BIAS AND UNFAIRNESS IN MACHINE LEARNING MODELS: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

One of the difficulties of artificial intelligence is to ensure that model decisions are fair and free of bias. In research, datasets, metrics, techniques, and tools are applied to detect and mitigate algorithmic unfairness and bias. This study aims to examine existing knowledge on bias and unfairness in Machine Learning models, identifying mitigation methods, fairness metrics, and supporting tools. A Systematic Literature Review found 40 eligible articles published between 2017 and 2022 in the Scopus, IEEE Xplore, Web of Science, and Google Scholar knowledge bases. The results show numerous bias and unfairness detection and mitigation approaches for ML technologies, with clearly defined metrics in the literature, and varied metrics can be highlighted. We recommend further research to define the techniques and metrics that should be employed in each case to standardize and ensure the impartiality of the machine learning model, thus, allowing the most appropriate metric to detect bias and unfairness in a given context.

Keywords Bias · Unfairness · Machine Learning · Artificial Intelligence

1 Introduction

In industry, prediction-based decision algorithms are widely utilized by governments and organizations that are rapidly embracing them [1]. These techniques are already commonly used in lending, contracting, and online advertising, and they are also used in criminal pre-trial proceedings, immigration detention, and public health, among other areas [2]. With the rise of these techniques, emerged the worry about the biases embedded in the models and how fair they are, defining their performance for issues related to sensitive social aspects such as race, gender, class, etc [3].

Systems that have an influence on people's lives raise ethical concerns about making judgments in a fair and unbiased fashion. As a result, bias and unfairness challenges have been extensively investigated taking into account the limits imposed by corporate practices, regulations, social traditions, and ethical obligations. [4]. Recognizing and reducing bias and unfairness are difficult tasks, since unfairness is defined differently in different cultures. As a consequence, user experience, cultural, social, historical, political, legal, and ethical considerations all have an impact on unfairness criterion [5].

When algorithms are applied in real life situations, they must be examined for bias and unfairness, as well as legal compliance. The outputs of those systems may have a significant, and often harmful, impact on people's lives. As a result, new data science, artificial intelligence (AI), and Machine Learning (ML) approaches are required to account for the aforementioned restrictions in algorithms [6].

The challenge worsens if key technological applications do not yet have ML models associated with the explainability of decisions made, or those can only be evaluated by the team that created them, which leaves researchers unable to

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obtain these explanations and conduct experiments [7]. Given the millions of parameters analyzed by the machine, obtaining a transparent algorithm is quite challenging. Another option is to interpret it without knowing each step taken by the algorithm [8].

Some solutions, such as AIF360, [9], FairLearn [10], Tensorflow Responsible AI [5] [11] [12] and Aequitas [13] already strive to assist developers by providing particular libraries and tools to address bias and unfairness.

However, the development approach to identify and mitigate bias and unfairness in ML models is left entirely to the developer, who often does not have adequate knowledge about the problem and has to take in consideration an additional factor for the final model's quality, confirming the necessity of a standard definition for handling the problem.

Another challenge is that most existing solutions for bias and unfairness mitigation are one-off applications for a specific problem or use case (UC). There are numerous approaches for recognizing bias and unfairness, known as fairness metrics, and this vast range makes it difficult to select the right assessment criteria for the issue one desires to mitigate [14].

This study aims to examine existing knowledge on bias and unfairness in machine learning (ML) models.

This paper is organized as follows: Section II describes the research method, Section III examines the findings, and Section IV presents our final considerations and suggestions for further research.

2 Method

A Systematic Literature Review (SLR) aims to consolidate research by bringing together elements for understanding it [4]. Literature reviews are a widely used methodology to gather existing findings into a research field [15]. This systematic review followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [16] and the method described in [17] was used, which encompasses five steps: Planning, Scoping, Searching, Assessing, Synthesizing.

2.1 Planning

During the Planning step, the knowledge bases that will be explored are defined [17]. The search for document patents was undertaken in the following knowledge bases:

- IEEE Xplore (www.ieeexplore.ieee.org/)
- Scopus (www.periodicos.capes.gov.br)
- Web Of Science (www.periodicos.capes.gov.br/)
- Google Scholar (www.scholar.google.com)

These bases were chosen because they are reliable and multi-disciplinary knowledge databases of international scope, with comprehensive coverage of citation indexing, allowing the best data from scientific publications.

2.2 Scope Definition

The Scope Definition step ensures that questions relevant to the research are considered before the actual Literature Review is carried out [17]. A brainstorming session was held with an interdisciplinary group composed of eleven experts on machine learning models, which selected two pertinent research questions to this systematic review address, namely:

Q1: What is the state of the art on the identification and mitigation of bias and unfairness in ML models?

Q2: What are the challenges and opportunities for identifying and mitigating bias and unfairness in ML models?

2.3 Literature Search

The Literature Search involves exploring the databases specified in the Planning step in a way that aims to solve the questions defined in the scope [17].

Initially, we used the keywords to search the knowledge bases observed in Figure 1. Aside from studies on bias or sensitive attributes using fairness or mitigation strategies for machine learning, it should include studies using the "AIF360", "Aequitas" or "FairLearn" tools for ML, with 17 publications returned. Additionally, a Google Scholar

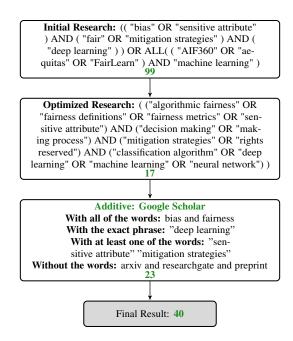


Figure 1: Papers Selection Process with the number of papers

search was undertaken, and 23 publications were selected based on their Title and Abstract fields. The search was based on the string used in the databases by applying the same keywords in the advanced search criteria, as can be seen in Figure 1.

2.4 Assessing the Evidence Base

The Assessing the Evidence Base step selects the most relevant articles based on bibliometric analysis and reading the article abstracts.

Initially, searches in the four knowledge bases retrieved 99 articles, with the fields Title, Abstract, and Keywords serving as search criteria. We included only Review Articles, Research Articles, and Conference Proceedings published between 2017 and 2022, as shown by the bibliometric analysis in Figure 3. The red line represents the average difference in the number of articles over the previous five years, with a decrease in the final year due to the time span covered by the search.

A graph of the relationship between the keywords obtained in the search was generated using the biblioshiny tool [18] from the bibliometrix package [19] in the R language. Figure 2 illustrates some clusters that exemplify themes addressed in the RSL papers. The red cluster relates to "machine learning" and decision-making in models, the green cluster considers "fairness" and its economic and social impacts. It is also worth to highlight aspects related to transparency, interpretability, and the relationship of these keywords with the state of the art.

