

Fairness and Bias Mitigation in Computer Vision: A Survey

Sepehr Dehdashtian*, Ruozhen He*, Yi Li, Guha Balakrishnan, Nuno Vasconcelos, *Fellow, IEEE*,
Vicente Ordonez, *Member, IEEE*, and Vishnu Naresh Boddeti *Member, IEEE*

Abstract—Computer vision systems have witnessed rapid progress over the past two decades due to multiple advances in the field. As these systems are increasingly being deployed in high-stakes real-world applications, there is a dire need to ensure that they do not propagate or amplify any discriminatory tendencies in historical or human-curated data or inadvertently learn biases from spurious correlations. This paper presents a comprehensive survey on fairness that summarizes and sheds light on ongoing trends and successes in the context of computer vision. The topics we discuss include 1) The origin and technical definitions of fairness drawn from the wider fair machine learning literature and adjacent disciplines. 2) Work that sought to discover and analyze biases in computer vision systems. 3) A summary of methods proposed to mitigate bias in computer vision systems in recent years. 4) A comprehensive summary of resources and datasets produced by researchers to measure, analyze, and mitigate bias and enhance fairness. 5) Discussion of the field's success, continuing trends in the context of multimodal foundation and generative models, and gaps that still need to be addressed. The presented characterization should help researchers understand the importance of identifying and mitigating bias in computer vision and the state of the field and identify potential directions for future research.

Index Terms—Computer Vision, Fairness, Bias Mitigation, Visual Recognition, Visual Representation Learning, Survey.

1 INTRODUCTION

THE field of computer vision has gone through several major advances throughout the years. The introduction of machine learning and statistical methods created a wave of interest and progress in visual recognition, e.g. [1, 2, 3], which eventually motivated much of the recent advances in deep learning methods using neural networks [4, 5, 6] and large-scale datasets [7, 8]. The rapid progress in the recognition problem also inspired a search for the right methods and models for a diverse array of other problems, such as U-Nets [9] for image segmentation or Latent Diffusion Models [10] for image synthesis.

Machine learning and statistical methods, however, rely on training datasets and loss functions that can induce, propagate, or magnify statistical biases. Such biases are undesirable when correlated to *sensitive protected attributes* such as demographic variables related to people, e.g. race, gender, age, or ethnicity. Models that learn the inherent correlations or rely on spurious correlations with these attributes can produce disparate outcomes, thereby leading to ethical or legal concerns [11, 12]. The goal of *fairness and bias mitigation* [13, 14] is to prevent or minimize the impact of such biases on model decisions.

* S. Dehdashtian and V. N. Boddeti are with the Department of Computer Science and Engineering at Michigan State University, East Lansing, Michigan. R. He and V. Ordonez are with the Department of Computer Science at Rice University, Houston, Texas. G. Balakrishnan is with the Department of Electrical and Computer Engineering at Rice University, Houston, Texas. Y. Li and N. Vasconcelos are with the Department of Electrical and Computer Engineering at the University of California, San Diego, California.

E-mail: sepehr, vishnu@msu.edu, vicenteor, catherine.he, guha@rice.edu, yil898, nuno@ucsd.edu

* Equal contribution

To make computer vision systems widely adopted, accepted, and trusted, it is necessary to avoid societal inequalities and enhance their reliability. This has motivated interest in issues of fairness and biases, intending to develop responsible visual recognition and related systems capable of serving society equitably. From early studies revealing biases in image captioning [15] or face recognition [16] to recent efforts in mitigating biases in various tasks [14, 17, 18, 19], there has been a significant body of work in studying fairness and proposing bias mitigation methods for computer vision. In this paper, we survey this literature and related problems solved by machine learning systems trained with large-scale datasets for applications where societal biases are relevant.

The survey first introduces the notation, origins, and definitions of fairness while summarizing the commonalities with fairness studies in the broader machine-learning literature. Then, we briefly discuss prior work on discovering and analyzing bias in computer vision datasets and models. We then present a synthesis of the proposed methodologies and datasets used to study bias and its mitigation. Finally, we discuss current trends in discovering and mitigating bias in multimodal foundation models and open problems in this field. The survey aims to serve as a quick reference and starting point for new research on adapting or designing novel methods to maximize the fairness of emerging computer vision models in a rapidly evolving space.

What makes the study of fairness in computer vision models distinct from those in other domains, such as tabular data and graphs? The general framework of fairness consists of quantifying the disparate outcomes from a model for groups belonging to different categories of a *sensitive protected attribute* and proposing methods to alleviate or mitigate these disparities. For instance, COMPAS [20], a

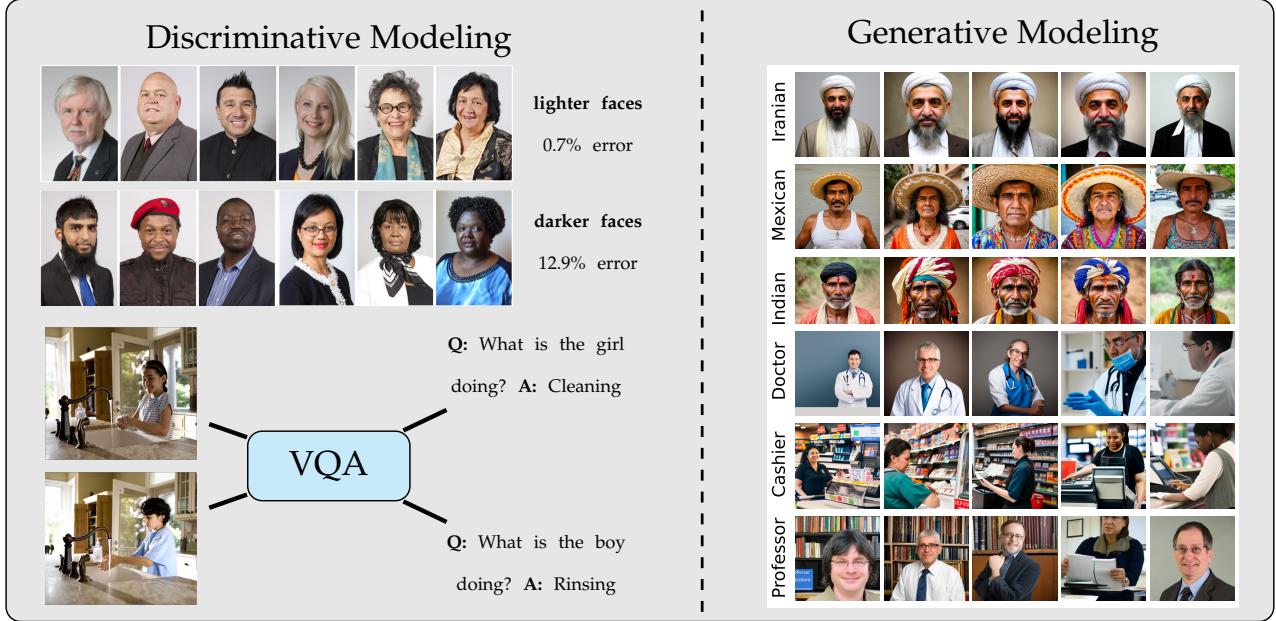


Fig. 1: Examples of Bias and Unfairness in discriminative and generative computer vision systems. **Left:** Bias in discriminative modeling shown through face recognition [16] and Situation Recognition [21, 27] examples. **Right:** Stereotypical bias in generative modeling with examples from three cultures and three professions [28].

commonly used tabular dataset to analyze fairness in machine learning, uses race as a sensitive protected attribute, which is included as a categorical variable. In contrast, computer vision datasets usually lack explicit categorical labels for sensitive attributes. Instead, these attributes are implicitly encoded in the combination of input image pixels and task-specific target attributes that are to be inferred by a model. For instance, in the absence of bias mitigation, a computer vision model trained to predict human activities from images, e.g. *cooking vs. not-cooking*, will likely predict the activities at disparate rates for images depicting people of different *gender* [21]. The challenge is to disentangle the effect of people’s appearance, which is typically correlated with gender, and the activities being performed. Since this is a difficult goal, bias mitigation in computer vision presents unique challenges that are not present in tabular datasets. This justifies a comprehensive survey of computer vision methods, with a brief review of the more general literature on fairness. For a comprehensive survey on fairness in machine learning, we refer the reader to Mehrabi et al. [22], Pessach and Shmueli [23], Le Quy et al. [24], Caton and Haas [25]. Perhaps more related and complementary to ours is the recent survey by Parraga et al. [26], which focuses on vision-and-language models. In contrast, our survey provides a more comprehensive summary of the fairness literature related to more traditional computer vision tasks such as image classification, object detection, activity recognition, and face recognition and analysis.

Another challenge in computer vision is the lack of access to explicit labels for *sensitive protected attributes*. Commonly, information for demographic variables such as gender, race, or ethnicity is not annotated or provided explicitly by the same individuals depicted in computer vision datasets. Therefore, most annotations on these datasets can only be considered as proxies for the real values based on the perceived judgments of data annotators. Moreover,

Scheuerman and Brubaker [29] argue that tech workers and scientists have also had a significant role in defining categories related to identity for people in computer vision datasets. As a result, demographic markers such as gender have only been studied as binary variables for previous works, and race is often studied as a set of discrete categories. Several works summarized in this survey acknowledge some of these issues, but the overall field should be judged in this context.

