l . Therefore, the whole dataset A^l is split into A^l groups, each group has A^l samples with A^l and A^l samples with A^l samples with

For a typical machine learning model (e.g., a neural network) f, it takes X as the input and outputs the prediction of Y, \hat{Y} . We use a distance criterion M to evaluate the difference between Y and \hat{Y} , that is,

$$\hat{Y}_i = f(X_i), \tag{1}$$

$$D_i = M(Y_i, \hat{Y}_i). \tag{2}$$

Then, for a group $g, g \in [1, G]$, we compute its performance D^g by simply averaging the distances of all samples in group g, that is,

$$D^{g} = \frac{1}{N_{g}} \sum_{i=1}^{N_{g}} D_{i}.$$
 (3)

Therefore, absolute fairness means that $D^1 = D^2 = D^3 = \dots = D^G$. Once the criterion D^g is not the same, first-order or higher-order statistics is computed for unfairness evaluation. In

this paper, we use *privileged* to refer to groups that have performance higher than average, and *unprivileged* to refer to groups that have performance lower than average. Details about how to measure the degree of unfairness can be found in Section 2.5.3.

2.2. Type of sensitive attributes

From the above description, it is clear that, sensitive attributes include any information that can be extracted from patients. For categorical attributes, we can use it to separate the whole dataset easily. However, if sensitive attribute is a continuous variable, we need extra processing before fairness analysis, for example, we can factitiously divide age into young group and elder group using a threshold age considering the dataset distribution.

From the aspect of the relationship between sensitive attributes and patients, we can categorize sensitive attributes into congenital and postnatal. More attention should be paid when dealing with postnatal attributes, since the definition of postnatal attributes may introduce noise to fairness evaluation. For instance, in some cases, patients that drink more than twice a week are regarded as bibulosity while in other cases, only patients who drink more than 5 times weekly are regarded as bibulosity.

In Fig. 2, we list the sensitive attributes commonly used in medical applications and categorize them from the aspect of value type and the aspect of relationship to patient.

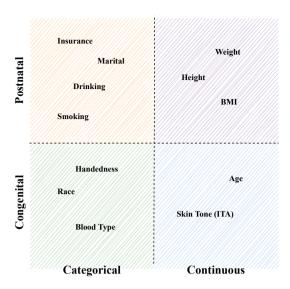


Fig. 2: The categorization of commonly used sensitive attributes. The space of sensitive attributes is split into four parts by an axis that describes the consecutiveness of attributes (*discrete* or *continuous*), and an axis that describes the relationship between attributes and patient (*congenital* or *postnatal*).

2.3. Similarity and difference between similar concepts

For a clear understanding of fairness issue and distinguishing fairness from similar concepts, we below compare fairness with data imbalance, domain adaptation, treatment effect estimation and privacy preserving, which all have a close relationship with fairness.

<u>Data Imbalance</u> is a common issue in deep learning research, which refers to imbalanced distribution of values of the response variable (Thabtah et al., 2020). There are two major differences between fairness and data imbalance. First, data imbalance concentrates on the difference in the distribution of ground truth labels of target task, while fairness focuses on the difference in the performance of the groups with different sensitive attributes. Second, it is not clear whether data imbalance is the source of unfairness. According to the experiment results in 4.2.1, we can find that even the dataset is balanced, unfairness still exists.

Domain Adaptation is another concept that is similar with fairness. Usually, there are two (or more) domains in a typical domain adaptation, source domain S and target domain T (Wang and Deng, 2018), which is akin to group of different sensitive attributes in fairness. In domain adaptation, we aim to improve the performance in target domain, making it approximate to the performance in the source domain. Similarly, in fairness, we want the groups with different sensitive attributes to have the same performance. However, there are two major differences between domain adaptation and fairness. First, there is a clear primary and secondary relationship between source domain and target domain, while in fairness, there is no explicit privilege relationship between groups with different gender; Second, in fairness issue, usually we can mitigate unfairness by degrading the performance of privileged group. However, in domain adaptation, the performance of source domain is fixed, which means that we can regard fairness as a weaker task of domain adaptation to some extent.

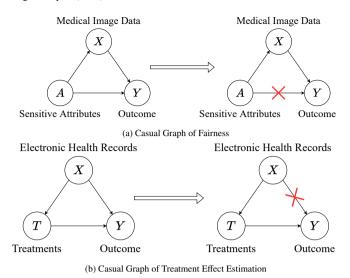


Fig. 3: Casual graph of treatment effect estimation and fairness. (a) Casual graph of fairness. In order to achieve fairness, we need to break the relationship between sensitive attributes and outcome. (b) Casual graph of treatment effect estimation. In treatment effect estimation, we need to avoid information in electronic health records influencing outcome.

Treatment Effect Estimation, another similar concept to fairness, is a measure used to compare treatments in randomized experiments and medical trials by measuring the difference in average outcomes between units assigned to the treatment and units assigned to the control (Kaddour et al., 2021). Fig. 3 shows the comparison of a typical causal graph of fairness and treatment effect estimation. From the figure we can find that in treatment effect estimation, the target is to establish the relationship between binarized treatment T and output Y, and the confounder is electronic health records (medical image data). While in fairness, the target is to establish the relationship between medical image data X and output Y, and the confounder is a sensitive attribute, which is reflected in the results, having the same performance on the groups with different sensitive attributes. Although the dimension of treatments and medical image data vary considerably, we can find that the causal structure and logical relationship of these two tasks are the same. Therefore, we hold the opinion that treatment effect estimation is a kind of fairness task.

Privacy Preserving is an important concern of recent interest. Dataset may include unwanted or sensitive information about the source of data. For example, sex information of facial images (CelebA Dataset (Liu et al., 2015)) and the spot for photography of street images (Cityspace Dataset (Cordts et al., 2016)). Therefore, algorithms that try to hide private information are proposed. One of the typical privacy preserving method is Federal Learning (FL) (Yang et al., 2019), which trains model on server using different databases on separated clients. We hold the opinion that federal learning is one of the directions for unfairness mitigation since the goal of these two tasks is to hide protected information in some contexts. Besides, considering a specific scenario in federal learning that each client only contains samples with the same sensitive attributes (for example, samples in Client A are all captured from male patients while Client B only contains samples of female patients). Such a scenario yields a federal learning method that is almost totally fair.

2.4. Sources of unfairness

In the former part, we give fairness a clear definition by formulas and comparison with similar concepts. Here, we introduce potential sources of unfairness. According to (Moustapha Cisse, 2019), we categorize the sources into inherent sources (unfairness from data) and postnatal sources (unfairness from algorithm).

2.4.1. Unfairness from data

The inherent reasons of unfairness mainly come from four aspects: social bias, anatomy bias, annotation bias and distribution bias.

Social Bias is the first reason for unfairness and the hardest to solve, which usually comes from historical problems. Taking employment problem for example, some companies prefer to employ male staff rather than female staff (Kuhn and Shen, 2013). Besides, in COMPAS dataset (Yoon, 2018), we can find that black inmates have higher recidivism than white defendants from the 2-year follow-up study. Due to complex historical and environmental reasons, it is difficult for researchers to separate social bias from target task for fair algorithm development. Thus, this factor is not considered in this paper because social bias is more like an ethic problem rather than an algorithmic problem.

Anatomy Bias. Different from the fairness in other applications, the source of unfairness in medical imaging analysis is more complex. For example, Ganz et al. (Ganz et al., 2021) find that in chest X-Ray diagnosis, predicting some diseases are much easier in one demographic group than other due to anatomical differences. Ensuring fairness across demographic groups in this case is far from obvious. Webb et al. (Webb et al., 2022) find that racial bias may influence the signal when using a neuroscience equipment for physiological data collection, because people of different races usually have different skin conductance response and thus add unwanted information in electroencephalography data. This brings us more difficulties in disentangling the causes of other categories of fairness and developing real fair algorithms.

Annotation Bias of datasets is another reason of unfairness. In recent years, with the surge in demand for annotated data, crowd-sourcing becomes a common method for data labeling (Chen and Joo, 2021). However, since the quality of labeling by crowd-sourcing is uncontrollable, additional noisy annotation is generated, which does harm to fairness, e.g., many facial expression datasets contain significant annotation biases between genders, especially on happy and angry expressions, which cannot be mitigated by traditional methods (Chen and Joo, 2021). In medical applications, it is common that different doctors have different annotations on the same patient, which also produces noisy labels especially on difficult cases. When measuring oxygen saturation of patients with COVID-19 using pulse oximetry, pulse oximetry overestimates arterial oxygen saturation among Asian, Black and Hispanic patients compared with White patients (Fawzy et al., 2022), which not only validates unfairness among different races, but also influences the

judgement of COVID-19 therapies. Besides, a recent research on COVID-19 finds that the words used in medical texts are starkly different when describing dark-skinned population versus light-skinned populations, which although might have little influence on disease diagnosis, but shows an overall disappointing unfairness (Gonzalez, 2021).

<u>Distribution Bias</u>. Data distribution also causes unfairness, due to the characteristics of "data-driven" of machine learning methods, which leads to over (or under) expression of features of data and further causes unfairness. Ganz *et al.* (Ganz *et al.*, 2021) find that the performance disparity fluctuates significantly when training the same model with different ratios between male and female patients.

2.4.2. Unfairness from algorithm

In addition to unfairness due to the use of data, there also exist some postnatal reasons for unfairness, including network architecture and loss function. These factors constitute the focus of this paper.

Network Architecture. The network architecture of deep learning is a postnatal source of unfairness. According to (Ramesha et al., 2010), in training step, network tries to optimize its parameters using the easiest feature, which usually builds unwanted connection between outputs and confounders (sensitive attributes). In other words, errors in feature extraction can lead to unfairness in target task performance. Experiments in (Muthukumar, 2019) show that, even state-of-the-art open source gender classifier can be affected by skin type changes, thereby leading to unfair predictions.