As a result of the optimized string, 40 articles were selected for discussion. Figure 1 illustrates the selection method and the criteria and filters that were employed.

2.5 Synthesis and Analysis

The Synthesis and Analysis step consist in reading and evaluating the selected articles to identify patterns, differences, and gaps that might be studied further in future research on bias and unfairness in machine learning models.

3 Results and Discussion

This section presents and analyses the 40 selected studies, which are included in Table 1, according to the research questions Q1 and Q2 set in the Scope Definition step. The results are organized in five sections: Types of Bias, Identified Datasets, Mitigation techniques and models, Technique for identification of the sensitive attribute and Fairness metrics. Those sections represent fundamental aspects on the discussion of bias and fairness.

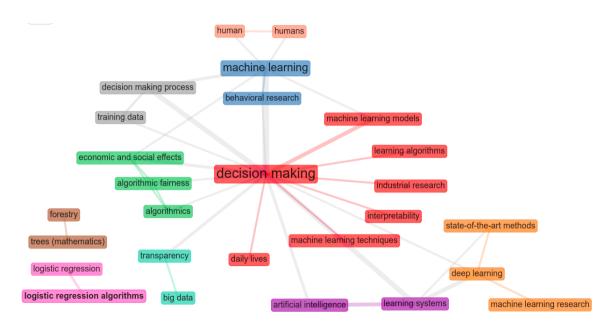


Figure 2: Keyword co-occurrence network

The studies examined revealed issues that support the concern about bias and fairness in ML models. [7] addresses issues such as the lack of transparency of ML models, organizations such as Facebook and Telegram's lack of commitment to revealing the measures being taken in this effort, and even the constraints of resources, whether human or computer.

Initially [7], criticizes the complexity of comprehending ML models, which can only be examined by the team that developed them, and which frequently does not understand all of the model's features or why it made certain judgments. Furthermore, the more complex the model, the more difficult it is to analyze its decision-making process.

[20] aims to provide an overview and a systemic view regarding recent criteria and processes in machine learning development, and to conduct empirical tests on the use of these for credit scores. The authors selected which fairness criteria best fit for these scores and cataloged state-of-the-art fairness processors, using them to identify when loan approval processes are met. Using seven datasets of credit scores, they performed empirical comparisons for different fairness processors.

The [21] study found security and transparency issues with automated decision systems (ADS), warning and urging data engineers to develop a more fair and inclusive procedure. For the authors, ADS must be accountable in the following areas: development, design, application, and usage, as well as rigorous regulation and monitoring, so that they do not perpetuate inequality.

The [8] study addresses advantages and disadvantages of transparency in machine learning models, defining bias, fairness, and arguing that a transparent algorithm is extremely difficult to obtain given the millions of parameters analyzed by a machine. Then, a transparent output is proposed that can be analyzed and understood without having to comprehend every step made by the algorithm. To define transparency, two categories are used: process transparency and result transparency.

The term "process transparency" refers to an understanding of the algorithm's underlying characteristics, such as the attributes it weighs in its decisions. The term "result transparency" refers to the capacity to understand decisions and patterns in classification process answers. In addition, the model must meet two requirements: global and local explanation. The Local explanation includes a detailed examination of which characteristics were most important in reaching a particular decision, whereas the Global explanation evaluates all decisions based on certain metrics. The author suggests a mental model of the main system for this evaluation, and if it can predict what the classification of the main model is, it is on the correct course to transparency. Finally, it is stated that a premise of white-box and black-box models might bring out implicit and explicit features of the models and facilitate auditors' job [8].

ML models, whether classification or regression, can be of type *White-box* or *Black-box*, depending on their availability and constraints:

Item	Study	Year
1	One-Network Adversarial Fairness [22]	2019
2	Cyber gremlin: Social networking, machine learning and the global war on al-qaida-and is-inspired terrorism [7]	2019
3	Fairness research on deep learning [23]	2021
4	Mdfa: Multi-differential fairness auditor for black box classifiers [24]	2019
5	Algorithmic fairness: Choices, assumptions, and definitions [2]	2021
6	Dynamic fairness – breaking vicious cycles in automatic decision making [25]	2019
7	Recycling privileged learning and distribution matching for fairness [26]	2017
8	We need fairness and explainability in algorithmic hiring blue sky ideas track [6]	2020
9	Detecting bias: Does an algorithm have to be transparent in order to be fair? [8]	2018
10	Fairness-Aware Instrumentation of Preprocessing Pipelines for Machine Learning [27]	2020
11	Improving machine learning fairness with sampling and adversarial learning [28]	2021
12	Responsible data management [21]	2020
13	Using Machine Learning in Admissions: Reducing Human and Algorithmic Bias in the Selection Process [29]	2021
14	Analysis bias in sensitive personal information used to train financial models [30]	2019
15	VITAL-ECG: A de-bias algorithm embedded in a gender-immune device [31]	2020
16	Dataset bias: A case study for visual question answering [32]	2019
17	A causal bayesian networks viewpoint on fairness [33]	2018
18	Constraining deep representations with a noise module for fair classification [34]	2020
19	Algorithm Bias Detection and Mitigation in Lenovo Face Recognition Engine [35]	2020
20	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy [36]	2019
21	Cost-sensitive hierarchical classification via multi-scale information entropy for data with an imbalanced distribution [37]	2021
22	Fair adversarial gradient tree boosting [38]	2019
23	Harnessing artificial intelligence (AI) to increase wellbeing for all: The case for a new technology diplomacy [39]	2020
24	Privacy and Ethical Challenges in Big Data [40]	2018
25	Singular race models: Addressing bias and accuracy in predicting prisoner recidivism [41]	2019
26	Fairness in Credit Scoring: Assessment, Implementation and Profit Implications [20]	2022
27	When Politicization Stops Algorithms in Criminal Justice [42]	2021
28	A survey on bias and fairness in machine learning, [43]	2021
29	Evolution and impact of bias in human and machine learning algorithm interaction [44]	2020
30	Benchmarking Bias Mitigation Algorithms in Representation Learning through Fairness Metrics [45]	2021
31	Fairness for image generation with uncertain sensitive attributes [46]	2021
32	Mitigating Demographic Bias in Facial Datasets with Style-Based Multi-attribute Transfer [47]	2021
33	Constructing a Fair Classifier with the Generated Fair Data [48]	2021
34	Enforcing fairness in logistic regression algorithm [49]	2020
35	Fairness metrics and bias mitigation strategies for rating predictions [50]	2021
36	Fairness via Representation Neutralization [51]	2021
37	Improving fairness of artificial intelligence algorithms in Privileged-Group Selection Bias data settings [52]	2021
38	A Survey on Bias and Fairness in Machine Learning [43]	2021
39	Fairness in Deep Learning: A Computational Perspective [53]	2021
40	Risk Identification Questionnaire for Detecting Unintended Bias in the Machine Learning Development Lifecycle [54]	2021
-	Table 1: Papers returned by the search string	