Beyond these issues, navigating the challenges of fairness and bias mitigation in computer vision is still a complex endeavor due to the nature of biases, the diversity of datasets and tasks, and trade-offs between model performance and fairness. This survey explores core computer vision tasks and identifies primary challenges associated with achieving fairness and mitigating biases for each task. Figure 1 illustrates the type of demographic bias and unfairness prevalent in computer vision systems. Tables 1 and 2 extensively summarize task-specific debiasing methods developed in the computer vision literature and the associated datasets employed for studying bias and fairness, respectively. A detailed overview of common methods for bias mitigation and a comprehensive discussion of the datasets categorized by bias attributes and tasks can be found in Section 4 and Section 5, respectively.

2 ORIGINS AND DEFINITIONS OF UNFAIRNESS

We start with a note on terminology. The term *bias* has been overloaded in the context of the study of fairness. A statistical bias simply refers to the degree to which a certain methodology provides a skewed representation of a true phenomenon. For instance, opinion surveys conducted only through the workplace overlook unemployed people and are thus not representative of the sentiment of the general population. In computer vision, biases can manifest

TABLE 1: **Methods:** Bias analysis and mitigation techniques by task and protected attributes. While task-specific bias mitigation methods have been proposed bias mitigation for generic visual representation learning received a lot of attention.

Task	Attribute	References
Representation Learning	Gender	Park et al. [30], Li et al. [31], Dehdashtian et al. [19], Dehdashtian et al. [14], Sadeghi et al. [32], Qraitem et al. [33], Jang and Wang [34], Wang and Russakovsky [35], Zhang et al. [36], Tang et al. [37], Meister et al. [38], Ranjit et al. [39], Jeon et al. [40], Park et al. [41], Wang et al. [42], Seo et al. [43], Chai and Wang [44], Zhu et al. [45], Tartaglione et al. [46], Ramaswamy et al. [47], Kim et al. [48], Wang and Russakovsky [49], Wang et al. [50], Wang et al. [51], Seth et al. [52], Hall et al. [53], Chuang et al. [54], Van Miltenburg [55]
	Color	Park et al. [30], Jang and Wang [34], Zhang et al. [36], Park et al. [41], Seo et al. [43], Zhu et al. [45], Wang et al. [56], Jung et al. [57], Tartaglione et al. [46], Kim et al. [48], Wang et al. [50], Li and Vasconcelos [58]
	Corruption	Park et al. [30], Zhang et al. [36]
	Age	Li et al. [31], Dehdashtian et al. [14], Sadeghi et al. [32], Qraitem et al. [33], Park et al. [41], Zhu et al. [45], Tartaglione et al. [46], Seth et al. [52], Chuang et al. [54]
	Race	Qraitem et al. [33], Dehdashtian et al. [19], Dehdashtian et al. [14], Sadeghi et al. [32], Wang and Russakovsky [35], Park et al. [41], Chai and Wang [44], Zhu et al. [45], Seth et al. [52], Chuang et al. [54], Van Miltenburg [55]
	Geography	Wang and Russakovsky [35], Shankar et al. [59], Wang et al. [60]
	Context	Zhang et al. [36], Wang et al. [56], Chuang et al. [54], Wang et al. [60]
	Scene	Mo et al. [61]
	Skin Tone	Schumann et al. [62]
Analysis	Texture	Wang et al. [56], Kim et al. [48]
	Action	Li and Vasconcelos [58]
Classification	Social	Sirotnik et al. [63], Birhane et al. [64], Brinkmann et al. [65]
	Gender	Meister et al. [38], Birhane et al. [64], Iofinova et al. [66], Guilbeault et al. [67]
Action Recognition	Gender	Kim et al. [68], Zietlow et al. [69], Bendekgey and Sudderth [70], Lee et al. [71], Jung et al. [72], Zhang et al. [73], Roy and Boddeti [74], Sadeghi et al. [75], Dehdashtian et al. [19], Sadeghi et al. [32], Dehdashtian et al. [14], Gustafson et al. [76]
	Age	Kim et al. [68], Sadeghi et al. [75], Dehdashtian et al. [19], Sadeghi et al. [32], Dehdashtian et al. [14], Gustafson et al. [76]
	Race	Lee et al. [71], Jung et al. [72], Dehdashtian et al. [19]
	Illumination	Roy and Boddeti [74], Sadeghi et al. [75]
	Hair Color	Dehdashtian et al. [14]
	Skin Tone	Gustafson et al. [76]
Face Recognition	Other	Singh et al. [77], Kim et al. [68], Chiu et al. [78], Jia et al. [79], Li and Xu [80]
	Scene	Choi et al. [81], Zhai et al. [82], Li et al. [17]
Generative Models	Contextual	Choi et al. [81]
	Gender	Buolamwini and Gebru [16], Vera-Rodriguez et al. [83] Quadrianto et al. [84], Domnich and Anbarjafari [85], Dhar et al. [86], Gong et al. [87], Ma et al. [88], Liang et al. [89], Dooley et al. [90], Chen and Joo [91], Chouldechova et al. [92], Terhörst et al. [93], Shankar et al. [59], Zietlow et al. [69], Georgopoulos et al. [94], Li and Abd-Almageed [95], Gong et al. [96]
	Race	Buolamwini and Gebru [16], Wang and Deng [97], Gong et al. [87], Ma et al. [88], Liang et al. [89], Dooley et al. [90], Chouldechova et al. [92], Terhörst et al. [93], Shankar et al. [59], Georgopoulos et al. [94], Gong et al. [96]
	Data Imbalance	Liu et al. [98], [93]
	Skin Tone	Balakrishnan et al. [99], Dhar et al. [86], Terhörst et al. [93], Georgopoulos et al. [94]
	Age, Hair & Facial Hair	Balakrishnan et al. [99], Terhörst et al. [93], Shankar et al. [59], Georgopoulos et al. [94], Gong et al. [96]
Object Detection	Other	Terhörst et al. [93]
	Race	Maluleke et al. [100], Tan et al. [101], Wu et al. [102]
Other	Data Imbalance	Yu et al. [103], Zhao et al. [104]
	Gender	Xu et al. [105], Tan et al. [101], Karakas et al. [106], Choi et al. [107], Wu et al. [102]
	Age	Tan et al. [101], Karakas et al. [106]
	Other	Jalal et al. [108], Wu et al. [102], Choi et al. [107], Kenfack et al. [109], Karakas et al. [106], Tan et al. [101]
	Income	Sudhakar et al. [110]
Other	Skin Tone	Wilson et al. [111]
	-	Kong et al. [112], Yenamandra et al. [113], Qiu et al. [114], Shankar et al. [59], Chu et al. [115], Garcia et al. [116], Biswas and Ji [117], Tang et al. [118]

TABLE 2: **Datasets:** Tasks, datasets, and sensitive protected attributes studied for bias quantification and mitigation. Next to each dataset, we reference either the original paper or the paper that adapted it specifically for bias analysis.

Task	Protected Attribute	Datasets
Basic Image Bias Analysis	Social Context ^S , Gender ^G , Age ^A , Background ^B	Social Context [119][63] ^S , MSCOCO [8][21][38] ^G , OpenImages [120] [38] ^{GA} , CelebA [121][66] ^G , IAT [122][67] ^G , Waterbird [123][113] ^B , NICO++ [124][113] ^B
Representation Learning	Geography ^P , Gender ^G , Color ^L , Background ^B , Age ^A , Ethnicity ^E , Context ^C , Texture ^X , Other ^O	ImageNet [7] [59] ^P , Open Images [120] [59] ^P , MSCOCO [8] [21] [51] ^G , CIFAR-10S [125] [50] ^L , Corrupted CIFAR10 [125] [126] [48] ^O , BAR [127] [48] ^B , bFFHQ [128] [48] ^G , IMDB Face [129] [68] [46] ^{GA} , CelebA [121] [127] [46] ^G , UTKFace [130] [84] ^E , NICO [131] [56] ^C , ImageNet-A [56, 132] ^{LX} , mPower [68] [45] ^A , Adult [133] [45] ^{GRO} , LFW [134] [42] ^G , DollarStreet [135] [35] ^P , GeoDE [136] [35] ^P , MST [62] ^T , PATA [52] ^C , VisoGender [53] ^G
Image Classification	Color ^L , Age ^A , Gender ^G , Context ^C , Ethnicity ^E , Background ^B , Social Context ^S , Other ^O	Colored MNIST [137] [68] ^L , Dogs and Cats [138] [68] ^L , IMDB Face [139] [68] ^{AG} , MSCOCO-Stuff [140] [77] ^C , UnRel [141] [77] ^C , Deep Fashion [142] [77] ^C , AwA [143] [77] ^C , CelebA [121] [80] ^{GEAO} , Faces of the World [144] [70] ^G , UTKFace [130][72] ^{EG} , COMPAS [145] [72] ^{EG} , CIFAR-10-B [125][78][78] ^B , CIFAR-100-B [125][78][78] ^B , Extended Yale B [146] [74] ^{GL} , Waterbird [123] [19] ^B , CFD [147] [19] ^G , FairFace [148] [19] ^S
Action Recognition	Background ^B	UCF-101 [149] [81] ^B , HMDB-51 [150] [81] ^B , Diving48 [151] [81] ^B , THUMOS-14 [152] [81] ^B , JHMDB [153] [81] ^B , MiTv2 [154] [82] ^B , SCUBA [17] ^B , SCUFO [17] ^B
Face Recognition and Analysis	Gender ^G , Race ^R , Age ^A , Skin Tone ^T , Other ^O	PPB [16][99] ^{GR} , IJB-A [155][16] ^{GR} , Adience [156][16] ^{GR} , DiF [157][84] ^G , Adult [133][45] ^G , LFW[134][98] ^O , YTF[158][98] ^O , MegaFace[159][98] ^O , Transect[99] ^{GTAO} , IJB-C[160] ^{GT} , RFW [161] ^{GR} , MFR [162][88] ^R , IJB-B [163][88] ^G , DigiFace-1M [164][88] ^O , VGGFace2 [165][90] ^{GR} , KDEF [166][91] ^G , CFD [147][19] ^{GR} , ExpW [167][91] ^G , RAF-DB [168][91] ^G , AffectNet [169][91] ^G , CausalFaces [89] ^{GR} , MORPH [170][94] ^{GRA} , MAAD-Face (47 attributes) [171][93], FairFace [148] ^{GRA} , CelebA [69, 121][84] ^G , CACD [172][94] ^{GA} , KANFace [173][94] ^{GA} , UTKFace [130][72] ^{GAT} , MS1MV2 [174, 175][176] ^O , MS-Celeb-1M [96, 174] ^{GR} , CFP-FP[177][176]
Image Retrieval	Gender ^G	Occupation 1 [178][112] ^G , Occupation 2 [179][112] ^G , MSCOCO [8][112] ^G , Flickr30k [180][112] ^G
Object Detection	Skin Tone ^T , Income ^I	BDD100K [181][111] ^{TI}
Person Reidentification	Clothing ^H	PRCC-ReID [182][18] ^H , LTCC-ReID [183][18] ^H
Image Captioning	Gender ^G , Race ^R	MSCOCO-Bias [15] ^G , MSCOCO-Balanced [15] ^G , MSCOCO [8][184] ^{GR}
Image Question Answering	Language ^N , Context ^C , Gender ^G , Race ^R	VQA [185][186] ^N , MSCOCO [8][186] ^N , VQA-CP-v2 [187][188] ^N , VQA-v2 [189][188] ^{NC} , VQA-Gender [190][190] ^G , VQA-introspect [191] ^C , IV-VQA [192] ^C , CV-VQA [192] ^C , VQA-CP [187] ^L , GQA-OOD [193] ^L , VQA-CE [194] ^L , Visual7W [195] ^{RG} , OK-VQA [196] ^G
Scene Graph Generation	Composition ^M	VG [197][198] ^M , MSCOCO [8][118] ^M
Text-to-Image Synthesis	Gender ^G , Skin Tone ^T	CelebA [121][199] ^G , FAIR [200][199] ^T , FairFace [148][100] ^{GR}