<u>Loss Function.</u> Since the degree of fairness is quantized by numeric metrics, it is apparent that the degree of unfairness is more severe when loss function does not consider mitigation of unfairness, such as adding constraints and regularization for specific fairness metrics.

2.5. Fairness evaluation

In this part, we introduce methods for fairness evaluation. With loss of generality, we present the case of a binary single sensitive attribute, *i.e.*, $A \in \{0,1\}$. A convenient example is that the sensitive attribute is male or female. First, we list traditional fairness metrics that have ethical meanings, which is used in classification tasks. Then, we broaden the scope of fairness metrics in a classification task and other common tasks in medical applications. Finally, we introduce scores that measure the trade-off between fairness and performance of target task. We note that, although these metrics are defined using binary sensitive attributes, they can be expanded to multi-value or continuous sensitive attributes easily.

2.5.1. Traditional fairness metrics

Barocas et al. (Barocas et al., 2017) define a number of fairness criteria which are firstly used for fairness evaluation on tabular datasets. To be consistent with its description, when introducing traditional fairness metrics, we suppose that target task is a binary classification task, *i.e.*, $Y \in \{0, 1\}$, where Y = 1 represents positive result and Y = 0 represents negative result, we use \hat{Y} to represent the model output.

Demographic Parity (DP). The criterion of demographic parity states that the model outcome should not be affected by any sensitive attribute, which is given by the following formula:

$$P(\hat{Y} = 1 \mid A = 0) = P(\hat{Y} = 1 \mid A = 1),$$
 (4)

i.e., the ratio of patients who are positive should be the same in male patients group and female patients group. Fig. 4(a) shows a simple example that the model reaches demographic parity among male and female patients.

Equality of Odds. This criterion requires the independence of the outcome of model and sensitive attribute. In other words, disparities in groups with different values of sensitive attributes should be completely justified by the outcome of model (Castelnovo et al., 2021). This can be expressed as follows:

$$P(\hat{Y} = 1 \mid A = 1, Y = y) = P(\hat{Y} = 1 \mid A = 0, Y = y),$$
 (5)

where $y \in \{0, 1\}$. Among all the patients who are positive, the ratio of male patients who are predicted as cancerous should be equal with the ratio of female patients who are predicted as cancerous. Fig. 4(b) shows a simple example that the model reaches equality of odds among male and female patients.

Equal Opportunity. This criterion is a relaxed criterion of Equality of Odds (Hardt et al., 2016). Equal opportunity only concerns on negative samples, which is defined by the following formula:

$$P(\hat{Y} = 1 \mid A = 1, Y = 1) = P(\hat{Y} = 1 \mid A = 0, Y = 1).$$
 (6)

Fig. 4(c) shows a simple example that the model reaches equal opportunity among male and female patients.

Accuracy Equality. This criterion requires the classification system to have equal misclassification rates across sensitive groups (Zafar et al., 2017):

$$P(\hat{Y} \neq y \mid A = 1, Y = y) = P(\hat{Y} \neq y \mid A = 0, Y = y).$$
 (7)

That is, the ratio of misclassified patients in male group should equals that in female group. Fig. 4(d) shows a simple example that the model reaches accuracy equality among male and female patients.

2.5.2. Generalized fairness metrics

The above four fairness metrics are only applicable for classification tasks and are derived from a confusion matrix. Specifically, demographic parity is based on positive prediction rates (Predictive Positive / Total Population); equality of odds based on true positive rates (TPR) and false positive rates (FPR); equal opportunity based on false negative rate (FNR); accuracy parity based on accuracy (ACC)). In this paper, we generalize the fairness metrics for classification tasks with several other statistics, such as Negative Predicted Value (NPV) and F1 score, derived from a confusion matrix.

Furthermore, there is no proper fairness measurement metrics for other image processing tasks like segmentation, detection, etc. We choose Dice Similarity Coefficient and Hausdorff Distance 95% as fairness metrics for segmentation tasks, and IOU and Average Precision for detection tasks. Notice that

Task	Fairness Criteria
Classification	PPV, FPR, FNR, ACC, NPV, F1
Segmentation	Hausdorff Distance (95%)
Detection	Average Precision, FFPI

Table 1: Fairness criteria on different tasks.

for other special-interest image tasks including registration and landmark detection, and some detection tasks that only concern False Positive Per Image (FFPI) (Yan et al., 2018b), researchers can use commonly used metrics that can be averaged on groups as fairness metrics. The list of these generalized metrics is shown in Table 1.

2.5.3. Overall unfairness measurement

After computing these fairness criteria for each sensitive groups, there is a need for measuring the overall degree of unfairness. The commonly used measurements including subtraction (Bird et al., 2020), division (Bird et al., 2020) and standard deviation (Wang and Deng, 2020). Let M^g , $g \in [1, G]$ represent an arbitrary fairness criterion of the g-th sensitive group, these three overall measurements are given by the following equations:

$$O_{\text{Subtraction}} = \max(\{M^g\}) - \min(\{M^g\}); \tag{8}$$

$$O_{\text{Division}} = \frac{\min(\{M^g\})}{\max(\{M^g\})};\tag{9}$$

$$O_{\text{STD}} = \sqrt{\frac{\sum_{g=1}^{G} \left(M^g - \bar{M}\right)^2}{n-1}}.$$
 (10)

In this paper, we use $O_{\mathrm{Subtraction}}$ as an overall unfairness measurement.

2.5.4. Fairness-Accuracy trade-off score

Previous studies have shown that, in order to improve the degree of fairness, the average performance of algorithms will decrease (Sarhan et al., 2020; Suriyakumar et al., 2021; Song et al., 2019). Therefore, when evaluating the performance of an algorithm, we must consider both its performance on target task and fairness criterion, that is, the trade-off between performance and fairness should be taken into consideration. The commonly used methods for performance-fairness trade-off analysis and fairness mitigation methods evaluation can be separated into curve-based and value-based.

<u>Curve-based Method</u> is proposed in (Creager et al., 2019), which draws a figure containing several algorithms. The horizontal axis represents one kind of fairness measurement (for example, demographic parity ΔDP among sensitive groups), while the vertical axis shows average performance on the whole dataset (for example, classification accuracy of skin lesion). The closer the curve is to the top left corner, the smaller tradeoff it has. This method can only give qualitative results on different models. An example of curve-based method is shown in Fig. 5, since the curve in blue is the closest to top left corner, model A has the best performance-fairness trade-off.

<u>Value-based Method</u> uses numeric computation to evaluate the trade-off between fairness and performance. Dhar *et*

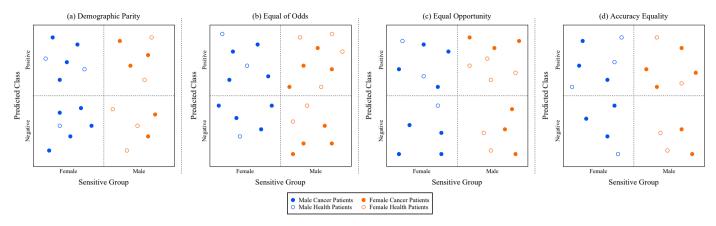


Fig. 4: Graphical illustration of traditional Fairness Criteria. (a) Demographic Parity: Male $(\frac{6}{12})$ = Female $(\frac{5}{10})$. (b) Equality of Odds: for Y = 1, Male $(\frac{4}{8})$ = Female $(\frac{4}{8})$, for Y = 0, Male $(\frac{2}{3})$ = Female $(\frac{4}{6})$. (c) Equal Opportunity: Male $(\frac{4}{8})$ = Female $(\frac{4}{8})$. (d) Accuracy Equality: Male $(\frac{4}{10})$ = Female $(\frac{4}{10})$.

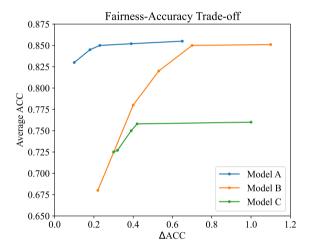


Fig. 5: Curve-based method for trade-off evaluation. Horizontal axis: absolute difference in demographic parity between demographic groups. Vertical axis: classification accuracy. The closer the curve is to the top left corner, the better performance-fairness trade-off it has.

al. (Dhar et al., 2021) introduce a metric called bias performance coefficient (BPC) defined by the following equation:

$$BPC = \frac{Bias - Bias_{\text{deb}}}{Bias} - \frac{Acc - Acc_{\text{deb}}}{Acc},$$
 (11)

where *Bias* and *Bias*_{deb} represent the origin model that does not consider fairness and the improved model that considers fairness, respectively. *Acc* and *Acc*_{deb} represent average accuracies of these two models, respectively. BPC is like 'normalized fairness-accuracy trade-off' to some extent.

2.6. Unfairness mitigation

After evaluating the degree of unfairness in specific task, the key point is to use improved method to mitigate unfairness as much as possible. The direction of unfairness mitigation is three fold:

1. Reduce difference between demographic groups while maintaining overall performance.

- 2. Improve overall performance while maintaining difference between demographic groups.
- 3. Reduce difference between demographic groups while improving overall performance.

Noticing that due to the contradictions between different fairness metrics, we cannot achieve better fairness on all fairness metrics. Therefore, selecting a proper fairness metrics before mitigating unfairness is important.