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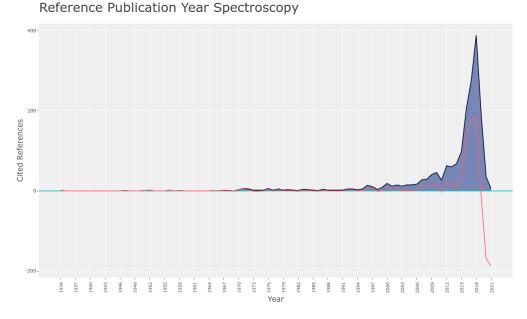


Figure 3: Year of the references cited in the papers

- White-box: These are machine learning models that deliver easy to understand outcomes for application domain specialists. Typically, these models provide a good tradeoff between accuracy and explainability [55] and hence have less constraint and difficulties for structural adjustments. The structure and functioning of this model category are simple to grasp.
- **Black-box**: ML models that, from a mathematical perspective, are extremely difficult to explain and comprehend by specialists in practical areas [55]. Changes to the structure of models in this category are restricted, and it is difficult to grasp their structure and functioning.

[2] corroborates the argumentation of [7] emphasizing that when dealing with people, even the finest algorithm will be biased if sensitive attributes are not taken into consideration. One of the first issues raised is that the prejudice and justice literature is often confined to addressing the situation of a group or individual experiencing injustice in the present time. In this case, one must broaden the search and analyze how the individual's effect impacts his or her community and vice versa. Dataset and people behavior is fluid and can diverge dramatically over a few years, but the algorithm may retain a bias in its training and be unable to adapt to this shift. A group that is mistreated in the actual world would almost certainly be wronged by the algorithm, and that this type of bias just reflects the reality rather than being a biased dataset.

With similar opinion, [42] opposes the use of models for decision-making, defining the use of tools for risk assessment in models for pre-judgment as a justification. The authors argue that the implementation of these tools can introduce new uncertainties, disruptions, and risks into the judgment process. By conducting empirical experiments with unfair models, they conclude that the process of implementing these tools should be stopped.

Furthermore, [25] states that while there are various fair models for classification tasks, these are restricted to the present time, and because they embed the human bias, there is a propensity to repeat and escalate the segregation of particular groups through a vicious cycle. Whereas a classifier that gives a group a higher number of good ratings will give it an advantage in the future, and vice versa for negative ratings.

Meanwhile, [7] also claims that algorithms frequently disregard uncommon information, framing the act as censorship, such as Islamism and terrorist content. Because of this issue, decision-making algorithms tend to be biased toward more common occurrences in their case-specific databases.

Finally, [36] brings together the perspectives of different various experts, emphasizing opportunities from the usage of AI, evaluating its impact, challenges, and the potential research agenda represented by AI's rapid growth in various fields of industry and society in general. Tastes, anxieties, and cultural proximity seem to induce bias in consumer behavior, which will impact demand for AI goods and services, which is, according to the study, an issue that is yet under research.

Inferring patterns from large datasets in an unbiased environment and developing theories to explain those patterns can eliminate the need for hypothesis testing, eradicating the bias in the analysis data and, consequently, in the decisions [1].

In [36] work, general issues surrounding ML are addressed, where governments are increasingly experimenting with them to increase efficiency in large scale customization of services based on citizen profiles, such as predicting viral outbreaks and crime hotspots, and AI systems used for food safety inspections. Bias in this context implies governance issues, which pose hazards to society, because algorithms might develop biases that reinforce historical discrimination, undesirable practices, or result in unexpected effects due to hidden complexities. Other related topics include ethics, transparency and audits, accountability and legal issues, justice and fairness, protection against misuse, and the digital divide and data deficit.

Furthermore, [39] emphasizes the significant challenges that nations face, highlighting the need for a continuing international policy of coordination as a crucial instrument to handle the ethical, cultural, economic, and political issues associated with AI. The author recommends that the concept must expand to include technology diplomacy as a facilitator of global policy and governance alignment for the development of AI systems. It also discusses the importance of implementing core ethical concepts in AI, such as beneficence, non-maleficence, decision-making, justice, explainability, reliable AI, suggested human supervision, alternative decision plans, privacy, traceability, non-discrimination, and accountability.

The work [40] addresses the question of data privacy as well as other ethical challenges related to Big Data research, such as transparency, interpretability, and fairness of algorithms based on this data. It is critical to explore methods to evaluate and quantify the bias of algorithms that learn from Big Data, particularly in terms of potential hazards of discriminating against population subgroups, and to suggest strategies to rectify unjustified prejudice. According to [40], another crucial difference is between individual and group justice, in individual justice, which states that individuals who are similar except for the sensitive attribute should be treated similarly and receiving similar decisions. This relates to the legal concept of unequal treatment when the decision-making process is based on sensitive attributes. However, individual justice is only relevant when the decision-making process causes discrimination and therefore cannot be used when the goal is to address biases in the data. Group justice, on the other hand, depends on the statistics of the outcomes of the subgroups indexed in the data and can be quantified in various ways, such as demographic parity and equalized odds, and thus can have the bias addressed in the data.

3.1 Types of Bias

[21] defines three types of bias: pre-existing, technological, and emergent. The pre-existing bias category refers to data that reflects inequalities absorbed by the algorithm, hence spreading them. The technical category relates to bias worsening pre-existing prejudice caused by one of the algorithm's internal decision processes, and this may be addressed rather simply in comparison to the others. Finally, the emergent category refers to bias that occurs as a result of the usage of one or more users. For example, if a manager assigns higher performance to male employees, the algorithm is likely to begin favoring them and/or incorrectly rating women in the same division of the organization.

The paper [43] goes further in this concept, listing the 23 most common sources of bias, and these are divided into three categories organized in order to consider the feedback loop, they are: data, algorithm, and user interaction. So we have some examples of biases:

- Historical and social: coming from the data;
- Emerging and popularity: coming from the algorithm;
- Behavioral and presentation bias: caused by interaction with the user.

The paper [44] studied filter bias, active learning bias, and random baseline bias in the field of information filtering algorithms, and classified them as capable of affecting their performance. Furthermore, the authors proposed a framework to analyze bias in these systems and were able to conclude that filter bias, prominent in personalized user interfaces, can limit a user's ability to discover relevant information that could be presented to them. In addition, they address the importance and damage caused by feedback cycles and how algorithm performance and human behavior influence each other and can deny certain information to a user, also accounting for the impact of this influence on long-term performance.

3.2 Identified Datasets

References were still found for some Datasets that are relevant because they have sensitive attributes.