in multiple ways. For example, Torralba and Efros [201] studied bias in early visual recognition models, showing that training on a particular dataset did not generalize well to others. Classifiers trained on one dataset were skewed to produce satisfactory results only for images resembling those in that dataset. In this case, the bias is w.r.t. the *dataset* variable. Ideally, a classifier trained on a combination of several datasets should perform well across test splits for all datasets. In the context of action recognition, Li et al. [151] showed that datasets frequently have clues, such as objects, backgrounds, etc., that enable good recognition performance by video representations that only account for a single or a few video frames. In this case, the bias is w.r.t. the *representation* variable. Various datasets [151, 202] have since been introduced to combat this problem by requiring the classification of fine-grained actions, distinguishable only by long-term motion patterns. We will refer to methods proposed to correct biases as *mitigation* techniques, which

are also often referred to as *debiasing* techniques.

References to fairness and mitigating biases in machine learning models are often used interchangeably when bias mitigation targets a *sensitive protected attribute*. Typical examples of this type of attribute in computer vision include sensitive demographic variables such as the gender, race/ethnicity, age, and skin tone of people depicted in images. For instance, the work of Buolamwini and Gebru [16] showed disparities in the success rate of a gender classifier depending on the skin tone of the depicted individuals. However, depending on the context, other variables, such as geographical location, could be considered sensitive protected attributes. For instance, Shankar et al. [59] uses geo-location as a protected attribute to study disparities in the performance of visual recognition models for images obtained from different parts of the world. Our survey aims to cover bias analysis, and mitigation works that deal with sensitive protected attributes to improve the fairness

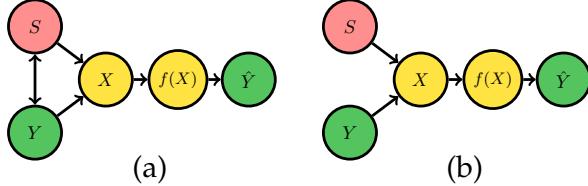


Fig. 2: Dependence graphs [19] illustrating how biases from (a) inherent relations and (b) spurious correlations arise.

of computer vision model predictions. However, we also consider work that uses synthetic or simulated protected attributes introduced to study fairness. For instance, Wang et al. [50] proposes a variant of the CIFAR-10 dataset where a percentage of images were converted to grayscale and uses *coloring* as a protected attribute. Similarly, we also consider work that proposes bias mitigation techniques where the protected attributes are contextual cues from language or image backgrounds that should be irrelevant to the intended task. For instance, Choi et al. [81] uses the background scene of a video as a protected attribute for the action recognition task. A well-behaved action recognition model should detect an action regardless of the background scene in which it takes place. We also acknowledge that there is significant work outside the scope of this survey that might share a similar methodology but whose main goal is to improve privacy, transparency, or accountability.

The rest of this section discusses two important aspects of fairness. In Section 2.1, we discuss factors that contribute to biases in current computer vision models. In Section 2.2, we discuss criteria used in the literature to define fairness across sensitive protected attributes.

2.1 Bias Origins

It is well documented that multiple machine learning and computer vision models have exhibited biases w.r.t. *sensitive protected attributes* in various contexts and applications e.g., gender or skin tone [14, 64, 203, 204, 205] and even non-demographic attributes e.g., image background or illumination [206, 207]. These biases are a manifestation of both *social* and *machine learning* biases, with the former largely arising from the training data on which the models are trained.

From a *social perspective*, the world is frequently biased; for example, expensive cars are more common in affluent than poor neighborhoods. These biases can be amplified by the publication of data on the internet, where most of the large public datasets are collected, e.g., expensive car manufacturers or owners tend to post images of the cars against landmarks or beautiful scenery. As a result, biases found in trained models are largely inherited from the data used to train them, which studies have shown to exhibit similar biases [21, 51, 208, 209]. Datasets can also amplify biases due to data collection practices, e.g., data collection predominantly in some countries or continents [210, 211, 212]. Ultimately, the biases in the data are either inherited from human biases as reflected on the Internet or the methodology used to collect and annotate it.

From a *machine learning perspective*, biases can be understood based on dependencies between data attributes, as illustrated in Fig. 2. The data X (e.g., face images) depends both on the target attribute Y (e.g., identity) and a sensitive

attribute S (e.g., skin tone) that induces bias. The goal of bias mitigation is to ensure that the prediction \hat{Y} is statistically independent of S . The biases can be grouped into those arising from two scenarios: (1) Y and S are inherently dependent (fig. 2a). We refer to this type of correlation as *intrinsic dependence*. (2) Y and S are independent (fig. 2 b). In this case, we refer to any observed correlation as a *spurious correlation*. In the latter case, we expect a bias-free model's performance w.r.t. Y to be independent of S . However, the same is not so in the former case, where there will necessarily be a trade-off between performance and fairness.

Beyond the biases in the dataset, model design choices such as the objective function optimized during training, the sampling process used during training [58], neural network architecture, etc., also have an influence on biases in the model predictions. These choices can either amplify or mitigate the biases in the training data. This is evidenced in the fact that models trained from the same biased training data can be made more or less biased by bias mitigation strategies [15, 21, 50, 51].

To understand the *impacts* of biases, it helps to separate *demographic biases* from *non-demographic biases*. Demographic biases occur when models behave differently for different demographic groups. These groups can be defined in many ways and are usually specified by a protected attribute, such as *gender*, *race*, or *age*, among several others. Ideally, we expect the task performance of a bias-free model to be independent of such attributes. This reflects the goal of producing computer vision systems that are fair, inclusive, and equitable across segments of the world population. For example, the face recognition system of Fig. 1 should not be more accurate for lighter than darker faces. Non-demographic biases are not related to such demographic issues. For example, a person re-identification system can perform very effectively on certain datasets by simply matching clothing. However, this is only an illusion of good performance, as such systems will not be able to match people across images collected on different days. In this case, biases are spurious correlations that the computer vision systems learn to solve the task. These biases are not necessarily w.r.t. a known attribute, even though such attributes can be identified for many tasks, e.g. the *clothing* attribute for re-identification, or the *scene* and *context* attributes for all recognition problems. Demographic and non-demographic biases are quite similar in the sense that they tend to originate from dataset or model biases and can be mitigated by similar algorithms. Hence, in what follows, we cover the two types of biases without much differentiation.

2.2 Fairness Definitions

Multiple definitions of fairness [213] have originated from social studies. Next, we describe the primary definitions of fairness in the computer vision literature.

2.2.1 Individual Fairness

Individual fairness seeks to “treat similar individuals similarly” [214]. One of the first attempts to formulate this objective was made by [215], where Lipschitz conditions were employed. According to this condition, a *small distance*

in feature space must translate to a small change in the model’s decision. The objective is defined as

$$\text{dist}(\hat{y}_i, \hat{y}_j) < L \cdot \text{dist}(z_i, z_j) \quad (1)$$

where \hat{y}_i and \hat{y}_j are decisions of the model, $z_i = f(x_i)$ and $z_j = f(z_j)$ are features of sample i and j , respectively, and L is the Lipschitz constant.