3. Algorithms

Studies have shown the importance and necessity of paying attention to the fairness of deep learning models besides target task performance (Zhang et al., 2018). Analyzing fairness issues has been a long-standing problem in deep learning (Du et al., 2020; Lyu et al., 2020), from the fundamental research in tabular datasets (Wightman, 1998; Kohavi et al., 1996; Ding et al., 2021), to higher level research including fairness in natural language processing (Bolukbasi et al., 2016; Brunet et al., 2019; Zhao et al., 2018b,a; Rudinger et al., 2018; Vanmassenhove et al., 2019), fairness in recommendation systems (Beutel et al., 2019; Beigi et al., 2020), fairness in image caption (Hendricks et al., 2018; Zhao et al., 2021) and vision question answering (Park et al., 2020; Hirota et al., 2022) and fairness in facial recognition (Quadrianto et al., 2019; Wang et al., 2020b; Xu et al., 2021; Zietlow et al., 2022; Wang et al., 2022; Zhao et al., 2021; Lokhande et al., 2020) etc.

Generally, algorithms in fairness mainly focus on two aspects: one is evaluating the existence and degree of fairness in a specific task; the other is developing new methods for unfairness mitigation. According to (Deho et al., 2022), unfairness mitigation methods can be categorized into pre-processing method, in-processing method and post-processing method according to targeting stage.

• Pre-processing Method focuses on the quality of training dataset. Researchers collect novel fair datasets, use additional external datasets, use GANs or VAEs to generate extra images with different sensitive attributes. Besides,

sampling strategies are also usually applied for training a more fair model.

- In-processing Method generally follows one of two research directions. The first is adversarial network architecture, which is derived from domain adaptation area that regards sensitive attribute as domain-specific label and tries to only use domain-irrelevant features for target task. The other direction is by introducing extra fairness constraints in the training algorithm (Deho et al., 2022).
- Post-processing Method does not need to change or retrain pretrained models. This type of methods usually modifies the output of a previously trained network on different sample groups to achieve a specific fairness metric.

In this section, we review studies that have addressed fairness issues in training deep learning models for MedIA. Since the research in fairness in MedIA is in its infancy, we also mention several algorithms in facial recognition, which carries a significant portion of literature on fairness. The organization of this section is shown in Fig. 6.

3.1. Fairness evaluation

The foundation of unfairness mitigation is to evaluate whether there exists unfairness in a specific task. Larrazaba et al. (Larrazabal et al., 2020) are the first to shed light on the importance of gender balance in MedIA. They train three deep learning models on two well-known public available X-ray image datasets for various thoracic disease diagnosis. They find that when training a DenseNet using data from one gender group, the testing performance on another gender group is much lower than that on the same gender group. The result shows that when a minimum balance is not fulfilled, the performance for unprivileged gender group deceases consistently. This finding illustrates that more attention should be paid to gender imbalance when proposing novel algorithms.

On the contrary, Petersen *et al.* (Petersen et al., 2022) train a Logistic Regression model and a 3-D CNN model on ADNI dataset and analyze whether there is a linear relationship between network performance and female ratio in the training set in the AD / HC classification and sMCI / pMCI classification tasks. The result shows that there is only a weak dependence of classifier performance for male and female test subjects on the sex composition of training dataset, which to some extent proves the difference between data imbalance and algorithm fairness.

Glocker *et al.* (Glocker and Winzeck, 2021) hold the opinion that if the test set is not sampled in a balanced fashion, the bias and unfairness will remain. Besides, they use a multi-task architecture to predict sex / race and illness simultaneously, view the feature vector in latent space, and find that race and sex are not encoded in their classification network.

Forde *et al.* (Forde *et al.*, 2021) also find that, even the models are trained with the same training procedure (same data and same structure), there still exists significant differences in their group performances. They train a baseline X-ray classifier CheXNet on ChestX-Ray8 dataset for fifty times with the same

optimizer and hyper-parameters, and find that even though there is little difference between overall performance on the whole dataset among these models, the disparity of TPR between male group and female varies a lot. This result shows that unfairness may occur in the procedure of model selection.

Kinyanjui *et al.* (Kinyanjui *et al.*, 2020) try to evaluate unfairness between the groups with different skin tones. They first use a segmentation model to split the dermatology image into skin part and lesion part, and measure the Individual Typology Angle (ITA) on skin part, which can represent different skin tones. Their result illustrates that there exist significant differences on classification accuracy among different skin tone groups on the SD-136 dataset.

Unlike former work, Lu *et al.* (Lu et al., 2021a) use several epistemic uncertainty measurements to assess the disparity between different races on the Digital Mammographic Imaging Screening Trial (DMIST) dataset and find that there exists disparity on all these measurements.

Recently, Zhang et al. (Zhang et al., 2022) benchmark nine different unfairness mitigation strategies on two commonly used chest X-ray datasets, CheXpert and MIMIC-CXR, and find that there is a tradeoff between the group fairness and overall classification performance. The methods that achieve group fairness usually have worse average performance for the whole dataset. They also advocate for investigating unfairness-inducing mechanisms in the underlying data distribution.

3.2. Unfairness mitigation

Following (Deho et al., 2022), we cover the literature on unfairness mitigation algorithms with the three categories of preprocessing, in-processing and post-processing methods.

3.2.1. Pre-processing methods

Methods including sampling strategy, dataset mixup and data augmentation are used in the procedure of pre-processing.

Sampling strategy. Puyol et al. (Puyol-Antón et al., 2021) mitigate unfairness on different gender and race in a cardiac MR segmentation task. By using stratified batch sampling and dataset balancing method, they decrease the value of fairness criteria a lot comparing with baseline model (nn-UNet). This work also highlights the concerning issue of unfairness in medical segmentation tasks, while all other studies focus on classification task. Besides, Zietlow et al., (Zietlow et al., 2022) use an adaptive sampling algorithm that evaluates the worstperforming group after each iteration using a held-out dataset and augments a random batch from this group. For each iteration, they sample a random batch from the original dataset / the augmented dataset with a probability λ for maintaining a certain proportion of the original data in the training set. Also, Kehrenberg et al. (Kehrenberg et al., 2020) introduce a null-sampling procedure that can produce invariant representations in the data domain. They apply this procedure on a cVAE model and cFlow model and show a lower difference of demographic parity while having comparable performance compared with baseline models.

Dataset mixup. Seyyed-Kalantari *et al.* (Seyyed-Kalantari et al., 2020) train a DenseNet-121 on three chest x-ray datasets,

	Fairness Algorithm											
Fairness	Evaluation		Unfairness	Mitigation								
1 00 10000 1		Pre-Processing	In-Prod	cessing	Post-Processing							
Mammographic	Chest X-Ray	Sampling Strategy	Adversarial Model	Fair Constraints	Enemble Learning							
• Lu et al.	• Larrazaba et al.	• Puyol-Anton et al.	• Zhao et al.	• Sarhan et al.	• Zhou et al.							
Brain MRI	• Forde et al.	• Zietlow et al.	• Adeli et al.	• Du et al.	Model Pruning							
• Peterson et al.	• Zhang et al.	• Kehrenberg et al.	• Abbasi et al.	• Cherepanova et al.	• Wu et al.							
<u>Dermoscope</u>	• Glocker et al.	Dataset Mixup	• Li et al.	• Jeon et al.	Adaptive Threshold							
• Kinyanjui et al.		Seyyed-Kalantari et al.	• Bevan et al.	Federal Learning	• Kamiran et al.							
		Data Augmentation	Subgroup Model	• Fan et al.	• Hardt et al.							
		• Joshi et al.	• Puyol-Anton et al.	Model Distillation	• Pleiss et al.							
		• Ramaswamy et al.	Reinforcement	• Jung et al.	<u>Perturbation</u>							
		• Zietlow et al.	<u>Learning</u>	MetaData Norm	• Wang et al.							
		Pseudo Label	• Wang et al.	• Vento et al.								
		• Jung et al.	_									
• First Author et al.	Fairness algorithm in	medical image analysi	s. • First Author et	al. Fairness algorithm	n in facial recognition							

Fig. 6: The list of the algorithms concerning fairness.

ChestX-Ray8, CheXpert and MIMIC-CXR separately, and find that there exists unfairness on different age and gender groups by computing TPR disparity and TPR disparity in proportion to membership. Then, they notice that when training the models using a combination of these three datasets, the disparity among groups decreases significantly, demonstrating the potential of mitigating unfairness by expanding the scale of train set.

Data augmentation. Joshi et al. (Joshi and Burlina, 2021) believe that unfairness comes from distribution disparity on different groups, therefore, they use StyleGAN to synthesize fudus images with age-related macular degeneration (AMD) for patients with different races. This data synthesis method helps mitigate the disparity of accuracy between Caucasians and African Americans from 17.53 % to 5.84 %, which shows the ability of this approach for improving fairness. In facial recognition tasks, parameter-controllable image synthesis is usually used for unfairness mitigation. Ramaswamy et al. (Ramaswamy et al., 2021) use GANs to generate realistic-looking images and augments the original dataset by these images. By vector operations in the latent space, the synthesis images have the same target label with the original image, while having the opposite sensitive attributes to the original image. The experiments on augmented dataset shows both quantitative and qualitative improvements comparing with training with original dataset. Besides, Zietlow et al., (Zietlow et al., 2022) also propose a generalized variant of SMOTE (g-SMOTE) by a linear interpolation between a data point and a random point among this data point's m nearest neighbors for k times for improving data diversity and train the model based on the synthesis dataset for unfairness mitigation.

<u>Pseudo label.</u> For tasks that not all the training data have group labels, Jung *et al.* (Jung et al., 2022) first train a group

classifier to generate pseudo group label, by setting the classification threshold based on uncertainty, and then they use existing in-processing method to train a fair model. This method can solve the extreme lack of sensitive attributes in medical datasets due to privacy protection.

3.2.2. In-processing methods

Current studies using in-processing methods in MedIA mainly consist of two directions: adversarial model and additional fair constraints.