[23] analyzed six datasets that have sensitive attributes causing bias in the models: Propublica COMPAS, MEPS, Aank marketing data set, Boston housing price data set and Gremancredit data set.

[24] examined the Propublica COMPAS dataset and successfully detected a difference in the treatment of African Americans, who were rated "high risk" 2.7 times higher than Native Americans. The Adult Dataset, German Credit Data dataset and the Communities and Crime Dataset were also examined, and the Multi- Differential Fairness (MDFA) algorithm was able to identify subgroups that suffered some disadvantage due to sensitive attributes.

[26] Experiments were carried out using the Propublica COMPAS dataset as well as the Adult Dataset. The findings for COMPASS showed a significant increase in fairness metrics without loss of accuracy, while the Adult Dataset showed an improvement in both fairness and accuracy.

Finally [22] carried out experiments using the Propublica COMPAS and Adult datasets, with the findings indicating that an increase in fairness led to an increase in neural model accuracy as well.

The articles used the same datasets, which are listed in Table 2. The datasets identified were: Propublica COMPAS (COMPAS), Adult, Medical Expenditure Panel Survey (MEPS), Aank marketing (Aank), Boston housing price (Boston), German credit (German), Communities and Crime (Communities). These datasets are known to include unfairness and biases in their data, and they may be used to test and validate techniques that aim to solve these issues.

	[22]	[23]	[24]	[26]
COMPAS	yes	yes	yes	yes
Adult	yes	not	yes	yes
MEPS	not	yes	not	not
Aank	not	yes	not	not
Boston	not	yes	not	not
German	not	yes	yes	not
Communities	not	not	yes	not

Table 2: Table with the datasets present in each paper.

Propublica COMPAS dataset [56] brings a binary classification task, that show if a defendant will relapse in two years or not, where the sensitive attribute is the race value. This is one of the most used datasets for bias and justice experiments, with a controversial and relevant theme.

Adult [57] is one of the most extensively used datasets, with 32,561 full instances representing adults from the 1994 US census. The task is to predict if an adult's salary is greater than or less than \$50,000 based on 14 features. The sensible attribute sex is an instance in the datasets data that can be male or female.

The MEPS [58] is a set of surveys of families and individuals in the United States, as well as their medical providers and employers, that provide information on the cost and usage of health care or insurance.

Adult German credit [57] is a dataset with 1000 items and 20 categorical attributes. Each entry in this dataset represents a person who receives credit from a bank. According to the attribute set, each individual is assessed as a good or bad credit risk.

The Communities and Crime [57] dataset compares various socioeconomic situations of US citizens in the 1990s to the crime rate, identifying the per capita rate of violent crime in each community.

3.3 Mitigation techniques and models

As noted previously, bias mitigation and fairness techniques and models can originate in pre-processing, in-processing, and post-processing stages.

[45] focuses on bias mitigation in deep learning models for classification. The authors point to the need for a systemic analysis of different bias mitigation techniques, having in mind different metrics for analyzing the results. Making use of a dataset that allows the creation of different biased sets, they performed an in-depth analysis of mitigation models recently attributes proposed in the literature. Forcing the models to the limit through the extreme use of their settings they showed the correlation between eligibility and sensitive attributes, the possible presence of bias even when there are non-sensitive attributes, and the importance of seed choice for model performance.

The [23] study grouped solutions for each bias situation. Pre-processing techniques such as Synthetic Minority Over-sampling Technique (SMOTE) and Data Augmentation, for example, are mentioned for mitigating bias in data.

In the study [27], The FairDAGs library is proposed as a generator of acyclic graphs that describe data flow during pre-processing. It aims to identify and mitigate bias in the distribution and distortions that may arise with the protected groups, while also allowing for direct observation of changes in the set. The objective is to reduce data bias before it enters the model. The four kinds of treatment are: bias by filtering the data, standardizing missing values, changes in the proportion of the dataset after replacing NaN values, and, for natural language processing (NLP) systems, filtering out odd names or words that the computer may not recognize. The annotations of the target variable and protected groups are sent into the library as input. Adult Dataset and Propublica COMPAS were used in the experiments. The results demonstrated that DAG was capable of identifying and representing differences in the data that occurred during preprocessing, as well as correcting unbalances in the examined datasets.

The paper [46] presents several intuitive notions of group equity, its incompatibilities and trade-offs, applied to image enhancement problems. Because of the uncertainty in defining which clusters are more assertive, since, for the author, there are no ground truth identities in the clusters, and the sensible attributes are not so well defined. In this way, two notions of fairness were introduced, one extending demographic parity which he called Representation Demographic Parity (RDP), and another conceptually new one, called Conditional Proportional Representation (CPR). In the experiments, it could be seen that the demographic parity metric is strongly dependent on clusters, which is problematic for generating images of people, since the races are ill-defined and/or ambiguous. In CPR, implemented using the Langevin dynamics, this phenomenon does not occur, and it can be observed in the results obtained that, for any choice of protected groups, the expected properties are displayed.

The paper [47] points out that models for face recognition and analysis commonly exhibit demographic bias even in models where accuracy is high, this is usually due to databases with underrepresented categories, whether for identifying identity, gender, or expressions of the human face. The biases can be in relation to age, gender, and skin tone. Therefore, a bias mitigation technique with increase facial dataset was proposed. Where, to increase the demographic diversity of the facial dataset, a style transfer approach using Generative Adversarial Networks (GANs) was used to create additional images, transferring multiple demographic attributes to each image in a biased set. The method utilized a relaxation of the dependency on a single attribute label, and the introduction of a tensor-based mixing structure that captures multiplicative interactions between attributes in a multilinear fashion, with an extension of AdaIN to combine the different representations capturing facial patterns by employing a tensor-based mixing structure, resulting in a single conditioning variable. The solution was evaluated with qualitative and quantitative experiments on the LFW, CelebA, MOPRH and MOPRH datasets. It was found that the mitigation was successful, reducing the bias in the dataset under the TPRs and EO metrics.

The article [48] uses a VAE-GAN architecture to generate a new training dataset that has no disparity in distribution, quality, or noise, ensuring that all classes are treated equally. While this method showed great improvements in model impartiality, the use of artificial data during training limited its ability to understand real data, reducing accuracy and precision. To minimize the trade-off, the model trained with artificial data used transfer learning techniques to perform a fit of the weights with real data, which caused improvement in both accuracy and precision, demonstrating that the model achieved good results in both fairness and accuracy.