2.2.2 Group Fairness

Group fairness requires the model’s decisions to be independent or conditionally independent of a sensitive (group) attribute. For example, university admissions’ approval or rejection decisions must be independent of the applicant’s *gender*. In this example, the sensitive (group) attribute is *gender*. There are three main definitions of group fairness: Demographic Parity (DP), Equal Opportunity (EO), and Equality of Odds (EOO). DP is defined as

$$P(\hat{Y} = y|S = s) = P(\hat{Y} = y|S = s') \quad \forall s, s' \in S, \forall y \in Y \quad (2)$$

The university admissions example requires that the acceptance probability be equal for all genders. Although DP is a popular fairness definition, some studies [14, 216] have argued that it is not practically relevant since it does not consider the true target label Y for the decision. This problem is addressed by the other two definitions.

Equal opportunity (EO) is defined as

$$P(\hat{Y} = y|Y = y, S = s) = P(\hat{Y} = y|Y = y, S = s') \quad \forall s, s' \in S, \forall y \in Y \quad (3)$$

In the university example, EO requires that the acceptance probability must be equal for all *eligible* applicants from different sensitive groups. Finally, equality of odds (EOO) requires equal probability for mistakenly classifying accepted applicants from different sensitive groups as accepted applicants. It is formally defined as,

$$P(\hat{Y} = y_1|Y = y_2, S = s) = P(\hat{Y} = y_1|Y = y_2, S = s') \quad \forall s, s' \in S, \forall y_1, y_2 \in Y \quad (4)$$

2.2.3 Counterfactual Fairness

Counterfactual fairness, defined by Kusner et al. [217], requires identical decision probabilities for a sample and its counterfactual counterpart. It requires intervention on sensitive attributes to not change the distribution of the model’s decision [218]. It is formally defined as,

$$P(\hat{Y}_{S \leftarrow s}(U) = y|X = x, S = s) = P(\hat{Y}_{S \leftarrow s'}(U) = y|X = x, S = s) \quad \forall s, s' \in S \quad (5)$$

where U is an unobserved variable in the causal graph (fig. 2). In the university’s admission example, if the model accepts a *male* applicant, it should make the same decision if the applicant were *female*, assuming all other attributes are adjusted accordingly. Note that counterfactual samples are not created merely by changing the sensitive attribute; instead, they are generated by considering the changes in other attributes that result from the alteration of the sensitive attribute due to causal relationships between them.

2.2.4 Bias Amplification

Another phenomenon studied in bias quantification is the exacerbation of biases beyond those present in the dataset during model training. This is usually called *bias amplification* [21, 49]. It is understood as the difference in the biases exhibited by a trained machine learning model relative to the biases present in the data used to train such a model. This term, first used in Zhao et al. [21] for the task of situation recognition, has been used to provide a notion of bias that does not depend on any pre-existing notion of fairness w.r.t. parity. Reducing bias amplification in a model is equivalent to reducing the biases only to the extent to which they are already present in the training set. For instance, a model that predicts a label at disparate rates for people of different genders will only be considered to suffer from bias amplification if the rates are different from those present in the training data. Wang and Russakovsky [49] define the notion of *directional bias amplification*, which further refines the bias amplification measure by accounting for varying base rates of the protected attributes.

3 BIAS DISCOVERY AND ANALYSIS

This section discusses a series of works that discover or analyze biases in computer vision datasets and models. The goal is to identify inherent biases that threaten fairness and generalization. Uncovering such biases raises awareness of potential limitations and biases in computer vision systems and helps guide future work to develop more equitable and robust computer vision systems.

3.1 Biases in Datasets

Dataset biases can propagate to computer vision models or get amplified by the models, thereby influencing their fairness and performance. We review studies that analyze biases in commonly used datasets.

Meister et al. [38] delve into gender biases in large-scale visual datasets, exploring how gender information can be removed from datasets and how visual cues, or “gender artifacts”, influence model predictions. Guilbeault et al. [67] compare gender biases in images and text across massive online corpora, revealing how visual content may amplify gender biases more than textual content. Shankar et al. [59] investigate the geographical diversity of large datasets such as ImageNet [219] and Open Images [120], revealing noticeable Amerocentric and Eurocentric biases that affect model performance across different global regions. In the context of facial image datasets Chen and Joo [91] found that significant gender biases were introduced in the annotations, especially related to facial expressions. More recently, in the context of foundation models, Birhane et al. [204, 205] examined the presence of hate content in the text annotations of LAION [220], a large-scale dataset commonly used for training vision-language models. They found significant levels of hate content which increased by 12.26% when scaling from LAION-400M to LAION-2B.

3.2 Biases in Models

Biases in computer vision models can impact their performance and fairness, especially when these models are

deployed in the real world. Numerous studies sought to identify the presence and impact of biases in different types of learning methods and pretrained models across a diverse set of visual recognition tasks.

In their pioneering work, Buolamwini and Gebru [16] evaluated and uncovered gender and skin-tone biases in many commercial face recognition systems and highlighted serious implications for high-stakes contexts such as health-care and law enforcement. Domnich and Anbarjafari [85] investigated bias w.r.t. gender in various facial expression recognition models, assessing and identifying which architectures and emotions are more influenced by gender.

Sirokin et al. [63] investigated the origins and impact of social biases in self-supervised learning (SSL) methods, revealing the correlations between the different SSL algorithms and the number of inherent biases. Iofinova et al. [66] examine how model compression algorithms like pruning induce or exacerbate biases, particularly affecting marginalized groups by increasing systematic and category biases under high sparsity levels. Analysis on vision transformers [65] measured factors contributing to social biases by investigating training data, objectives, and architectures. Wilson et al. [111] explore the performance disparities of object detection models in autonomous driving, explicitly revealing poorer detection rates for pedestrians with Fitzpatrick skin types 4 to 6, and investigate contributing factors such as training set composition, measurement issues, and the impact of loss function prioritization.

A few studies proposed approaches to audit computer vision models for potential biases. Ranjit et al. [39] propose a framework to audit and analyze pretrained visual recognition models for biases w.r.t. sensitive visual attributes, evaluating how these biases change after fine-tuning. Studies on biases of pretrained models on downstream tasks show that such models can inherit biases related to spurious correlations and underrepresentation, but these biases can be mitigated by carefully curating the finetuning dataset [35]. Similarly, Birhane et al. [64] found that transformer-based CLIP models inherited racial biases prevalent in the LAION dataset on which they were trained.

Concurrently, Sadeghi et al. [32] and Dehdashtian et al. [14] defined and estimated the near-optimal trade-offs between model performance (accuracy of predicting target attributes) and different group fairness definitions. These trade-offs were utilized to evaluate (a) more than 100 pretrained CLIP models from OpenCLIP [221], (b) more than 900 pre-trained image models from Pytorch Image Models [222], and (c) existing fair representation methods on CelebA and FairFace datasets. The results (shown in Fig.4) revealed that, out of the box, pre-trained models were far from the best achievable limits of performance and fairness, thus identifying the significant limitations of existing computer vision models and the dire need for further research to make computer vision systems more socially responsible and equitable. Furthermore, such an evaluation can also help the community identify trends and pre-trained models that best suit their specific task and dataset.

3.3 Biases Beyond Demographic Attributes

Various forms of biases beyond demographic attributes have also been studied in computer vision datasets and

models. Torralba and Efros [201] first introduce the notion of *dataset bias*, and identify the distribution gaps between different vision datasets w.r.t. viewpoints, styles, and scenes. Geirhos et al. [223] discover and analyze the *texture bias* in CNN object classifiers, finding the models more sensitive to local textures while overlooking object shapes. Li et al. [151] study the *representation bias* in action recognition datasets, in which action labels are implied through scenes and background objects. Zhang et al. [224] investigate *unimodal bias* in VQA datasets and show that many visual questions can be answered correctly by using language prior alone.

These studies pave the way for the collection of new, bias-controlled datasets [151, 187, 223], either to evaluate the models under an unbiased setting or as training data to remedy model bias. They also offer insights into how vision models inherit biases from the data, and as discussed next leading to various mitigation methods for training models less susceptible to biases [14, 19, 32, 75, 81, 225, 226, 227].

4 BIAS MITIGATION METHODS

This section summarizes common approaches to mitigate bias across various tasks. Each subsection is dedicated to a specific category of algorithms, detailing their applications. By organizing the algorithms this way, we aim to provide a clear understanding of bias mitigation in computer vision.

4.1 Fairness through Unawareness

A naive approach to fairness is to withdraw sensitive protected attributes from data or to avoid those protected attributes as input to the machine learning model. This is often referred to as fairness through *blindness* or fairness through unawareness. It has been well documented in the machine learning literature that this approach is frequently ineffective. As discussed above, correlations between sensitive protected attributes and other attributes can still lead to biases in model predictions, e.g., zip codes being informative of race in the case of credit scoring systems.

In computer vision, fairness through unawareness could be attempted by blurring people's faces or removing people entirely from images. Such an approach parallels the drawbacks observed in the machine learning literature. For instance, background pixels that are not blurred or obscured may correlate highly with sensitive attributes, e.g. men more commonly wear ties and women more commonly wear dresses, so clothing will correlate highly with gender. Another drawback is that for many vision tasks, such as human activity recognition, the visual features of people are essential to accomplish the task accurately. Hence, blurring or obscuring people interferes with this goal. Wang et al. [51] used fairness through unawareness as a baseline and demonstrated that adversarial bias mitigation by explicitly modeling the sensitive attribute leads to better outcomes.