Adversarial model. An adversarial model attempts to predict sensitive attributes from input image data. As shown in Fig. 7, the network architecture of an adversarial model genenrally contains two branches. The target branch \mathbb{TB} aims to predict skin lesion and the adversarial branch \mathbb{AB} attempts to predict sensitive attribute from extracted feature vector. Let $\theta_f, \theta_y, \theta_a$ represent the weights of feature extractor \mathbb{FE} , \mathbb{TB} , \mathbb{AB} , respectively. L_y denotes the loss, say cross-entropy, between ground truth label y and outcome of target branch \hat{y} , and L_a denotes the cross-entropy loss between sensitive attribute a and outcome of adversarial branch \hat{a} . Hence, the overall objective function of this model is given by the following formula. This min-max game between two networks is a typical feature of GAN formulations.

$$L_{v} = L_{CE}(\hat{y}, y) \tag{12}$$

$$L_a = L_{CE}(\hat{a}, a) \tag{13}$$

$$\min_{\theta_f, \theta_y} \max_{\theta_a} (L_y - \lambda L_a) \tag{14}$$

where λ is the trade-off coefficient between target task and fairness

Zhao et al. (Zhao et al., 2020) train three models for HIV diagnosis from MRIs, sex prediction from adolescent brain MRIs, and bone-age prediction from hand X-ray images, respectively. Sensitive attributes in consideration are age, pubertal development score (PDS), and gender, respectively. For these three binary classification tasks, they use binary crossentropy score as prediction loss and back-propagate the loss of confounder prediction branch with a negative coefficient. By adding this branch, the model is optimized to not distinguish sensitive attributes, and the disparity between groups is mitigated. In (Adeli et al., 2021; Abbasi-Sureshjani et al., 2020; Bevan and Atapour-Abarghouei, 2022), a similar method is used for mitigating unfairness on HIV diagnosis task and skin lesion diagnosis task. The major difference lies in the choice of loss functions for sensitive attribute prediction. Li et al. (Li et al., 2021) also propose a novel adversarial network for unfairness mitigation on skin lesion diagnosis task. Unlike former work, the structure of their sensitive attribute prediction branch is more complex. In addition to a discrimination module that predicts sensitive attributes, they also propose a critical module that predicts fairness score of the last input batch at training step. This module helps mitigate unfairness on sensitive attributes, including age, gender, and skin tone, and leap a step forward comparing with discrimination-only method.

Fair constraints. Methods in this category focuses on the choice of loss functions, in other words, adding specific constraints or regularizers that are related with fairness. Sarhan et al. (Sarhan et al., 2020) use a multi-task-like framework that enforces the target representation to be agnostic to sensitive attribute by maximizing the entropy between target representation for a target task and residual representation. The experiments on Heritage Health Dataset and ABIDE dataset show the decrease of accuracy disparity between different age groups and gender groups. The result of t-SNE visualization of learned embedding also proves that, when all sensitive attributes are mixed, a higher degree of fairness is achieved. Du et al., (Du et al., 2022) propose a disentanglement contrastive learning method to mitigate unfairness in dermatology classification task, by using a sensitive attribute branch discarding the skin-type information and a contrastive branch improving the quality of representation. Experiments in (Cherepanova et al., 2021) show that, by adding fair penalties on optimization objective, the unfairness between different gender groups drops slightly. However, this type of method may lead to overparametrization and overfitting problems, which cause a fluid decision boundary that is proved to fairness gerrymandering. Vento et al. (Vento et al., 2022) extend MetaData Normalization method (Lu et al., 2021b), which use residual architecture to remove the influence of sensitive attributes on feature vectors, to mitigate unfairness in brain MRI classification by adding additional trainable penalty. Besides, Jeon et al., (Jeon et al., 2022) find that CNN contains more unfairness in deeper layers, and they propose a conservative approach that hierarchically mitigates unfairness along the multiple layers with orthogonal regularization.

Others. There also exist other in-processing methods. Puyol-Anton *et al.* (Puyol-Antón et al., 2021) first separate the whole train set into subsets using sensitive attributes, and train group-

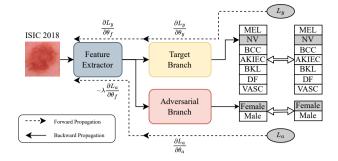


Fig. 7: Unfairness mitigation via adversarial network architecture. This model contains two branches: a target branch that aims to predict skin lesion and an adversarial branch attempts to predict sensitive attribute from extracted feature vector. Note that the gradient of adversarial branch is reversed before propagating to feature extractor.

specific segmentation network for each group. However, although it achieves better unfairness mitigation than other methods in testing, it requires the accessibility of sensitive attributes at test step, which is unrealistic in practical medical applications. Therefore, this method can only be achievable for few situations and can not be generalized easily. Wang et al. (Wang and Deng, 2020) formulate the process of finding the optimal margins for non-Caucasians as a Markov decision process and employ deep Q-learning to learn policies for an agent to select appropriate margin by approximating the Q-value function. Besides, Fan et al. (Fan et al., 2021) consider the privacy and fairness preserving simultaneously, and find that, although it cannot have considerable fairness performance with training groupspecific models for each sensitive group, training with swarm learning can get more fair results than vanilla method. Jung et al. (Jung et al., 2021) devise a systematic approach that tries to mitigate unfairness by model distillation. A student model S and a teacher model T are proposed and two regularization terms associated with KD and fairness are introduced to distillate features from T to S.

3.2.3. Post-processing methods

Most of the post-processing methods focus on setting an adaptive threshold or classification boundaries for different demographic groups (Kamiran et al., 2010; Hardt et al., 2016; Pleiss et al., 2017). However, recently, several other post-processing methods are proposed.

Zhou et al. (Zhou et al., 2021b) propose an unfairness mitigation method via post-processing by integrating the prediction of PENet that takes CT image as input, and the prediction of ElasticNet that processes EHR data (contains patient medical records including demographics, vitals, inpatient/outpatient medications, ICD codes and lab test results) using a mean-pooling strategy. They find that by this post-processing, the accuracy of pulmonary embolism detection is improved significantly while keeping a relatively small disparity between different demographic groups.

Wu *et al.* (Wu *et al.*, 2022) compute the saliency of each feature in the network, and use a pruning strategy to remove features associated with specific group, and thus prevent to encode sensitive information into the network.

Wang et al. (Wang et al., 2022) use a generator to pose a perturbation on input image to avoid fairness-related features been extracted by the modified classification network, which allows fairness mitigation without network retraining.

4. Evaluations

In this section, we first list datasets with sensitive attributes that are commonly used in MedIA, offering playgrounds for those who have research interest in fixing the unfair issues. Then, we present our experiments on ISIC 2018 skin lesion classification dataset (Codella et al., 2019) about fairness related issues, in which we explore the difference between data imbalance and unfairness, the effect of data augmentation on fairness, the existence of fairness issues in common MedIA tasks, and the effectiveness of some fairness mitigation methods in other areas on medical applications. By implementing these experiments, our goal is to attract the attention of MedIA society to the fairness issue and the importance and necessity of taking fairness into consideration when developing new algorithms.

4.1. Datasets

According to the definition of fairness, sensitive attributes are indispensable for analyzing whether an algorithm is fair or not. However, unlike tasks in facial recognition and NLP, there is a privacy concern among patients, which makes us harder to address the fairness issues in MedIA. In this part, we survey the datasets appeared in top conference / journals in recent years. According to the type of task, we categorize the datasets with sensitive attributes into classification, segmentation and detection. The conferences / journals we choose to survey includes: International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI), The IEEE International Symposium on Biomedical Imaging (ISBI), IEEE Transactions on Medical Imaging (TMI) and MedIA (MIA) and the timeline is from 2018 until present. We use task as keywords for paper selection and the datasets with sensitive attributes is listed in Tables 3, 4, and 5.

4.2. Experiments

4.2.1. Difference between data imbalance and unfairness

In this section, we attempt to verify whether unfairness is not equivalent to data imbalance. Our data is extracted from the open 7-classes skin lesion analysis dataset, Skin ISIC 2018 (Codella et al., 2019). In order to access sensitive information in this dataset, we only use the training set. This dataset contains 10,015 RGB images, each image is labeled as one type of seven skin lesions, including actinic keratosis (AKIEC), basal cell carcinoma (BCC), dermatofibroma (DF), melanoma (MEL), nevus (NV), pigmented benign keratosis (BKL), and vascular lesions (VASC). The original dataset is split into training (8,025 images) and test (1,990 images) sets with a ratio of 8:2. We use sex as the sensitive attribute. According to (Li et al., 2021; Abbasi-Sureshjani et al., 2020), female is unprivileged group and male is privileged group. DenseNet-201 with ImageNet pretrained weights is used as classification network.

Then, 7 sets of experiments with varying female:male ratios (2:8, 3:7, 4:6, 5:5, 6:4, 7:3, and 8:2) are used to analyze the relationship between fairness and data imbalance. In these experiments, we only use simple data augmentation strategies including horizontal flip, vertical flip, rotation, random resized crop and normalization in order to minimize the interference of irrelevant factors. Besides, in order to get a comparable result with state-of-the-art algorithms, we use weighted cross entropy loss to balance the difference of the number of samples with different lesions.

The results are shown in Table 6. All the experiments are repeated for 3 times with different random seeds to avoid random noise in train procedure. From the chart we can find that, for all fairness metrics except Δ FPR on sex attribute, the sign of the metric remains the same despite the different female:male ratios. As for Δ FPR, most of its values are positive, showing a strong consistence. The reason for the negative values when female: male = 7: 3 and 8: 2 could be the extreme skew of the training set.