In [22] a preexisting, biased model must be updated to become fair, minimizing injustice without causing abrupt structural changes. The study uses an adversarial learning technique with the distinction that the generator model is the original network, however the adversarial model comprises an extra hidden layer, rather than a second model, with the aim of predicting which sensitive attribute influenced the generator's decision. The main element of this model competition is that if the discriminator finds the sensitive attribute that influenced the decision the most, it demonstrates the generator model's dependency, which suggests bias. The generator moves away from the sensitive attributes and performs a classification that is not dependent on them, eventually lowering the discriminator's hit rate until it completely loses its predictive ability. Another aspect addressed in the study is the significance of diversity in each minibatch. [22].

To avoid the models from gathering data that is too similar to the initial ones, random beginning data is supplied to the first minibatch, and then the points with the least similarity to the initial ones are added, aiming to achieve the maximum possible variation in each of the sets. The changes to the original network architecture may be categorized into three parts: adding an adversarial layer on top of the network, balancing the distribution of classes across minibatches, and adapting sensitive attributes until they are no longer present. The technique was developed for classification tasks, but it may be used to any neural network with biases beginning with sensitive attributes. [22].

The model proposed by [26] Privileged Information is a technique that trains the model with all of the original dataset's features, including sensitive data, and then tests it without these attributes. This renders the model independent of sensitive attributes while retaining its capacity to produce accurate predictions, hence respecting protected information for decision-making. As a result, the model is also distinguished by being an in-processing type that acts directly on its tuning, with the goal of mitigating unfairness. His approach creates a model that fits all existing conceptions of justice

and bias and can adapt to any that emerge in the future, resulting in an almost timeless model. The author emphasizes the strength of his model in identifying the best predictor for the case at hand, having the sensitive attributes be optional, and yet using Privileged Information.

Using the Adult dataset, [28] examines metrics and combinations of bias reduction techniques. The study was carried out using basic RNA models and a Split model, which trains the basic model by permuting the attribute classes as training criteria in order to identify which one is sensitive. Another model based on the Classifier-Adversarial Network (CAN) architecture, in which the adversarial network predicts the sensitive attribute based on the basic model's output. Finally, there is the CAN with Embedding (CANE) architecture, which takes as input the basic model output as well as the weights created in the penultimate layer. The experiments aim to provide answers to the following questions:

- Is it possible for a simple neural network to improve its fairness metrics?
- Which network architecture yields the least biased predictions?
- What is the most effective data sampling strategy for increasing fairness?
- Can we improve our findings by combining good architecture with data sampling?

The study [28] suggested an in-processing method for mitigating bias in various model architectures. Their experiments revealed that the Basic RNA model can enhance accuracy but not bias, but the CAN and CANE models improved both accuracy and bias reduction, with CANE being the best of the trained networks in both aspects. There were no studies conducted on additional datasets or circumstances.

Another in-processing solution was proposed by [29], who reports that the diversity of students in a school comes from individuals with various profiles and worldviews. Schools are increasingly striving to incorporate diversity into the classroom using holistic and often subjective methods, perhaps resulting in human bias in the selection process. In this perspective, machine learning algorithms capable of admitting a diverse student population have been developed, but from them emerges a bias in selection processes for groups with historical disadvantages. Thus, the authors developed and tested a model for admissions that minimizes the current human bias in the data. They state that algorithm bias might result from unbalanced data, outdated training techniques, or data scope limitations. The study examined the impact of characteristics such as income, color, and gender on student admission rates and if this data might be deemed sensitive.

To prevent model bias, most of the literature on fairness and machine learning adds data that has minimal or, if feasible, no relevance to sensitive attributes. [34] has applied a noise conditioning operation to the data supplied into the model, which is a method of achieving model fairness by inducing the neural network to disregard sensitive attributes. Thereunto, a model R is proposed that creates a fair representation of the data named r, that will be utilized to make predictions. This model will be regarded fair if it is unable to predict y on its own, and will only be considered useful if y is correctly classified. Aside from the 'R' model there is a Y model and a S model. The Y model predicts the variable y based on the representation received r, whereas the S model predicts the sensitive attribute s that was relevant to the classification of Y. The goal of the R model is to create a r representation that is as accurate as possible, effectively predicting y, being fair, making S unable to identify the s attribute [34].

Adult, German credit, Bank Marketing, and COMPAS datasets have been used in experiments. Each dataset was used to train models using the logistic regression and Random Forest techniques, with the former yielding results that were generally superior or equal to the latter. [34].

Another in-processing model was proposed by [41], With a novel classification approach for race-based datasets, with the goal of increasing prediction accuracy and reducing racial bias in crime recidivism. To accomplish so, the model was evaluated using a three-layer RNA and several justice metrics. The Florida Department of Corrections (FDOC) and the Florida Department of Law Enforcement (FDLE) datasets were utilized (FDLE). In contrast to alternative approaches such as K-nearest Neighbors (KNN), Random Forest, AdaBoost, Decision Tree, and Support Vector Machines, the RNA was chosen. The prediction accuracy was the sole metric utilized to choose the RNA. Then, models for predicting recidivism were developed, taking into account any type of individual offense, including violent, property, drug, and other crimes. For the groups "all crimes", "Caucasian dataset", and "African American dataset", the results still had bias, although it was smaller than the baseline model. The corresponding ratios were 41:59, 34:66, and 46:54.

The work [49] presents an in-processing mitigation solution for a logistic regression model using the COMPAS and Adult dataset for group bias, for this it used the fairness metrics Equalized Odds and Equal opportunity. An interesting solution used was Pareto Optimal which aims to ensure a better accuracy loss function while keeping the fairness metrics at the threshold set at 80%. The author affirms that the in-processing solution, where the algorithm is adjusted during learning, would be a natural solution, because the pre-processing algorithms would be altering the original data, hurting ethical norms, however it is possible to work with data balancing, without altering the users' data [52].

The research [50] presents a focus on the ways in which bias can occur recommendation systems, while also addressing the lack of a systematic mapping to address unfairness and bias in the current literature. In the experiments, the researchers mapped sources of unfairness that can occur in recommendation tasks, while evaluating whether existing bias mitigation approaches successfully improve different types of fairness metrics. In addition, the paper presents a mitigation strategy in which the algorithm learns the difference between predicted and observed rankings in subgroups, identifying which bias is present and correcting the prediction. The results show that fairness increased in most use cases, but performance for MSE and MAE varied in each case.

The work [51] demonstrated that it is possible to make a classification model fairer by removing bias only in its output layer, in a process that occurs during its training. In the paper, a technique is introduced where training samples that have the same ground truth and different sensitive attributes, are neutralized, causing the dependence of the model on these attributes to be reduced. The main advantage demonstrated by the method is the tiny loss of accuracy in exchange for an expressive increase in fairness indicators, without requiring access to the sensitive attributes of the database. In addition, the authors argue that it is possible to increase the quality of the technique by combining it with others, for example, using a fairer base than the one used in the experiments.