4.2 Fair Representation Learning

Over the last decade, several approaches have been developed for learning fair image representations (see Figure 3 for an illustration). These approaches follow the template of adopting a fairness constraint (e.g., $Z \perp\!\!\!\perp S$ for demographic parity or $Z \perp\!\!\!\perp S|Y = y$ for Equality of Odds) as a

TABLE 3: Bias analysis and mitigation for vision and language models

Task	Attribute	References
Image Captioning	Gender	Burns et al. [228], Bhargava and Forsyth [184], Hirota et al. [229]
	Race	Zhao et al. [230]
	Social	Hirota et al. [231]
Text-to-Image Synthesis	Gender	Esposito et al. [232], Friedrich et al. [233], He et al. [234], Luccioni et al. [235], Cho et al. [236]
	Race	Esposito et al. [232], Friedrich et al. [233], Bansal et al. [237], He et al. [234], Luccioni et al. [235]
	Adjective	Luccioni et al. [235]
	Profession	Wang et al. [238], Luccioni et al. [235], Cho et al. [236]
	General	Chinchure et al. [239], Zhang et al. [199]
	Stereotype	Bianchi et al. [28]
	Pose	Ruiz et al. [240]
	Culture	Liu et al. [241]
	Geography	Basu et al. [242]
Question Answering	Skin Tone	Cho et al. [236]
	Language	Manjunatha et al. [186], Kv and Mittal [188], Niu et al. [243], Kervadec et al. [193], Dancette et al. [194], Wen et al. [244], Cho et al. [245], Basu et al. [246]
	Gender	Park et al. [190], Hirota et al. [198]
	Visual Context	Selvaraju et al. [191]
	Correlations	Agarwal et al. [192], Gupta et al. [247]
CLIP De-biasing	Race	Hirota et al. [198]
	Gender	Dehdashtian et al. [19], Seth et al. [52], Chuang et al. [54], Berg et al. [248], Alabdulmohsin et al. [249]
	Race	Dehdashtian et al. [19], Berg et al. [248], Chuang et al. [54], Seth et al. [52]
Other	Background	Dehdashtian et al. [19], Chuang et al. [54], Phan et al. [250]
	-	Kong et al. [112], Yenamandra et al. [113], Qiu et al. [114], Shankar et al. [59], Chu et al. [115], Garcia et al. [116], Biswas and Ji [117], Tang et al. [118], Cui et al. [251]

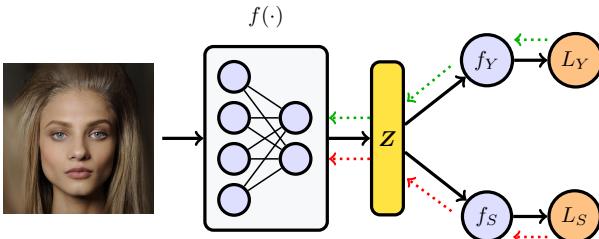


Fig. 3: **Fair Representation Learning.** An encoder $f(\cdot)$ maps images to a representation Z . A target branch maximizes the statistical dependence between Z and Y , while a fairness branch minimizes the statistical dependence between Z and the protected attribute S . Methods in this class differ in the choice of loss functions L_Y , L_S , models for f_Y and f_S , and learning (iterative vs closed-form, local vs global optima).

regularizer in addition to the objective for the target task. The approaches differ in two respects: (a) the choice of measure as a proxy for quantifying the statistical dependence corresponding to $Z \perp\!\!\!\perp S$ and $Z \perp\!\!\!\perp S|Y = y$, and (b) the associated optimization technique.

From a *proxy dependence measure* perspective, existing approaches either measure (i) the degree of linear dependence between Y and Z , (ii) the degree of mean dependence, i.e., $\mathbb{E}(Z) \perp\!\!\!\perp S$ or matching only the first moment of the distribution, or (iii) the degree of full statistical dependence, i.e., matching all moments of the distribution. Adversarial representation learning (ARL) [51, 74, 252, 253, 254] adopts neural network-based classifiers or regressors as a

proxy measure of statistical dependence between Z and S , which is equivalent to mean dependence [255] only. State-of-the-art approaches [14, 19, 32, 84], however, adopt non-parametric independence measures like the Hilbert-Schmidt Independence Criterion (HSIC) [256] and its variants [32], which measures full statistical dependence and can enforce independence-based fairness constraints more effectively.

From an *optimization* perspective, solutions have either adopted iterative approaches like two-player zero-sum min-max optimization for ARL [253] that converge to local optima or closed-form solvers [32, 75] that lead to global optima of the underlying optimization. Due to the inherent instability of zero-sum min-max optimization, several variants of ARL have been proposed. Roy and Boddeti [74] proposed a non-zero-sum variant of ARL to improve the convergence properties of the ARL optimization. Sadeghi et al. [75] studied ARL from an optimization perspective and obtained a closed-form solution that affords global optima of the ARL optimization through spectral learning and provided theoretical guarantees for achieving utility and fairness. Sadeghi et al. [257] used a kernel ridge regressor to model the adversary and backpropagated through its closed-form solution, resulting in stable optimization and improved performance utility-fairness trade-off. Sadeghi et al. [32] proposed a non-parametric dependence measure to capture all non-linear statistical dependencies and obtained a global optimum of the underlying optimization problem through a closed-form solution, thus obtaining provably near-optimal utility-fairness trade-offs.

A majority of the debiasing methods in computer vision are based on ARL. For instance, cross-sample adversarial debiasing (CSAD) disentangles target and bias features to prevent biased decision-making [45]. The Causal Attention Module (CaaM) employs an adversarial minimax fashion to disentangle and optimize complementary attention mechanisms [56]. The Lottery Ticket Hypothesis is adopted to find fair and accurate subnetworks without weight training, leveraging fairness regularization and adversarial training for bias mitigation [37]. Furthermore, fairness-aware adversarial perturbation (FAAP) modifies input data to conceal fairness-related features from deployed models without adjusting the model parameters or structures [42]. FAIRRE-PROGRAM introduces fairness triggers appended to inputs, optimizing them under a min-max formulation with an adversarial loss to obscure demographic biases [73].

In face recognition, adversarial learning reduces the encoding of sensitive attributes in face representations. For instance, adversarial learning frameworks can disentangle demographic information from identity representations, reducing bias in face recognition and demographic attribute estimation [96]. The Protected Attribute Suppression System (PASS) employs a discriminator to prevent networks from embedding protected attribute information, thereby mitigating gender and skin tone biases without end-to-end training [86]. Techniques using the Hilbert-Schmidt independence criterion transform input data into fair representations that maintain semantic meaning while ensuring statistical independence from protected characteristics [98]. For generative models, adversarial methods harmonize adversarial training with reconstructive generation to improve data coverage and include minority groups more effectively [103]. Lastly, unknown biased attributes in classifiers can be identified by optimizing a hyperplane in a generative model’s latent space using total variation loss and orthogonalization penalty [80].

4.3 Accuracy-Unfairness Trade-Offs

In scenarios where the target attribute Y and the sensitive attribute S exhibit considerable statistical dependency, the objectives of learning a fair representation—specifically, removing information related to S while retaining information pertinent to Y —are in conflict. This conflict impacts the performance of these objectives. Consequently, a trade-off exists between the retention of Y -related information and the removal of S -related information. This trade-off can be observed through the accuracy, MSE loss, F1 score, etc., of predicting Y and the fairness of the decisions made by the model. We generally use the word *utility* to refer to the model’s performance in retaining Y -related information.

The existence of a utility-fairness trade-off has been well established both theoretically [32, 258, 259, 260] and empirically [14, 32]. Sadeghi et al. [32] characterize the near-optimal trade-off for multidimensional continuous/discrete attributes using a closed-form solution on the extracted features from a frozen feature extractor. Additionally, Dehdashtian et al. [14] define two trade-offs: the Data Space Trade-Off (DST) and the Label Space Trade-Off (LST). These trade-offs capture the intrinsic relationship between the Y and S labels independently of the samples. They achieve this by

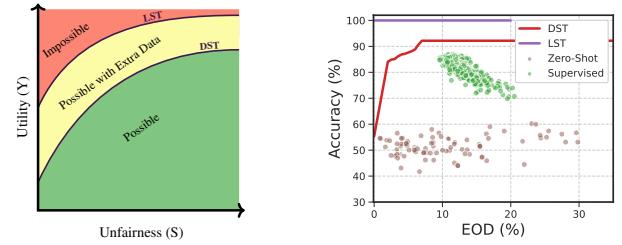


Fig. 4: **The utility-fairness trade-offs.**[14] (Left) Models can be evaluated by their utility (e.g., accuracy, MSE loss, F1 score, etc.) w.r.t. a target label Y and their unfairness w.r.t. a sensitive attribute S . Dehdashtian et al. [14] introduce two trade-offs, *Data Space Trade-Off* (DST) and *Label Space Trade-Off* (LST). (Right) Dehdashtian et al. [14] empirically estimate DST and LST on CelebA and evaluate the utility (high cheekbones) and fairness (gender & age) of over 100 zero-shot and 900 supervised image models.

employing a trainable feature extractor alongside a closed-form solution for the fair encoder. Although these studies focus on estimating trade-offs, the methods proposed can also serve as state-of-the-art bias mitigation techniques, as they identify and operate within the best achievable regions.

Estimating these trade-offs can be beneficial in several ways [14]: (1) they provide users with more information to make informed decisions when choosing a pre-trained model, and (2) they illustrate the extent to which fine-tuning can improve the utility or fairness of the model. Figure 4 illustrates the plausible trade-offs, their empirical estimation on CelebA [121], and their utility in empirically evaluating representations from pre-trained models.

4.4 Counterfactual Data Rebalancing

Counterfactual data rebalancing addresses bias by generating or reweighting data to create balanced representations of different groups. Several approaches have been proposed to operationalize this conceptual idea. In image classification, GAN-based data augmentation has been combined with adaptive sampling for disadvantaged group accuracy enhancement [69]. FlowAug employs flow-based generative models to create semantically augmented images, reducing subgroup performance discrepancies by addressing spurious correlations [78]. The Confidence-based Group Label assignment (CGL) method assigns pseudo group labels to unlabeled samples based on prediction confidence [72].