Thus, despite the distribution of different sensitive attributes in the train set, the privileged and unprivileged groups remain the same, which means that unfairness arises from not only the distribution of the train set, but also the inherent features of data. Another interesting phenomenon is that, even when the train set is totally balanced (Setting 4), the disparity of fairness criterion between different demographic groups is not equal to zero (even not the smallest among these 7 experiments), which is also a forceful evidence that unfairness is not the same with data imbalance.

4.2.2. Fairness in medical image classification

For classification task, several previous studies have shown that significant unfairness occurs in melanoma classification (Kinyanjui et al., 2020; Abbasi-Sureshjani et al., 2020; Li et al., 2021; Wu et al., 2022; Fan et al., 2021), chest x-ray classification (Larrazabal et al., 2020; Cherepanova et al., 2021; Forde et al., 2021; Seyyed-Kalantari et al., 2020; Luo et al., 2022), AMD diagnosis (Joshi and Burlina, 2021), and HIV diagnosis (Adeli et al., 2021; Zhao et al., 2020). These works illustrate that fairness does exist in medical classification tasks, and it has to be settled urgently.

In this paper, following the experiment settings in the preceding section, we also use Skin ISIC 2018 as dataset. DenseNet-201 with ImageNet pretrained weights is used for transfer learning. We split the whole dataset into training, validation, and test sets with a ratio of 7:1:2, and repeat the training step for 3 times for averaging. The results of group prediction and fairness metrics are shown in Table 7a, which illustrates that there is a little unfairness on age attribute (maximum disparity is about 0.012 on Δ FPR). while for sex attribute, it is clear that the degree of unfairness is much higher than that on age attribute (minimum disparity is about 0.012 on Δ ACC and Δ NPV).

4.2.3. Fairness in medical image segmentation

There is only one research about fairness evaluation and mitigation in medical segmentation task (Puyol-Antón et al., 2021), which considers the unfairness on gender and race in a cardiac

Donar	Year	Publication	Dataset			Sensiti	ve Attri	butes			Type of Method
Paper	rear	Publication		Age	Gender	Skin Tone	Race	PDS	Race	Insurance	Type of Method
Kinyanjui et al. (Kinyanjui et al., 2020)	2020	MICCAI	SD-198 ISIC			✓					Pre-processing
Sarhan et al., (Sarhan et al., 2020)	2020	MICCAI	Heritage Health Dataset ABIDE	\checkmark	✓						In-processing
Larrazabal et al. (Larrazabal et al., 2020)	2020	PNAS	Chest X-ray 14 CheXpert		✓						Only Evaluation
Abbasi-Sureshjani et al. (Abbasi-Sureshjani et al., 2020)	2020	IMIMIC	ISIC	✓	✓						In-processing
Zhao et al. (Zhao et al., 2020)	2020	Nat. Commun.	Private	✓	✓			✓			In-processing
Cherepanova et al. (Cherepanova et al., 2021)	2021	ArXiv	CheXpert	✓	✓						In-processing
Forde et al. (Forde et al., 2021)	2021	ICLR	Chest X-ray 8		✓						Only Evaluation
Li et al. (Li et al., 2021)	2021	ArXiv	ISIC	✓	✓	✓					In-processing
Puyol-Antón et al. (Puyol-Antón et al., 2021)	2021	MICCAI	UK Biobank	✓	✓						Pre-processing In-processing
			CheXpert								in processing
Seyyed-Kalantari et al. (Seyyed-Kalantari et al., 2020)	2021	PSB	Chest X-ray8 MIMIC-CXR	\checkmark	✓		✓			✓	Pre-processing
Joshi and Burlina (Joshi and Burlina, 2021)	2021	ArXiv	AREDS						√		Pre-processing
Zhao et al. (Zhao et al., 2020)	2021	WACV	Private	1	1				•		In-processing
Zhou et al. (Zhou et al., 2021b)	2021	ArXiv	Private	· /	· /		✓				Post-processing
Glocker and Winzeck (Glocker and Winzeck, 2021)	2021	ArXiv	ChestXpert MIMIC-CXR		✓		✓				Only Evaluation
Zhang et al. (Zhang et al., 2022)	2021	PMLR	ChestXpert MIMIC-CXR		✓		✓				Only Evaluation
Lu et al. (Lu et al., 2021a)	2022	ICML	DMIST				✓				Only Evaluation
Wu et al. (Wu et al., 2022)	2022	ArXiv	ISIC Fitzpatrick-17k MIMIC-CXR		✓	✓					Post-processing
Luo et al. (Luo et al., 2022)	2022	ArXiv	Chest X-ray8 PadChest		✓	✓					In-processing
Petersen et al., (Petersen et al., 2022)	2022	ArXiv	ADNI		✓						Only Evaluation
Fan et al. (Fan et al., 2021)	2022	ArXiv	ISIC	✓	· /						In-processing
Du et al. (Du et al., 2022)	2022	ECCVW	Fitzpatrick17k			✓					In-processing
			ADNI								In-processing
Vento et al. (Vento et al., 2022)	2022	MICCAI	UCSF SRI	\checkmark	✓						1
Bevan et al. (Bevan and Atapour-Abarghouei, 2022)	2022	MICCAIW	Fitzpatrick17k ISIC			✓					In-processing

Table 2: Current research on fairness issues in MedIA.

Dataset Name	Modelity	Dody Doet			Sensiti	ve Attribu	tes		
Dataset Name	Modality	Body Part	Age	Gender	Racial (Skin Tone)	Marital	Height	Weight	Handedness
PAD-UFES-20 (Pacheco et al., 2020)	Dermoscope	Skin	√	√	✓				
ISIC (Rotemberg et al., 2021)	Dermoscope	Skin	\checkmark	\checkmark					
Fitzpatrick 17k (Groh et al., 2021)	Dermoscope	Skin			\checkmark				
CheXpert (Irvin et al., 2019)	X-ray	Chest	\checkmark	\checkmark					
NIH ChestXray (Wang et al., 2017)	X-ray	Chest	\checkmark	\checkmark					
MIMIC-CXR (Johnson et al., 2019)	X-ray	Chest	\checkmark	\checkmark	\checkmark	\checkmark			
PadChest (Bustos et al., 2020)	X-ray	Chest	\checkmark	\checkmark					
BrixIA (Borghesi and Maroldi, 2020)	X-ray	Chest	\checkmark	✓					
JSRT (Shiraishi et al., 2000)	X-ray	Chest	\checkmark	\checkmark					
COVID-Chestxray (Cohen et al., 2020)	X-ray	Chest	\checkmark	✓					
CORD-19 (Wang et al., 2020a)	X-ray	Chest	\checkmark	\checkmark					
Montgomery County X-ray (Jaeger et al., 2014)	X-ray	Chest	\checkmark	\checkmark					
Shenzhen Hospital X-ray (Jaeger et al., 2014)	X-ray	Chest	\checkmark	\checkmark					
ODIR2019*	Funduscope	Eyes	\checkmark	\checkmark					
AREDS (Group et al., 1999)	Funduscope	Eyes	\checkmark	\checkmark	\checkmark				
ACDC (Bernard et al., 2018)	MRI	Heart	\checkmark				\checkmark	\checkmark	
ADHD (consortium, 2012)	MRI	Brain	\checkmark	\checkmark					✓
OASIS (Marcus et al., 2007)	MRI	Brain	\checkmark	✓					✓
ABIDE (Di Martino et al., 2014)	fMRI	Brain	\checkmark	\checkmark					✓
FCP (Milham et al., 2011)	fMRI	Brain	\checkmark	\checkmark					
PPMI (Marek et al., 2011)	MRI	Brain	\checkmark	\checkmark					✓
SRI (Adeli et al., 2018)	MRI	Brain	\checkmark	\checkmark					
UCSF (Zhang et al., 2016)	MRI	Brain	\checkmark	✓					

^{*} https://odir2019.grand-challenge.org/

Table 3: Medical image classification datasets with sensitive attributes.

		D 1 D				S	ensitive Attr	ibutes			
Dataset Name	Modality	Body Part	Age	Gender	Racial	Drinking	Smoking	Height	Weight	BMI	Handedness
ISIC (Rotemberg et al., 2021)	Dermoscope	Skin	√	√							
COVID-Chestxray (Cohen et al., 2020)	X-ray	Chest	\checkmark	\checkmark							
NSCLC (Ettinger et al., 2017)	CT	Chest	\checkmark	\checkmark	\checkmark		\checkmark		\checkmark		
Montgomery County X-ray (Jaeger et al., 2014)	X-ray	Chest	\checkmark	\checkmark							
COVID-19-CT (Shakouri et al., 2021)	CT	Chest	\checkmark	\checkmark							
OCTANGO (Díaz et al., 2018)	OCT	Eyes	\checkmark								
OCT_Manual_Delineations (He et al., 2019)	OCT	Eyes	\checkmark	\checkmark							
Sunnybrook (Radau et al., 2009)	MRI	Heart	\checkmark	\checkmark							
ACDC (Bernard et al., 2018)	MRI	Heart	\checkmark					\checkmark	✓	\checkmark	
UK-Biobank (Sudlow et al., 2015)	MRI	Heart	\checkmark	\checkmark							
KiTS (Heller et al., 2019)	CT	Kidney	\checkmark	\checkmark		✓	\checkmark			\checkmark	
BraTS (Bakas et al., 2018)	MRI	Brain	\checkmark								
CANDI (Frazier et al., 2008)	MRI	Brain		\checkmark							✓
TCGA-GBM (Clark et al., 2013)	MRI	Brain	\checkmark	\checkmark							
TCGA-LGG (Clark et al., 2013)	MRI	Brain	\checkmark	\checkmark							
Cambridge_Buckner (Milham et al., 2011)	MRI	Brain	\checkmark	\checkmark							✓
ITKTube (Kwitt et al., 2013)	MRI	Vessel	\checkmark	\checkmark	\checkmark						✓
HNSCC-3DCT-RT (Bejarano et al., 2019)	CT	Bone	✓	✓							

Table 4: Medical image segmentation datasets with sensitive attributes.