[24] proposes a solution with the post-processing method of an already trained model, seeking to identify whether certain groups receive a discriminatory treatment due to their sensitive attributes. With the identification of discrimination for a group, it is verified whether or not sensitive attributes are being passed to the model, even if indirectly. The technique was developed for balanced datasets, but can also be applied to unbalanced ones with a simple distribution of weights for the groups that represent minorities, making their importance equivalent to those of the dominant classes.

Both [23] and [24] present a post-processing model for identifying the group most disadvantaged by the decision algorithm, but for mitigation and identification, respectively.[23] emphasizes that there are numerous tools for post-processing, such as AEQUITAS, and techniques such as Adversarial Learning, which is also highlighted in [22].

In the [24] study, the model receives as input the attributes of the original dataset, whether their are sensitive or not, together with the output of the algorithm being evaluated. After that, it analyzes the MDFA, as the measure of disparity in the treatment received by groups with different sensitive attributes. Through this treatment difference, it becomes possible to identify which group is most harmed by the network. Also on this topic, one of the advantages of MDFA is that the user can choose a minimum violation threshold that indicates how large the disparity in treatment must be for a given group to be considered discriminated, making the algorithm more flexible to experimentation. The work allows for black-box type algorithms to be audited for bias mitigating injustice, but also understanding the treatment. It further reinforces that injustices can be identified by performing a comparison between the treatment received by one group versus another, through the MDFA, which aims to ensure that minority groups receive proper treatment regardless of their sensitive attributes [24].

In the study of [32] The detection of bias in developed models enables the recognition of whether questions are answered by a human with normal vision, a blind person, or a robot. It does so by utilizing visual question answering (VQA) datasets cataloged by individuals with normal vision, blind people, and a robot. The article discusses the issues of bias in this type of database and presents an algorithm capable of locating the source and determining whether the questions were asked by a sighted person, a blind person, or a computer, explaining the issues in each and what constitutes bias, and is an application of NLP. The first dataset evaluated was VQA 1, which was developed by individuals with regular vision and included questions on what people think of robots, resulting in questions with very broad scope (simple or difficult) and images with a high diversity of objetcs. The VizWiz dataset was developed by visually impaired persons and contains questions about object identification. Its bias may be seen in the most often asked question "what is this object?" as well as the low image quality in comparison to the others. The final dataset, CLEVR, was developed by robots and lacks images that depict real difficulties like as angle, lighting, and blurring, as well as questions that are rather unrealistic. Initially, tags such as "boy," "package," "grass," "airplane," and "sky" were assigned to each image. Also, questions referring to the image are transformed into tokens and go through a process of Term Frequency-Inverse Document Frequency (TF-IDF), producing a variable that supports prediction. Random Forest, K-Nearest Neighbors, Nave Bayes, and Logistic Regression algorithms were used for training. Logistic regression produced the greatest results, with 99 percent accuracy, recall, precision, and F1-score [32]. The authors found that the algorithms readily recognized the bias in each database and provided a means of tracing the origin of the questions and images [32]. The approach was post-processing, enabling the classification by recognizing the bias of the prediction.

Some solutions may have hybrid behavior in terms of mitigation type, handling data in pre-processing and models in in-processing. As an example, consider [30], [31] and [35].

[30] proposed a model for a banking system that can rectify skewed data collection by assuring the removal of customer data after output without affecting the ML model. The Trusted Model Executor (TME) was designed to monitor the data and assess the models, as well as to execute pre-processing operations on the data and post-processing operations

on the model outputs. The AIF360 tool mitigates bias in data and pre-trained models by adding correction metrics and creating reports regarding the source of data bias, generating artificial data based on actual data, and preserving customer privacy.

[31] points out that smartwatches and similar devices establish an incorrect difference between men and women in the identification of cardiovascular problems, evaluating more characteristics of the first group than the second. Thus, there must be a correction to suit the need of both genders. The Vital-ECG, a watch-like gadget that detects heart rate, blood pressure, skin temperature, and other bodily variables without distinguishing gender and with superior predictions, was developed for this purpose. The device use the AIF360 tool to do pre-processing operations such as rebalancing the distribution of data in the dataset and in-processing operations such as changing model weights. It also adjusts non-representative data for an accurate assessment of the user's health.

[35]'s research assessed the performance of diversity in Lenovo's internal facial recognition system, named LeFace. The algorithm developed is a semi-automatic data collection, cleaning, and labeling system. The training data is diverse in terms of race, age, gender, poses, lighting, and so on. This data system cleans and labels the face data with an algorithm that evaluates data balancing before applying data augmentation to obtain a balanced training dataset. Furthermore, LeFace employs an attention method to provide balanced data to the network during the training phase. The Racial Faces in the Wild (RFW) database was used to assess the algorithm's capacity to recognize different races. It is divided into four classes: African, Asian, Caucasian, and Indian. For the evaluation, it employed the metrics max accuracy, race-blind, Equal Opportunity, Equality odds, and Demographic Parity, and it states that further AI algorithms for face recognition will be tested in the future. They concluded that LeFace outperforms Face++ in terms of accuracy, and that when comparing ROC curves, LeFace is less biased against different races.

The work [52] proposes several methods to mitigate bias in selection models for hiring, having a lack of labeled information for rejected candidates. In this way it suggested three solutions, the first pre-processing and the others in-processing, with supervised and semi-supervised learning algorithms. Evaluated the fairness of AI algorithms in data settings for which unprivileged groups are extremely underrepresented compared to privileged groups. It shows that a model trained on data from the privileged group only, can lead to high levels of unfairness, despite being applied exactly the same to privileged and non-privileged groups. The COMPAS dataset was used and the proposed methods manage to improve the fairness considerably, with reasonable accuracy, outperforming the results of previous works, it also highlights the use of unlabeled data with semi-supervised techniques outperforming supervised techniques according to the fairness criteria. It also adds that the pre-processing technique obtained better results than the in-processing mechanisms.

Also in the work [43] a categorization is made relating the domain of ML techniques and its strategy for mitigation, in the criteria of pre-processing, in-processing and post-processing. Thus it is categorized as:

- pre-processing: Community detection, Word embedding, Optimized pre-processing and Data pre-processing
- in-processing: Classification, Regression, Adversarial learning;
- pos-processing: Word embedding and Classification

The work of [53] does a similar analysis, categorizing mitigation techniques into the same three stages:

- **pre-processing**: Sensitive features removal, Sensitive features replacement, Reweighing, Optimized pre-processing, Balanced dataset collection, Diverse dataset collection and Synthetic data generation;
- in-processing: Attribution regularization, Reduction game, Prejudice remover, Adversarial training, Adversarial fairness desideratum, Semantic constraints, Distance metrics, Transfer learning and Multi-task learning.
- post-processing: Calibrated distribution, Calibrated equalized odds and Troubling neurons turn off.