In face recognition, methods like INV-REG self-annotate demographic attributes and impose invariant regularization during training to learn causal features robust across diverse demographic groups [88]. StyleGANs transfer multiple demographic attributes simultaneously, enhancing dataset diversity and mitigating bias in face recognition systems [94]. It is also possible to generate synthetic images to supplement imbalanced datasets, creating a semi-synthetic balanced dataset to improve fairness in facial attribute and gender classification tasks [95].

In semantic segmentation, randomly dropping class-specific feature maps disentangles class representations and mitigates dataset biases [115]. In image captioning, a Debiasing Caption Generator (DCG) has been proposed to correct gender-biased captions, forming a model-agnostic

debiasing framework [229]. In action recognition, StillMix mitigates background and foreground static bias by mixing bias-inducing frames with training videos [17]. Person Re-identification methods introduce causal inference to eliminate clothing bias from identity representation learning [18].

In scene graph generation, counterfactual causality isolates and removes the effects of context bias [118]. In federated learning, Bias-Eliminating Augmenters (BEA) at each client generate bias-conflicting samples, thereby mitigating local data biases during distributed training [261]. For bias discovery, model reliance on spurious correlations is amplified to segregate bias-conflicting samples, which are then identified and mitigated through a slicing strategy [113].

In representation learning, biases can be mitigated through resampling, penalizing examples that are easily classified by a specific feature representation, and reweighting the dataset through a minimax optimization problem [58]. Methods like BiaSwap create balanced datasets through an unsupervised image translation-based augmentation framework that identifies and swaps bias-relevant regions in images [48]. Some methods use GANs to generate images with altered combinations of target and protected attributes to decorrelate them [47]. Creating bias-reducing positive and negative sample pairs from a self-supervised object localization method can also mitigate scene bias [61]. A fair contrastive learning method uses gradient-based reweighting to learn fair representations without demographic information by incorporating a small labeled set into the self-supervised training process [44]. Other methods identify bias pseudo-attributes via clustering and reweight these clusters based on their size and task-specific accuracy to improve worst-group generalization [43]. Some approaches identify intermediate attribute samples near decision boundaries and use them for conditional attribute interpolation to learn debiased representations [36]. Class-conditioned sampling mitigates bias by creating multiple balanced dataset variants, each with a subsampled distribution that mimics the bias distribution of the target class [33]. The Debiased Contrastive Weight Pruning (DCWP) method identifies bias-conflicting samples and uses them to train a pruned neural network [30].

4.5 Score Calibration and Loss Regularization

Score calibration adjusts the decision thresholds or prediction scores of models to ensure fair outcomes across different demographic groups. In image classification, score calibration can mitigate contextual bias by minimizing overlap in class activation maps and learning uncorrelated feature representations to ensure accurate recognition of both in and out of typical category contexts [77]. Some methods propose fairness surrogates to optimize constraints in network training [70], while others address spurious correlations and intrinsic dependencies with non-parametric measures of statistical dependence [19]. U-FaTE [14] quantifies utility-fairness trade-offs by optimizing a weighted combination of statistical dependence measures to evaluate and improve the fairness of pre-trained models.

In face recognition, a fair loss with an adaptive margin strategy optimized via reinforcement learning has been proposed to address class imbalance [98]. The Group

Adaptive Classifier (GAC) uses adaptive convolution kernels and channel-wise attention maps to learn general and demographic-specific patterns and reduce demographic bias in face recognition [87].

An Equalizer Model with two complementary losses has been proposed for image captioning to leverage gender-specific visual evidence and generate gender-neutral words when uncertain [15]. To achieve equal representation in the image retrieval task, a test-time post-processing algorithm creates fair retrieval subsets by using predicted gender or race attributes from the classifier or zero-shot inference [112]. For Bayesian networks, posterior inference can combine within-triplet priors with uncertain evidence to mitigate long-tailed bias [117]. In continual learning, task-induced bias can be mitigated using causal interventions with attention mechanisms that transform biased features into unbiased features [114].

In representation learning, a regularization strategy entangles features from the same target class and disentangles biased features [46]. Fairness-aware feature distillation improves fairness using maximum mean discrepancy to align the distributions of group-conditioned features from a student model with the group-averaged features of a teacher model [57]. A fair contrastive loss and a group-wise normalization are proposed in [41] to prevent the inclusion of sensitive attribute information and balance loss based on group cardinality, respectively. Leveraging hierarchical features and orthogonal regularization has also been shown to mitigate unknown biases [40].

5 DATASETS

In this section, we summarize various datasets used in fairness-related tasks in computer vision along with their corresponding sensitive attributes. The tasks and their datasets are listed in Table 1. The tasks range from action recognition and text-to-image to face recognition and classification. We also discuss datasets used in multiple tasks, those specialized for a single task, and the attributes investigated most and least.

5.1 Diversity of Datasets and Attributes

Some datasets in the table are used across multiple fairness-related computer vision tasks. For instance, MSCOCO [8] and its variants [15, 140] are used in bias analysis and evaluation of fairness in the context of classification, image captioning, image retrieval, scene graph generation, and VQA. Similarly, CelebA [121] is extensively used in evaluating and mitigating bias for classification, face recognition, and text-to-image tasks, emphasizing the need to address biases in gender, ethnicity, and age. UTKFace [130] is employed in fairness in classification, face recognition, and representation learning for investigating and mitigating biases related to *age*, *gender*, *ethnicity*, and *skin tone*. OpenImages [120] is also used in both bias analysis and representation learning with a focus on *gender* and *geography* biases. The repeated use of these datasets underscores their importance and highlights their value in providing diverse annotations for evaluating and mitigating bias across computer vision tasks.

It is evident from analyzing Table 2 that certain sensitive attributes are more frequently investigated across various

computer vision tasks, while others receive less attention. *Gender* stands out as the most frequently studied attribute across tasks such as bias analysis, classification, face recognition and analysis, image captioning, image retrieval, representation learning, text-to-image, and VQA. Datasets like MSCOCO [8, 15, 140], CelebA [121], OpenImages [120], IMDB Face [139], FairFace [148], and UTKFace [130] are often used to explore and mitigate *gender* biases. This reflects the bias of the computer vision community towards evaluating and mitigating *gender* biases.

Race and *ethnicity* are also critical attributes, especially in face recognition and representation learning tasks. Datasets such as PPB [16], IJB-A [155], Fairface [148], UTKFace [130], MSCOCO [8], and Adience [156] are frequently used to investigate these biases. Similarly, *age* is a commonly investigated attribute in classification, face recognition, and representation learning tasks with datasets like IMDB Face [129], UTKFace [130], MORPH [170], CACD [172], and MS-Celeb-1M [96, 174] being used to examine *age*-related biases.

Context is another frequently considered attribute, especially in classification, image captioning, representation learning, and VQA. This attribute is investigated using datasets like MSCOCO [8], UnRel [141], Deep Fashion [142], NICO++ [124], and PATA [52].

In contrast to the above-mentioned attributes, certain attributes have received less attention. For example, the *illumination* attribute is only addressed by the Extended Yale B [146] dataset within the classification task. Similarly, *Hair Color* is primarily referenced in the CelebA dataset. While *Skin Tone* is addressed in some tasks, it appears less frequently compared to attributes like *gender* or *race*. Additionally, *Texture* is an attribute less commonly investigated, appearing mainly in the ImageNet-A [132] dataset for representation learning. Lastly, *corruption* is mainly mentioned in the context of federated learning and representation learning in datasets like Corrupted CIFAR-10 [126].

5.2 Task Specific Diversity of Datasets and Attributes

Underscoring the need for a more detailed examination of biases in specific domains, a diverse array of datasets and attributes have been specialized for each domain.

The **action recognition** task exhibits a moderate diversity in its datasets, incorporating a range of scene contexts from UCF-101 [149] and HMDB-51 [150] to specialized datasets like Diving48 [151] and THUMOS-14 [152]. These datasets provide various environments and activities, ensuring varied training and evaluation conditions. However, the sensitive attribute used in this task is *scene*, as biases can arise from the background, objects, or context in which action occurs. This emphasis on scene-based attributes highlights the need to mitigate biases that stem from environmental contexts affecting action recognition performance. Without such mitigation, computer vision models can leverage context as a shortcut to solve the action recognition problem without understanding any action [151].

Papers in the **bias analysis** task leverage a diverse array of datasets, including MSCOCO [8], OpenImages [120], and CelebA [121], which cover multiple demographic and contextual attributes. The most commonly studied attributes in this task are *gender* and *age*, reflecting a significant concern

within the computer vision community regarding the impact of these biases on model decisions.

Frequently studied attributes in **face recognition and analysis** studies include *gender*, *ethnicity/race*, *skin tone*, and *age*. These studies have been performed on a diverse set of datasets like PPB [16], IJB-A [155], and Adience [156].

Federated learning tasks use specialized datasets, such as Colored MNIST [137] and Corrupted CIFAR-10 [126], focusing on attributes like color and corruption. While the diversity of the attributes is limited compared to other tasks, they are tailored to study specific biases and robustness issues prevalent in federated learning environments.

Image captioning tasks utilize datasets like MSCOCO-Bias [15] and MSCOCO-Balanced [15], which are designed to highlight and mitigate *gender* and *racial* biases in image descriptions, reflecting a desire for fair and representative captions. The diversity of these datasets lies in their annotations and the variety of contexts they provide.