Dataset Name	Modality	Pady Part					Sensiti	ve Attribute	s			
Dataset Name	Wiodanty	Body Part	Age	Gender	Racial	Marital	Drinking	Smoking	Height	Weight	BMI	Handedness
CheXpert (Irvin et al., 2019)	X-ray	Chest	✓	√								
MIMIC-CXR (Johnson et al., 2019)	X-ray	Chest	\checkmark	\checkmark	\checkmark	\checkmark						
NIH-NLST (Team et al., 2011)	X-ray,CT	Chest	\checkmark									
LNDb (Pedrosa et al., 2019)	CT	Lung	\checkmark	\checkmark								
SunnyBrook (Radau et al., 2009)	MRI	Heart	\checkmark	\checkmark								
KiTS (Heller et al., 2019)	CT	Kidney	\checkmark	\checkmark			\checkmark	\checkmark			\checkmark	
ADNI (Jack Jr et al., 2008)	fMRI	Brain	\checkmark	\checkmark								\checkmark
BraTS (Bakas et al., 2018)	MRI	Brain	\checkmark									
Cam-CAN (Shafto et al., 2014)	MRI,fMRI	Brain	\checkmark									
TCGA-GBM (Clark et al., 2013)	MRI	Brain	\checkmark	\checkmark								
OAI*	CT	Bone	\checkmark	\checkmark	\checkmark							
DeepLesion (Yan et al., 2018a)	CT	Body	\checkmark	\checkmark								

^{*} https://nda.nih.gov/oai

Table 5: Medical image detection datasets with sensitive attributes.

	Ratio	$\Delta ACC \times 10^{-1}$	Δ FPR \times 10 ⁻¹	Δ FNR \times 10 ⁻¹	$\Delta PPV \times 10^{-1}$	$\Delta NPV \times 10^{-1}$	Δ F1×10 ⁻¹
	2:8	0.05 ± 0.05	-0.21 ± 0.13	-0.00 ± 0.03	0.05 ± 0.03	0.05 ± 0.05	0.02 ± 0.03
	3:7	0.13 ± 0.07	-0.38 ± 0.15	-0.07 ± 0.03	0.12 ± 0.02	0.19 ± 0.10	0.09 ± 0.02
vouna old	4:6	0.22 ± 0.13	-0.73 ± 0.29	-0.17 ± 0.09	0.25 ± 0.09	0.25 ± 0.12	0.22 ± 0.09
young - old	5:5	0.24 ± 0.12	-1.06 ± 0.26	-0.17 ± 0.09	0.31 ± 0.08	0.13 ± 0.12	0.27 ± 0.08
	6:4	0.27 ± 0.12	-1.29 ± 0.25	-0.17 ± 0.06	0.32 ± 0.05	0.14 ± 0.13	0.28 ± 0.06
	7:3	0.36 ± 0.16	-1.52 ± 0.27	-0.21 ± 0.15	0.39 ± 0.13	0.32 ± 0.23	0.33 ± 0.15
	8:2	0.45 ± 0.20	-1.77 ± 0.32	-0.24 ± 0.18	0.44 ± 0.14	0.48 ± 0.29	0.38 ± 0.17
	2:8	-0.11 ± 0.04	0.07 ± 0.21	0.13 ± 0.04	-0.14 ± 0.04	0.14 ± 0.05	-0.15 ± 0.02
	3:7	-0.15 ± 0.04	0.08 ± 0.12	0.22 ± 0.03	-0.29 ± 0.04	0.42 ± 0.10	-0.28 ± 0.03
	4:6	-0.25 ± 0.09	0.11 ± 0.11	0.34 ± 0.16	-0.43 ± 0.19	0.57 ± 0.20	-0.43 ± 0.15
female - male	5:5	-0.32 ± 0.05	0.17 ± 0.22	0.38 ± 0.10	-0.53 ± 0.13	0.82 ± 0.13	-0.51 ± 0.11
	6:4	-0.31 ± 0.07	0.02 ± 0.29	0.35 ± 0.11	-0.50 ± 0.11	1.13 ± 0.17	-0.50 ± 0.10
	7:3	-0.34 ± 0.09	-0.07 ± 0.20	0.38 ± 0.17	-0.55 ± 0.12	1.40 ± 0.25	-0.55 ± 0.12
	8:2	-0.41 ± 0.08	-0.17 ± 0.23	0.51 ± 0.13	-0.66 ± 0.09	1.56 ± 0.22	-0.69 ± 0.09

Table 6: Disparity of fairness metrics between demographic groups with different sensitive attribute ratio. Lower absolute value indicates better fairness. Results are shown by $Mean \pm Std$. Values that lower than 0 are marked in red.

	Subgroup	ACC ↑	FPR↓	FNR↓	PPV↑	NPV↑	F1↑
Λ σο	young	0.922 ± 0.006	0.157 ± 0.020	0.111 ± 0.007	0.898 ± 0.002	0.773 ± 0.023	0.892 ± 0.004
Age	old	0.901 ± 0.005	0.070 ± 0.007	0.233 ± 0.002	0.769 ± 0.003	0.928 ± 0.004	0.767 ± 0.002
Corr	female	0.924 ± 0.006	0.107 ± 0.009	0.132 ± 0.016	0.872 ± 0.013	0.871 ± 0.015	0.869 ± 0.015
Sex	male	0.911 ± 0.006	0.088 ± 0.013	0.174 ± 0.008	0.832 ± 0.011	0.886 ± 0.005	0.828 ± 0.009

(a) Subgroup	prediction	in	classification tasks.	

	Δ	$\Delta ACC \times 10^{-2}$	$\Delta FPR \times 10^{-2}$	Δ FNR \times 10 ⁻²	$\Delta PPV \times 10^{-2}$	$\Delta NPV \times 10^{-2}$	Δ F1×10 ⁻²
Age	young - old	2.2 ± 1.1	8.7 ± 1.8	-12.2 ± 0.9	12.9 ± 0.5	-15.4 ± 2.7	12.5 ± 0.7
Sex	female - male	1.3 ± 1.2	1.9 ± 0.6	-4.2 ± 2.4	4.0 ± 2.4	-1.5 ± 1.9	4.1 ± 2.4

(b) Fairness metrics in classification tasks.

Table 7: Fairness in classification. (a) Experiments are repeated for three times and results are shown by $Mean \pm Std$. (b) Disparity of fairness metrics between demographic groups. Lower absolute value indicates better fairness. Value that lower than 0 are marked in red.

MR image segmentation task. In order to evaluate whether unfairness is a common issue in medical segmentation, we conduct experiments on the Multi-modal Brain Tumor Segmentation Challenge 2019 (BraTS19) (Bakas et al., 2017, 2018; Menze et al., 2014), which are widely used in the literature. BraTS 2019 datasets contain multi-institutional pre-operative MRI scans in 4 different modalities including T1, T2, T1ce and FLAIR, and focus on the segmentation of brain tumors intrinsically heterogeneous in appearance, shape, and histology. It also contains age information in metadata file. Because we can only access the ground truth of train set, we split the original train set into fair train and fair test sets with a ratio of 7:3.

The nnU-Net (Isensee et al., 2021) method is one of the most famous benchmark algorithms in medical image segmentation. It is the first segmentation method that is designed to deal with the dataset diversity found in the domain. It automates the keys decisions for designing a successful segmentation pipeline for any given dataset. We train nnU-Net with default hyper-parameters on fair train set for 1,000 epochs and evaluate the performance on fair test set, following former studies. Dice Similarity Coefficient (Dice) and Hausdorff Distance 95% (HD95) are used for evaluation. Since age is a continuous sensitive attribute, we split the test set into young and old subgroups using different threshold for minimum age (24) to maximum age (85) with a step of 5, and compute the disparity of performance on Dice and HD95. Because BraTS 2019 is a multi-class segmentation task, we compute these metrics on whole tumor (wt), tumor core (tc) and enhanced tumor (et), respectively. The average performance on whole fair test set and performance disparity between subgroups are shown in Table 8 and Fig. 8. From the figure we can observe that, young group is usually privileged to old group on both Dice and HD95 metrics as the Dice disparity for most thresholds is positive and the HD95 disparity for most thresholds is negative. This phenomenon illustrates that unfairness issues exist in medical segmentation task even when using state-of-the-art algorithms like nnU-Net.

4.2.4. Fairness in medical image detection

Since there is no research on fairness issues on medical detection tasks, in this section we evaluate three state-of-the-art medical detection algorithms including AlignShift (Yang et al., 2020), A3D (Yang et al., 2021), and SATr (Li et al., 2022b). We

use Deep Lesion Dataset (Yan et al., 2018b), a diverse large-scale lesion dataset that contains bounding boxes and size measurements of over 32K lesions and is widely used in medical detection tasks. We separate the dataset into training, validation and test using the original split, and train these three models with open source code following the instructions in their repositories. According to (Yang et al., 2020), we use the disparity in False Positive Per Image (FPPI) as fairness metrics when $FFPI = x, x \in \{0.5, 1, 2, 4, 8, 16\}$ as performance metrics, and evaluate the performance of these three methods on all samples, thin samples (thickness ≤ 2) and thick samples (thickness ≤ 5), respectively. We use sex as sensitive attribute and split the test set into male and female subgroups.