3.4 Techniques for Bias Analysis

The technique suggested in [8] includes a model that combines white-box and black-box features for local and global explanations, respectively. The local explanation entails determining which elements contributed the most to the classification of a particular piece of data, which may be accomplished using a visualization tool or by developing a second algorithm that can simulate and explain the original model's decisions in detail. In terms of the global explanation, all model decisions must be explained by comparisons of the ratings obtained by each group, utilizing graphs and metrics that may demonstrate the fairness with which the model treats the data.

The work [54] proposed a methodology for identifying the risks of potential unintended and harmful biases in ML, for which strategies have been proposed in the past, but with methods never concrete or fully operationalized. Thus, they developed a new hands-on risk assessment questionnaire to identify the sources of bias that cause unfairness and

applied their solution to use cases in areas such as criminal risk prediction, health care provisions, and mortgage lending. The questionnaire was validated with industry professionals, and 86% agreed that it is useful for proactively diagnosing unexpected issues that may arise in the ML model.

3.5 Technique for identification of the sensitive attribute

[33] research addresses a novel perspective on the concept of fairness by determining if an attribute is sensitive and outlining how it is assessed in a Causal Bayesian Networks model. This neural network examines the direct effects of one characteristic on another and determines if a sensitive attribute 'A' influences the output 'Y' of a model, producing correlation plots that strive to understand whether or not the decisions made were made fairly.

In the field of machine learning, not every unfair correlation represents an issue. For example, in a music test given at the start of the semester, female students obtain lower results than males, despite equal performance. However, in this study, the gender attribute has no effect on the model's output 'Y,' because the final course score is connected to musical talent, not gender. Finally, the paper analyzes COMPAS, reporting on the algorithm's history and unbalanced data, and conducts a causal investigation, reporting that the unbalance in data of white males, who have a spaced distribution in risk value relative to black males, has a direct impact on the model's 'Y' decisions, which associate an individual's color with their risk to society. [33].

Given the challenges posed by unbalanced datasets and sensitive attribute identification, [37] aims to combine hierarchical classification with sensitive cost learning to mitigate the effects of imbalance. A large scale classification problem is partitioned into multiple smaller scale problems, allowing the hierarchy to extract the primary features of each class and a logistic regression algorithm to analyze their patterns. Following that, for each class, an adaptive sensible cost factor is defined. This component balances the predictions between classes, boosting the precision and accuracy of minority while avoiding the error between levels, which is the gap between the predicted and actual value. Finally, a sensitive cost model is built using the hierarchical data and the cost factor for each class. Preliminary findings suggested an increased accuracy in minority classes.

This classification detects the item with the highest probability of belonging to the objective class; nevertheless, there are cases where numerous items have very close probabilities and bias the model, causing an error to propagate through several levels. To prevent this, the threshold needs a minimum degree of belonging for the data to be classified and triggers a maximum probability recalculation of the node. The sensitive cost then runs its own probability calculation on the data with the highest degree of belongingness. These calculations avoid bias caused by using only one probability or overfitting caused by using data with no prior context. Accuracy and Hierarchical measure, which evaluates the relationship between all descendants of the class and includes Hierarchical F1, Hierarchical Recall, and Hierarchical Precision, were employed as metrics. The threshold in its model is adaptable, without requiring user parameters, as there are metrics throughout the classification that can determine it. Even with fewer samples, it produced findings that were superior to the state of the art. [37].

[38] argues that research on fairness and bias in machine learning focuses only on neural networks, with few publications addressing them in other classification techniques. As a result, the author investigated Adversarial Gradient Tree Boosting to rank a data while the adversary progressively loses track of which sensitive attribute led to that prediction.

One contribution is the adversarial learning method for generic classifiers, such as decision trees. Another contribution is the use of the aforementioned learning to decision trees in order to improve the algorithm's fairness. Finally, it contributes by comparing numerous cutting-edge models to the one provided in the work, which covers two justice metrics. Boosting is performed using numerous decision trees in the model given. They make classifications, which are then sent through a weighted average to an opponent, who predicts which sensitive attribute was significant to the final decision. While the adversary is able to detect the sensitive attribute, a gradient propagation happens, updating the weights in the decision trees and seeking to prevent the sensitive attribute directly impacting the [38] classification.

The FAGTB model performed well on accuracy and fairness metrics for the datasets COMPAS, Adult, Bank Marketing, and Default, exceeding other state-of-the-art models on several of them and considerably outperforming the [38] network adversary. The study leaves certain questions unanswered for future research, such as an adversary using Deep Neural Decision Forests. If this method were employed to retrieve the gradient, theoretically, the model's transparency and the algorithm's complete decision route would be apparent because it consists only of trees. As a last disclaimer, they acknowledge that the algorithm treats distinct groups well, but neither Equalized Odds nor Demographic Parity measure treatment across individuals, which is an area for improvement.

3.6 Fairness metrics

[25] claims that machine learning models increasingly provide approaches to quantify bias and inequality in classification operations as a methodology for measuring bias and fairness. While many metrics have been developed, when it comes to long-term decisions, the models and scientific community have produced poor outcomes. Some existing metrics for measuring model bias are insufficient, either because they only evaluate the individual or the group, or because they are unable to predict a model's behavior over time. The authors offer the metric Demographic Parity as a solution, which when applied to a model ensures that the average classification of individuals in each group converges to the same point, achieving a balance between accuracy, bias, and fairness for the groups classified by the model.

In [26], Demographic Parity, which assures that decisions are unconnected to sensitive attributes, was one of the metrics used to evaluate the model. Equalized Odds, to guarantee parity between positive and negative evaluations, and Equality of Opportunity, to ensure that individuals meet the same criteria and are treated equally. Each of these metrics assures that groups are treated fairly and that the model's quality does not deteriorate or become biased over time, as addressed in [25].

Metrics for evaluating fairness must apply the same treatment to multiple groups, so that if one of the metrics misses a bias, another will be able to uncover it.

Five metrics for assessing fairness were established from the review of the papers: Equalized Odds, Equality of Opportunity, Demographic Parity, Individual Differential Fairness, and MDFA.

To understand the fairness metrics, the following statistical metrics must be defined: Positive Predictive Value (PPV), False Discovery Rate (FDR), False Omission Rate (FOR), Negative Predictive Value (NPV), True Positive Rate (TPR), False Positive Rate (FPR), False Negative Rate (FNR), and True Negative Rate (TNR), as defined by the equations below. [3]:

$$PPV = TP/(TP + FN) \tag{1}$$

$$FDR = FP/(TP + FP) \tag{2}$$

$$FOR = FN/(TN + FN) \tag{3}$$

$$NPV = TN/(TN + FN) \tag{4}$$

$$TPR = TP/(TP + FN) (5)$$

$$FPR = FP/(FP + TN) \tag{6}$$

$$FNR = FN/(TP + FN) \tag{7}$$

$$TNR = TN/(FP + TN) \tag{8}$$

Only the statistical metrics TPR and FPR are employed among the selected justice metrics.