The **image retrieval** task makes use of datasets such as Occupation 1 [178], Occupation 2 [179], MSCOCO [8], and Flickr30k [180], with a primary focus on *gender*.

Fairness studies in **object detection** utilize the BDD100K [181] dataset, focusing on attributes like *skin tone* and *income*. The diversity in this task is centered around addressing biases that are particularly relevant in autonomous driving and other detection-based applications.

Person re-identification tasks use datasets such as PRCC-ReID [182] and LTCC-ReID [183], primarily focusing on the attribute of *clothing*, highlighting the importance of mitigating biases w.r.t. clothing for this task.

Representation learning tasks demonstrate high diversity with datasets like ImageNet [7, 59], Open Images [59, 120], MSCOCO [8], and CIFAR-10S [262], addressing a broad range of attributes including *geography*, *gender*, *color*, *corruption*, *scene*, and *context*. The focus on multiple attributes indicates an effort to create robust models that generalize well across various demographic and environmental factors.

Scene graph generation employs datasets such as VG [197] and MSCOCO [8], with an emphasis on the attribute of *composition*. This task's diversity in datasets is geared towards understanding and mitigating biases in scene understanding and object relationships.

For debiasing **text-to-image** models datasets like CelebA [121], FAIR [200], and FairFace [148] are used. The primary focus in this task has been debiasing with respect to attributes such as *gender* and *skin tone*. By leveraging these diverse datasets, researchers aim to address biases that can arise from textual prompts influencing image generation.

In **visual question answering** (VQA), a variety of datasets are utilized, including VQA [185], MSCOCO [8], VQA-CP v2 [187], and Visual7W [195]. These datasets address attributes like *language*, *context*, *gender*, and *race*, ensuring comprehensive evaluation and mitigation of biases in multimodal understanding.

6 CURRENT TRENDS AND FUTURE WORK

Fairness in Generative Models: The availability of large multimodal datasets [220], coupled with significant advancements in generative modeling [263, 264, 265, 266, 267, 268, 269, 270], has substantially increased the capabilities

and potential applications of generative models [199]. Concurrently, some studies [28, 266, 268] began demonstrating that the content generated by these models exhibits biases. However, these have predominantly focused on the diversity of the generated images across different demographic groups. As such, a formal and precise mathematical definition of fairness still does not exist for generative models.

In the context of Text-to-Image (TTI) generation, approaches for increasing the diversity of generated content [108, 233, 235] can be categorized into two main groups, namely prompt engineering and guidance. *Prompt Engineering:* Methods [271] in this category focus on designing better text prompts to force the model to generate more diverse images. *Guidance:* These methods [272, 273, 274] seek to improve the diversity of generated images by modifying the distribution of generated images. However, all of these methods still struggle to achieve fine-grained control over the generation process, often resulting in unintended changes to other attributes when attempting to modify the protected ones. This challenge is primarily because different attributes are entangled with each other [271].

Fairness in Foundation Models: Recent advances in transformer architectures and large-scale pretraining have led to the development of families of multimodal foundation models [275, 276, 277] that demonstrate remarkable generalization capacity to novel tasks and domains. Just like application-specific models, foundation models also exhibit demographic and other biases across different downstream tasks. This has been observed for tasks including classification [278], retrieval [248], captioning [229] and visual question answering [279]. Bias analysis and mitigation methods in this area mainly concern two types of foundation models.

Image-Text Models: Some efforts have been made to address bias in the image and text representations learned by contrastive models such as CLIP [275] and SigLIP [280] in the context of zero-shot image classification and image-text retrieval tasks. These approaches typically employ a set of sensitive text or image queries to debias CLIP embeddings through prompt tuning [248], auxiliary modules [52, 207], and linear [54] or nonlinear [19] feature mappings. A distinguishing feature of FairerCLIP [19] is its ability to debias the representations without needing ground-truth labels Y and S . Data rebalancing [249] has also been explored as an alternative to model debiasing. Although these debiasing approaches have focused on zero-shot image classification and image-text retrieval tasks, understanding and mitigating biases in aligned image-text representations, have far greater implications, as CLIP-style models are commonly used as feature extractors in large multimodal models and text-to-image generation.

Large Multimodal Models: A few recent efforts [251, 281] have also been made to uncover biases in large multimodal models (LMMs), such as GPT-4V [282] and LLaVA [283], capable of more versatile tasks including captioning and VQA. Owing to the variety of tasks and the rapid evolution of multimodal architectures, work in this area is still scarce and does not fully capture the complexities of LMM fairness.

Apart from the initial forays discussed above, understanding and mitigating biases in foundation models largely remain an open problem. This state of affairs offers both new opportunities and new challenges to the computer vision

community. First, foundation models are often applied to solve downstream tasks in *zero-shot* or *few-shot* settings, which have not been the subject of much study in the debiasing literature. Second, while this literature typically addresses the fairness of specific tasks, there are no unified measures of fairness for the diverse tasks and contexts on which foundation models are evaluated. Finally, the most widely adopted notions of fairness are defined with respect to *closed vocabularies* of target labels and sensitive attributes. This is insufficient to quantify the fairness of foundation models, which target *open set* applications using vocabularies based on natural language.

7 CONCLUDING REMARKS

In this paper, we reviewed the advancements made by the research community in measuring and mitigating bias w.r.t. sensitive protected groups in various computer vision tasks. Specifically, we discussed the social and technical origins of bias in computer vision systems, the different definitions of fairness considered by the research community, and different bias mitigation techniques and benchmark datasets to evaluate and compare them. Finally, we discussed fairness and bias in the context of modern multimodal foundation and generative models. We hope this survey provides a helpful and detailed overview for new researchers and practitioners, provides a convenient reference for relevant experts, and encourages future progress in the informed design of fair and equitable computer vision systems.

Acknowledgments. This work was funded by NSF Awards No. 2221943, 2041009, and 2147116 and gift funding from Amazon through the NSF Program on Fairness in Artificial Intelligence in Collaboration with Amazon. We also thank the organizers of the NSF-Amazon PI Meeting in Arlington, VA, on January 2024.

REFERENCES

- [1] H. A. Rowley, S. Baluja, and T. Kanade, "Neural network-based face detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 1, pp. 23–38, 1998.
- [2] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *CVPR*, 2001.
- [3] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *CVPR*, 2005.
- [4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *NeurIPS*, 2012.
- [5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *CVPR*, 2016.
- [6] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly *et al.*, "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, 2020.
- [7] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, "Imagenet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, pp. 211–252, 2015.