The results are shown in Table 9. It is clear that for all these three methods, the performance on female group is lower than that on male group (the Δ FFPI=16 on thick samples using A3D and thin samples using AlignShift is close to zero). This consistent tendency illustrates the existence of unfairness on medical detection tasks, especially in state-of-the-art algorithms. Besides, although SATr has the highest performance, it is also the most unfair methods among these three methods. This phenomenon awakes us to pay attention to the fairness of algorithm except the performance.

4.2.5. Unfairness mitigation

In this section, we select three unfairness mitigation algorithms used in facial recognition tasks, including one pre-processing method (Yu et al., 2020), one in-processing method (Vera-Rodriguez et al., 2019) and one post-processing method (Robinson et al., 2020), and evaluate their performances on medical image datasets in order to understand how well unfairness is mitigated.

Pre-processing methods. According to (Yu et al., 2020), unfairness can be mitigated by adding additional external datasets to the train set. We follow this simple strategy, and use ISIC 2018 skin lesion classification dataset to train a baseline model. Then, we add PAD-UFES-20, another skin lesion dataset which contains 2,298 skin lesion images. However, among six types of lesions, only three of them overlap with ISIC 2018 dataset (BCC, NEV and MEL). Therefore, we extract samples of these illness (1,114 images) and add them to the train set. We train a DenseNet-201 for skin lesion classification. All the hyperparameters are the same as experiments in Section 4.2.2. The

Matrica	A ~~		Dice ↑			HD95 ↓	
Metrics	Age	$\mathrm{Dice}_{\mathit{WT}}$	Dice_{TC}	Dice_{ET}	$HD95_{WT}$	$HD95_{TC}$	$HD95_{ET}$
Avg	59.92	0.9252	0.9127	0.8647	3.932	3.312	2.657

Table 8: Average performance of nnU-Net on BraTS 2019 Fair_Test Set. $Dice_{TC}$, and $Dice_{TC}$ represent the Dice Score in Whole Tumor (WH), Tumor Core (TC), and Enhanced Tumor (ET), respectively. $HD95_{WT}$, $HD95_{TC}$, and $HD95_{ET}$ represent the HD95 values in Whole Tumor (WH), Tumor Core (TC) and Enhanced Tumor (ET), respectively.

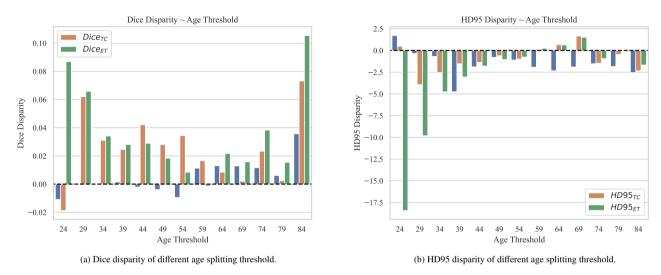


Fig. 8: Performance disparity of nnU-Net on BraTS 2019 subgroups. Dice Disparity and HD95 Disparity are computed by $\Delta = young - old$. (a) Most of Dice Disparity are larger than 0, indicating *young* group are superior to *old* group. (b) Most of HD95 Disparity are smaller than 0, indicating *young* group are superior to *old* group, which is consistent with Dice Disparity.

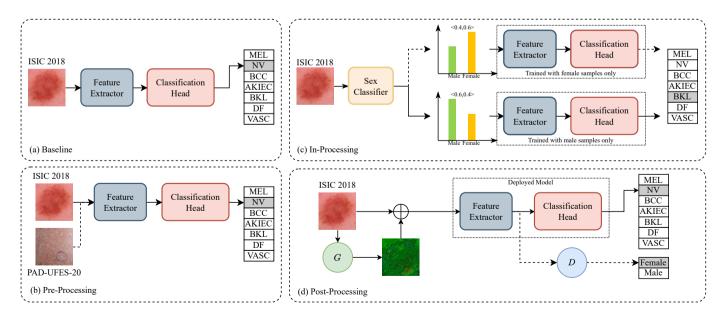


Fig. 9: Pipeline of unfairness mitigation methods, using sex as sensitive attribute for simplification. (a) Baseline model. (b) Pre-processing method: Use additional external PAD-UFES-20 dataset to train the model. (c) In-processing method: Use a sex classifier to predict pseudo sex label. Then, test sample is fed into subgroup-specific lesion classifier according to pseudo sex label. (d) Post-processing method: Use a generator to generate perturbation image that avoid the deployed model predicting sex attribute.

	FF	FFPI ↑		1	2	4	8	16
	All	female	0.789	0.847	0.897	0.924	0.948	0.966
	All	male	0.824	0.880	0.914	0.939	0.962	0.973
SATr (Li et al. 2022b)	Thin	female	0.811	0.867	0.907	0.931	0.951	0.964
SATr (Li et al., 2022b)	1 11111	male	0.846	0.892	0.922	0.946	0.965	0.973
	Thiele	female	0.766	0.829	0.885	0.916	0.944	0.967
	Thick	male	0.811	0.870	0.905	0.935	0.960	0.973
		female	0.765	0.835	0.881	0.918	0.943	0.965
		male	0.784	0.844	0.895	0.931	0.952	0.969
A2D (Vang et al. 2021)	Thin	female	0.783	0.846	0.889	0.917	0.947	0.966
A3D (Yang et al., 2021)		male	0.799	0.855	0.905	0.936	0.955	0.974
	Thick	female	0.743	0.823	0.873	0.913	0.939	0.964
	THICK	male	0.769	0.840	0.885	0.927	0.950	0.963
	All	female	0.760	0.825	0.872	0.899	0.927	0.950
	All	male	0.783	0.842	0.879	0.914	0.935	0.955
AlignShift (Yang et al., 2020)	Thin	female	0.791	0.840	0.884	0.910	0.939	0.958
	1 111111	male	0.796	0.846	0.890	0.918	0.939	0.957
	Thick	female	0.731	0.802	0.862	0.888	0.915	0.941
	THICK	male	0.771	0.839	0.870	0.909	0.930	0.952

(a) Group prediction performances.

(a) Group prediction performances.							
	Δ FFPI $\times 10^{-2}$	0.5	1	2	4	8	16
SATr	ALL	-3.5	-3.3	-1.7	-1.5	-1.5	-0.7
	Thin	-3.5	-2.4	-1.5	-1.5	-1.4	-0.8
	Thick	-4.5	-4.1	-2.0	-1.9	-1.6	-0.6
A3D	ALL	-1.9	-1.0	-1.3	-1.3	-0.9	-0.4
	Thin	-1.6	-0.9	-1.6	-1.9	-0.8	-0.8
	Thick	-2.6	-1.8	-1.2	-1.4	-1.2	0.1
AlignShift	ALL	-2.2	-1.7	-0.6	-1.5	-0.9	-0.5
	Thin	-0.5	-0.6	-0.6	-0.8	-0.0	0.1
	Thick	-4.0	-3.6	-0.8	-2.0	-1.5	-1.2

(b) Fairness metrics in detection tasks.

Table 9: Fairness in medical image detection. SATr, A3D and AlignShift are three state-of-the-art lesion detection algorithms. (a) Group prediction performances of three algorithms on All samples, Thin samples (thickness ≤ 2) and Thick samples (thickness = 5). (b) Disparity of fairness metrics between demographic groups. Lower absolute value indicates better fairness. Values that lower than 0 are marked in red.

pipeline is shown in the lower left of Fig. 9. We repeat baseline and pre-processing experiments for three times and the results are shown using lines in orange in Fig. 10 and Fig. 11.

As mentioned before, the curve at upper (lower for metric that smaller is better) and leftmost indicates better fairnessperformance trade-off and better combination property. From the figure we can conclude that simply using external dataset in training cannot mitigate unfairness effectively. Among all six metrics, none of them notices a better fairness - performance trade-off. The reason can be twofold: Firstly, for lack of data, only few datasets can be used for joint training. However, these datasets may contain huge domain gap due to the variance of capture devices. Secondly, different with human faces, medical images with same illness varies a lot in appearance, which makes it more difficult for a model to learn a proper feature representation. Therefore, we may conclude that unfairness mitigation via pre-processing methods (extending training dataset) only works on tasks that have several available external datasets, which is rare in medical tasks.

In-processing methods. For in-processing method, we follow the algorithm proposed in (Vera-Rodriguez et al., 2019). Since facial recognition tasks take image pairs as input while only a single image is used as input in classification task, we modified its algorithm to the following for skin lesion classification: First, we pre-process the ISIC 2018 skin lesion dataset as in 4.2.2 and train a sensitive attribute classification network on sex and age attributes, respectively. Then, subgroup models that only use female / male / young / old subgroup samples of train set are trained for skin lesion prediction. At the inference stage, the test samples are firstly fed into the attribute classification model to get pseudo subgroup label, and specific subgroup lesion classification model is used according to pseudo attributes. The pipeline of this method is shown in the upper right of Fig. 9. We repeat the training of lesion classification model for three times and the results are shown using the green lines in Fig. 10 and Fig. 11.

From Fig 10, we can observe that for all six metrics, using inprocessing method cannot mitigate unfairness significantly. Besides, the performance of in-processing method drops slightly comparing with baseline. One of the reasons for this result is that by splitting the train set into subgroups, the number of training samples is halved, which leads to inadequate model training.

Post-processing methods. Fairness mitigation via post-processing methods tends to fine-tune model's output based on fairness criteria (Wang et al., 2022). Besides, it can make full use of pretrained models since the deployed model do not need to retrain a second time.

In this section, we adopt a post-processing method called 'FAAP' (Fairness-Aware Adversarial Perturbation) proposed by Wang *et al.* in (Wang et al., 2022). It learns to perturb input data to blind deployed models by training an adversarial perturbation generator to avoid fairness-related features being extracted by the deployed model. The pipeline of this method is shown in the lower right of Fig. 9.

We use the same pre-processing method as 4.2.2 and use the trained baseline model as the deployed model in this method.