The objective of the metric Equalized Odds is to ensure that the probability that an individual in a positive class receives a good result and the probability that an individual in a negative class wrongly receives a positive result for the protected and unprotected groups are the same. That is, the TPR and FPR of the protected and unprotected groups must be the same. [59].

In contrast, the metric "Equality of Opportunity" must satisfy equal opportunity in a binary classifier (Z). As a result, the probability of an individual in a positive class receiving a good outcome must be the same for both protected and unprotected groups. That is, the TPR for both the protected and unprotected groups must be the same.[59].

According to the Demographic Parity metric, also known as Statistical Parity, the probability of a positive outcome should be the same for all groups, i.e., it is achieved if the absolute number of positive predictions in the subgroups is near to each other [59]. The formula below, which should be applied to each group, expresses it.

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$$DemographicParity = (TP + FP) \tag{9}$$

Thresholding is a parameter that, when used with Demographic Parity, can prevent the algorithm from entering a loop that disadvantages a class over time by continually executing a biased classification until it becomes the default.

4 Discussion

The 40 studies that were examined all addressed comparable techniques, case studies, datasets, metrics, and applications. The Adult dataset and the Propublic COMPAS dataset were utilized to address the bias cases, which were also the most often reported bias concerns.

The [23] research investigated the sources and implications of several sorts of biases, including their presence in the dataset, the model, and even forms of emergent bias, which is a bias that emerges after the model is built. The study undertakes a deep investigation of bias, offering state-of-the-art methods for eliminating it as well as constructing groups and subgroups that help comprehension of the problem, and discusses general categories such as temporal, spatial, behavioral, posterior, transcendental, and group bias. Specific cases, such as the Simpsons paradox or social behavior bias, are grouped within these categories.

The forms of bias observed by [23] are categorized as follows: dataset bias, model bias, and emergent bias, or preprocessing, in-processing, and post-processing, as previously described. In order to go deeper into these categories, the study [23] splits them into eight broad and 18 particular categories, as well as providing metrics and strategies for resolving each of them.

In terms of metrics, the most commonly used in model applications to achieve justice are a combination of Equalized Odds, Equality of Opportunity, and Demographic Parity. Thresholding, Person Differential Fairness, and Multi-Differential Fairness are further metrics that have proven relevance in the theoretical branch to assess the difference in treatment of the individual relative to his group and vice versa.

A frequent concern about the individual-group interaction is that few ML models handle it. According to [2], if a model is biased in rejecting loans to black males, for example, it will increase its database with rejections for this group, reinforcing the bias and initiating a vicious spiral that will reassert itself with each loan denial.

[25] focuses into the topic of vicious loops in machine learning, claiming that models may be free of bias in the present but may bias in the future. To overcome this, he suggests that the model fulfill the Demographic Parity metric, which ensures that the classification of varied groups is constantly converging and that no group is disadvantaged over time.

Except for [24] and [8], the model proposals were primarily white-box classification. The former proposes a model for bias elimination using Multi-Differential Fairness by integrating in-processing and post-processing, whereas the latter proposes that the focus of algorithm transparency should be on the output rather than the whole decision-making process of the algorithm.

There was no in-depth study of bias correction and identification tools other than the tests performed with the FairLearn, AIF 360, and MLG Fairness Gym tools. The topic of detecting biases in data was also addressed, with the Aequitas tool being the most frequently mentioned.

Continuing on this theme, all tools, both manually and automatically selected, confirm the importance of sensitive attributes in bias correction. According to the papers reviewed, sensitive attributes are defined as elements that should not directly impact the output of a model, such as color, race, gender, nationality, religion, and sexual preference, among others. According to US laws such as the Fair Housing Act (FHA) [60] and Equal Credit Opportunity Act (ECOA) [61], sensitive attributes should never favor, prejudice, or alter the outcome of individuals and groups who are in decision-making processes, such as hiring or a court penalty.

Finally, all studies have addressed the algorithm's transparency, or the capacity to explain the decision-making process that caused the model to classify a certain individual or group the way it did. This method must fundamentally explain either the local decision, which includes the classification of a single individual, or the global decision, which verifies the whole algorithm process. The relevance of transparency is to make it explicit to a customer, company, or court that the model does not consider sensitive attributes and does not discriminate against a specific group, just as it becomes possible to attribute responsibility to the model's developers if the model is biased.

The other evaluation metrics found are listed in Table 3, along with the support supplied by various tools, as well as the reviewed papers that mention the evaluation metrics.

	FairLearn	AIF 360	Aequitas	Responsible AI	Citations
Equalized Odds	Yes	Yes	Yes	Yes	[26] [59]
Equality of Opportunity	Not	Yes	Yes	Yes	[6] [26] [59]
Demographic Parity	Yes	Yes	Yes	Yes	[25] [26] [59]
Individual Differential Fairness	Not	Not	Not	Not	[24]
Multi-Differential Fairness	Not	Not	Not	Not	[24]

Table 3: Breakdown of the analyzed tools' metrics.

5 Final considerations

The objective of this study was to examine existing knowledge on bias and unfairness in machine learning (ML) models. Thus, the paper should answer the questions Q1 and Q2 from the 2.2 section.

To answer question Q1, the findings demonstrate that there is a focus on bias and unfairness identification methods for ML technologies, with well-defined metrics in the literature, such as fairness metrics, featured in tools, datasets, and bias mitigation techniques. This diversity ends up not defining the most appropriate approach for each context given that different solutions can be observed for the same problem, leading to a lack of definition about which one would be the most appropriate, without a generic solution for the identification and mitigation of biases. The vagueness raised in Q1's answer opens up aspects to be considered in Q2's answer.

To answer question Q2, where the existing opportunities should be highlighted, there is very limited support for black-box models, which contrasts with the abundance of information for white-box models. The need for transparency and explainability of ML algorithms, as well as the defining and preservation of sensitive attributes was also emphasized, with the selected datasets acting as a basis for research addressing the identification and mitigation of bias and unfairness.

As opportunities for future work, we conclude that further research is required to identify the techniques and metrics that should be employed in each particular case in order to standardize and assure fairness in machine learning models. For a definition on which metric should be used for each use case, more specific studies should be conducted under different architectures and sensitive attributes. This analysis would allow the context to define the most appropriate metric for identifying bias in protected groups, and whether the sensitive attribute can be a relevant element in defining the fairness metrics for a given context. It was observed that in a given dataset, the metrics do not present uniform results, pointing to different bias categories and their context-related particularities.

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