At the train stage, a U-Net like generator is used to generate perturbation image and a two-layer fully-connected network is used for distinguishing the protected attribute. At the inference stage, we only use the generator to generate adversarial perturbation on test samples and use the deployed model for skin lesion classification. We repeat this method for three times and the result on sex and age are shown using lines in red in Fig. 10 and Fig. 11.

These two figures illustrate that, using FAAP cannot improve fairness in this skin lesion classification task. Besides, we notice a significant drop in performance in all six metrics comparing with baseline model. The reasons can be twofold: first, by visualizing the generated perturbation image, we find that its intensity is too high that affects the diagnosis of skin lesion, which absolutely causes the drop in performance. Besides, comparing to facial images, medical images are more difficult to predict sensitive attributes directly from image data, thus the effectiveness of discriminator is doubtful. In conclusion, using post-processing method (FAAP) cannot mitigate unfairness in skin lesion classification task.

From the aforementioned experiments we can conclude that, to our surprise, methods that are effective in unfairness mitigation in facial recognition area seem not useful in medical image processing tasks. This phenomenon could result from domain gap in different medical datasets (pre-processing), small amount of samples in medical dataset (in-processing), difficulties in sensitive attribute prediction (post-processing), which calls for further research on fairness in MedIA. Besides, in order to mitigate unfairness in medical applications, more attention need to be paid to the unique characteristics of medical images.

5. Challenges

In this section, we list several challenges for fairness evaluation and mitigation in medical applications, which are categorized as data, algorithm, auditing and accountability.

5.1. Concepts

<u>Formula derivation.</u> Although there are several works on theories in fairness in tabular datasets or NLP, few theories focus on image data. For example, Zhang *et al.* (Zhang and Bareinboim, 2018) propose several formal conditions that a system must meet to be deemed fair from the aspect of structural causality. Martinez *et al.* (Martinez *et al.*, 2020) regard group fairness as a multi-objective optimization problem and provide a simple optimization algorithm to solve this problem. Only by understanding the inner relationship between fairness and the feature representation of input image data can we develop efficient unfairness mitigation algorithms.

Metrics. As shown in Chapter 2, there are various fairness metrics, which have different meanings and evaluate diverse aspects of algorithms. According to the definitions of metrics, a few of them are orthogonal, or even completely opposite. Thus, we cannot satisfy all the metrics simultaneously, which motivates us to select proper metrics under different situations. For example, the doctors in hospital might be concerned about the

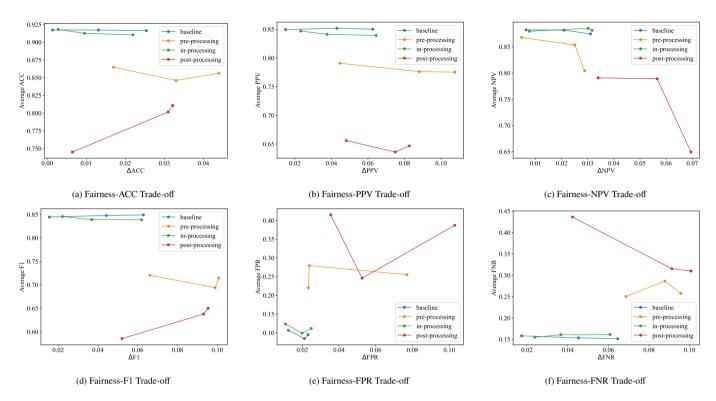


Fig. 10: Fairness-performance trade-off curves on *sex* attribute using different method. For (a) to (d), the closer the curve is to the top left corner, the better trade-off between fairness and performance the method have. For (e) and (f), the closer the curve is to the bottom left corner, the better trade-off between fairness and performance the method have.

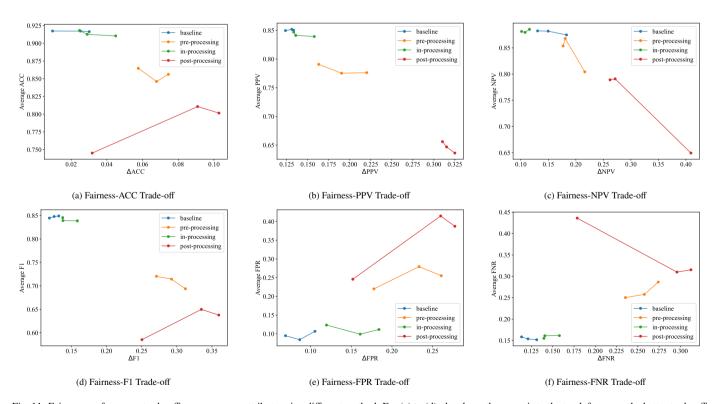


Fig. 11: Fairness-performance trade-off curves on *age* attribute using different method. For (a) to (d), the closer the curve is to the top left corner, the better trade-off between fairness and performance the method have. For (e) and (f), the closer the curve is to the bottom left corner, the better trade-off between fairness and performance the method have.

fairness of the diagnosis accuracy of patients, while the government staffs may pay more attention to the fairness of all people (both patients and healthy people).

<u>Casual inference.</u> Casual inference (Pearl, 2009), a concept that focuses on analyzing the response of the outcome variable to the changes in its cause variable, begins to attract the attention of researchers recently. By building causal graphs, causal inference offers us another aspect to understand fairness – counterfactual fairness (Kusner et al., 2017). Its intuition is that a decision is fair towards an individual if it is the same in the actual world and a counterfactual world, where the individual belongs to a different demographic group. Although current research on fairness in MedIA mainly concerns group fairness, we believe evaluating fairness by the view of causality is also important and meaningful.

5.2. Data

Limitation of data size. As mentioned before, the foundation of fairness evaluation in MedIA is medical datasets with sensitive attributes. However, due to the preciousness of data, the size of medical datasets is usually smaller compared with facial datasets. As shown in Table 1, only a few datasets have more than 1,000 individual samples. More disturbingly, the samples in each demographic group are more insufficient, which leads to higher uncertainty of fairness evaluation. There are two potential solutions: (i) building larger datasets with sensitive attributes; (ii) using individual fairness instead of group fairness as the criterion. For (i), it might be more difficult to build such a dataset for some rare illnesses. For (ii), computing individual fairness scores relies on more reliable distance measurements.

Deficiency of sensitive attributes. Another challenge in medical fairness evaluation is the deficiency of sensitive attributes, which are hard to acquire in medical datasets. As a comparison, the sensitive attributes (*e.g.*, gender, skin tone, and hair types) can be inferred directly from image in facial datasets. Besides, in order to protect the privacy of patients, sensitive attributes including age and gender are usually removed before being published, making it more difficult to evaluate fairness in medical applications.

5.3. Algorithm

<u>Task.</u> Current research on fairness in MedIA mainly focus on classification task, while other tasks (*e.g.*, segmentation, detection, registration) are ignored, which encourages more interesting works. Furthermore, for fair classification, only few modalities including dermoscope, chest X-Ray, heart MRI and brain MRI are evaluated, which shows broad research prospects of fairness in MedIA.

Computational cost. Existing research on fairness in MedIA mainly try to mitigate unfairness via pre-processing or inprocessing methods, which need to retrain the network and cannot make full use of pre-trained SOTA models, leading to extra computation cost. Therefore, more attention should be paid to developing post-processing mitigation methods.

Continuous sensitive attribute. A common practice is to split continuous sensitive attributes to binary by a chosen threshold without convincing reasons, *e.g.*, splitting the dataset on age

with a threshold of 60 years old. This process obviously influences the criterion and evaluation of fairness. Therefore, it sheds light on proposing more accurate and convincing evaluation protocols to evaluate the fairness on continuous sensitive attributes.

Multiple sensitive attributes. Generally, current papers in fairness only consider one sensitive attribute at a time for simplicity. However, as shown in Table 3, most datasets have more than one sensitive attributes. Moreover, researchers find that there is a common phenomenon that when mitigating unfairness on one sensitive attribute, the degree of unfairness on another sensitive attribute increases significantly. It is necessary to develop a powerful method to mitigate unfairness on multi sensitive attributes simultaneously.

<u>Unknown sensitive attributes</u>. Current works assume that the sensitive attributes are accessible in both training and inference stage. However, due to the specificity and privacy preserving of medical data, the information of sensitive attributes is usually not available in the training set, which raises a bigger challenge to mitigating unfairness in the inference stage. Xu *et al.* (Xu et al., 2021) use individual fairness to substitute group fairness by constraining FPR of each sample. However, this method cannot be directly adapted to MedIA. Another possible solution is to figure out demographic group that are most unfair (unprivileged), and mitigate unfairness via unsupervised method.

Trade-off between performance and fairness. The overall performance is usually sacrificed in order to reach fairness. Some SOTA unfairness mitigation methods decrease the performance of privileged group, rather than increase the performance of unprivileged one. More disturbingly, other SOTA methods even impact the performance of both privileged and unprivileged groups. It remains a great challenge to mitigate unfairness without impacting the original performance.

Interpretability. Interpretability is another noteworthy research field in MedIA. By explaining and understanding the mechanism of deep neural networks, we can open the 'black box' of deep learning, thus identifying and mitigating unfairness adequately and convincingly. Uncertainty, a powerful tool in interpretability, has shown its potential to address fairness issues (Singh et al., 2021). More attention and attempts are encouraged to utilize interpretability theories to reach fairness in MedIA.

5.4. Auditing and accountability

With the growing attention on fairness, how to audit and decide the accountability of unfairness of an algorithm becomes an inevitable question. Recently, Mehrabi *et al.* (Mehrabi *et al.*, 2021) propose two families of attacks targeting fairness measures, which urges us to audit algorithm fairness carefully.

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