- [8] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft COCO: common objects in context," in *ECCV*, 2014.
- [9] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: convolutional networks for biomedical image segmentation," in *MICCAI*, 2015.
- [10] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *CVPR*, 2022.
- [11] A. Howard, J. Borenstein, and K. Gosha, "NSF-funded Fairness, Ethics, Accountability, and Transparency (FEAT) Workshop Report," in *NSF Workshop Reports*, 2019.
- [12] J. Angwin, J. Larson, S. Mattu, and L. Kirchner, "Machine bias," in *Ethics of data and analytics*. Auerbach Publications, 2022, pp. 254–264.
- [13] V. Mhasawade, Y. Zhao, and R. Chunara, "Machine learning and algorithmic fairness in public and population health," *Nature Machine Intelligence*, vol. 3, no. 8, pp. 659–666, 2021.
- [14] S. Dehdashtian, B. Sadeghi, and V. N. Boddeti, "Utility-Fairness trade-offs and how to find them," in *CVPR*, 2024.
- [15] L. A. Hendricks, K. Burns, K. Saenko, T. Darrell, and A. Rohrbach, "Women also snowboard: Overcoming bias in captioning models," in *ECCV*, 2018.
- [16] J. Buolamwini and T. Gebru, "Gender Shades: intersectional accuracy disparities in commercial gender classification," in *FAccT*, 2018.
- [17] H. Li, Y. Liu, H. Zhang, and B. Li, "Mitigating and evaluating static bias of action representations in the background and the foreground," in *ICCV*, 2023.
- [18] Z. Yang, M. Lin, X. Zhong, Y. Wu, and Z. Wang, "Good is Bad: causality inspired cloth-debiasing for cloth-changing person re-identification," in *CVPR*, 2023.
- [19] S. Dehdashtian, L. Wang, and V. N. Boddeti, "FairerCLIP: Debiasing clip's zero-shot predictions using functions in rkhss," *ICLR*, 2024.
- [20] J. Angwin, J. Larson, S. Mattu, and L. Kirchner, "Machine bias," *ProPublica*, vol. 23, pp. 139–159, 2016.
- [21] J. Zhao, T. Wang, M. Yatskar, V. Ordonez, and K.-W. Chang, "Men also like shopping: Reducing gender bias amplification using corpus-level constraints," in *EMNLP*, 2017.
- [22] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A survey on bias and fairness in machine learning," *ACM Computing Surveys*, vol. 54, no. 6, pp. 1–35, 2021.
- [23] D. Pessach and E. Shmueli, "A review on fairness in machine learning," *ACM Computing Surveys*, vol. 55, no. 3, pp. 1–44, 2022.
- [24] T. Le Quy, A. Roy, V. Iosifidis, W. Zhang, and E. Ntoutsi, "A survey on datasets for fairness-aware machine learning," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 12, no. 3, p. e1452, 2022.
- [25] S. Caton and C. Haas, "Fairness in machine learning: A survey," *ACM Computing Surveys*, vol. 56, no. 7, pp. 1–38, 2024.
- [26] O. Parraga, M. D. More, C. M. Oliveira, N. S. Gavenski, L. S. Kupssinskü, A. Medronha, L. V. Moura, G. S. Simões, and R. C. Barros, "Fairness in deep learning: A survey on vision and language research," *ACM Computing Surveys*, 2023.
- [27] M. Yatskar, V. Ordonez, L. Zettlemoyer, and A. Farhadi, "Commonly uncommon: Semantic sparsity in situation recognition," in *CVPR*, 2017.
- [28] F. Bianchi, P. Kalluri, E. Durmus, F. Ladakh, M. Cheng, D. Nozza, T. Hashimoto, D. Jurafsky, J. Zou, and A. Caliskan, "Easily accessible text-to-image generation amplifies demographic stereotypes at large scale," in *FAccT*, 2023.
- [29] M. K. Scheuerman and J. R. Brubaker, "Products of positionality: How tech workers shape identity concepts in computer vision," in *CHI*, 2024.
- [30] G. Y. Park, S. Lee, S. W. Lee, and J. C. Ye, "Training debiased subnetworks with contrastive weight pruning," in *CVPR*, 2023.
- [31] J. Li, D. M. Vo, and H. Nakayama, "Partition-and-debias: Agnostic biases mitigation via a mixture of biases-specific experts," in *ICCV*, 2023.
- [32] B. Sadeghi, S. Dehdashtian, and V. Boddeti, "On characterizing the trade-off in invariant representation learning," *Transactions on Machine Learning Research*, 2022, Featured Certification.
- [33] M. Qraitem, K. Saenko, and B. A. Plummer, "Bias Mimicking: a simple sampling approach for bias mitigation," in *CVPR*, 2023.
- [34] T. Jang and X. Wang, "Difficulty-based sampling for debiased contrastive representation learning," in *CVPR*, 2023.
- [35] A. Wang and O. Russakovsky, "Overwriting pre-trained bias with finetuning data," in *ICCV*, 2023.
- [36] Y.-K. Zhang, Q.-W. Wang, D.-C. Zhan, and H.-J. Ye, "Learning debiased representations via conditional attribute interpolation," in *CVPR*, 2023.
- [37] P. Tang, W. Yao, Z. Li, and Y. Liu, "Fair Scratch Tickets: finding fair sparse networks without weight training," in *CVPR*, 2023.
- [38] N. Meister, D. Zhao, A. Wang, V. V. Ramaswamy, R. Fong, and O. Russakovsky, "Gender artifacts in visual datasets," in *ICCV*, 2023.
- [39] J. Ranjit, T. Wang, B. Ray, and V. Ordonez, "Variation of gender biases in visual recognition models before and after finetuning," *arXiv preprint arXiv:2303.07615*, 2023.
- [40] M. Jeon, D. Kim, W. Lee, M. Kang, and J. Lee, "A conservative approach for unbiased learning on unknown biases," in *CVPR*, 2022.
- [41] S. Park, J. Lee, P. Lee, S. Hwang, D. Kim, and H. Byun, "Fair contrastive learning for facial attribute classification," in *CVPR*, 2022.
- [42] Z. Wang, X. Dong, H. Xue, Z. Zhang, W. Chiu, T. Wei, and K. Ren, "Fairness-aware adversarial perturbation towards bias mitigation for deployed deep models," in *CVPR*, 2022.
- [43] S. Seo, J.-Y. Lee, and B. Han, "Unsupervised learning of debiased representations with pseudo-attributes," in *CVPR*, 2022.
- [44] J. Chai and X. Wang, "Self-supervised fair representation learning without demographics," *NeurIPS*, 2022.
- [45] W. Zhu, H. Zheng, H. Liao, W. Li, and J. Luo, "Learn-

- ing bias-invariant representation by cross-sample mutual information minimization," in *ICCV*, 2021.
- [46] E. Tartaglione, C. A. Barbano, and M. Grangetto, "EnD: entangling and disentangling deep representations for bias correction," in *CVPR*, 2021.
- [47] V. V. Ramaswamy, S. S. Kim, and O. Russakovsky, "Fair attribute classification through latent space debiasing," in *CVPR*, 2021.
- [48] E. Kim, J. Lee, and J. Choo, "BiaSwap: removing dataset bias with bias-tailored swapping augmentation," in *ICCV*, 2021.
- [49] A. Wang and O. Russakovsky, "Directional bias amplification," in *ICML*, 2021.
- [50] Z. Wang, K. Qinami, I. C. Karakozis, K. Genova, P. Nair, K. Hata, and O. Russakovsky, "Towards fairness in visual recognition: Effective strategies for bias mitigation," in *CVPR*, 2020.
- [51] T. Wang, J. Zhao, M. Yatskar, K.-W. Chang, and V. Ordonez, "Balanced datasets are not enough: Estimating and mitigating gender bias in deep image representations," in *ICCV*, 2019.
- [52] A. Seth, M. Hemani, and C. Agarwal, "Dear: Debiasing vision-language models with additive residuals," in *CVPR*, 2023.
- [53] S. M. Hall, F. Gonçalves Abrantes, H. Zhu, G. Sudunke, A. Shtedritski, and H. R. Kirk, "Visogender: A dataset for benchmarking gender bias in image-text pronoun resolution," *NeurIPS*, 2024.
- [54] C.-Y. Chuang, V. Jampani, Y. Li, A. Torralba, and S. Jegelka, "Debiasing vision-language models via biased prompts," *arXiv preprint arXiv:2302.00070*, 2023.
- [55] E. Van Miltenburg, "Stereotyping and bias in the flickr30k dataset," *arXiv preprint arXiv:1605.06083*, 2016.
- [56] T. Wang, C. Zhou, Q. Sun, and H. Zhang, "Causal attention for unbiased visual recognition," in *ICCV*, 2021.
- [57] S. Jung, D. Lee, T. Park, and T. Moon, "Fair feature distillation for visual recognition," in *CVPR*, 2021.
- [58] Y. Li and N. Vasconcelos, "REPAIR: removing representation bias by dataset resampling," in *CVPR*, 2019.
- [59] S. Shankar, Y. Halpern, E. Breck, J. Atwood, J. Wilson, and D. Sculley, "No classification without representation: Assessing geodiversity issues in open data sets for the developing world," *arXiv preprint arXiv:1711.08536*, 2017.
- [60] A. Wang, A. Liu, R. Zhang, A. Kleiman, L. Kim, D. Zhao, I. Shirai, A. Narayanan, and O. Russakovsky, "REVISE: a tool for measuring and mitigating bias in visual datasets," *International Journal of Computer Vision*, vol. 130, no. 7, pp. 1790–1810, 2022.
- [61] S. Mo, H. Kang, K. Sohn, C.-L. Li, and J. Shin, "Object-aware contrastive learning for debiased scene representation," *NeurIPS*, 2021.
- [62] C. Schumann, F. Olanubi, A. Wright, E. Monk, C. Helldreth, and S. Ricco, "Consensus and subjectivity of skin tone annotation for ml fairness," *NeurIPS*, 2024.
- [63] K. Sirokin, P. Carballeira, and M. Escudero-Viñolo, "A study on the distribution of social biases in self-supervised learning visual models," in *CVPR*, 2022.
- [64] A. Birhane, S. Dehdashtian, V. Prabhu, and V. Boddeti, "The Dark Side of Dataset Scaling: evaluating racial classification in multimodal models," in *FAccT*, 2024.
- [65] J. Brinkmann, P. Swoboda, and C. Bartelt, "A multi-dimensional analysis of social biases in vision transformers," in *ICCV*, 2023.
- [66] E. Iofinova, A. Peste, and D. Alistarh, "Bias in pruned vision models: In-depth analysis and countermeasures," in *CVPR*, 2023.
- [67] D. Guilbeault, S. Delecourt, T. Hull, B. S. Desikan, M. Chu, and E. Nadler, "Online images amplify gender bias," *Nature*, vol. 626, no. 8001, pp. 1049–1055, 2024.
- [68] B. Kim, H. Kim, K. Kim, S. Kim, and J. Kim, "Learning not to learn: Training deep neural networks with biased data," in *CVPR*, 2019.
- [69] D. Zietlow, M. Lohaus, G. Balakrishnan, M. Kleindessner, F. Locatello, B. Schölkopf, and C. Russell, "Leveling down in computer vision: Pareto inefficiencies in fair deep classifiers," in *CVPR*, 2022.
- [70] H. C. Bendekgey and E. Suderth, "Scalable and stable surrogates for flexible classifiers with fairness constraints," *NeurIPS*, 2021.
- [71] S. Lee, Z. J. Wang, J. Hoffman, and D. H. P. Chau, "VisCUT: visual auditor for bias in cnn image classifier," in *CVPR*, 2022.
- [72] S. Jung, S. Chun, and T. Moon, "Learning fair classifiers with partially annotated group labels," in *CVPR*, 2022.
- [73] G. Zhang, Y. Zhang, Y. Zhang, W. Fan, Q. Li, S. Liu, and S. Chang, "Fairness reprogramming," *NeurIPS*, 2022.
- [74] P. C. Roy and V. N. Boddeti, "Mitigating information leakage in image representations: A maximum entropy approach," in *CVPR*, 2019.
- [75] B. Sadeghi, R. Yu, and V. Boddeti, "On the global optima of kernelized adversarial representation learning," in *ICCV*, 2019.
- [76] L. Gustafson, C. Rolland, N. Ravi, Q. Duval, A. Adcock, C.-Y. Fu, M. Hall, and C. Ross, "FACET: fairness in computer vision evaluation benchmark," in *ICCV*, 2023.
- [77] K. K. Singh, D. Mahajan, K. Grauman, Y. J. Lee, M. Feiszli, and D. Ghadiyaram, "Don't judge an object by its context: Learning to overcome contextual bias," in *CVPR*, 2020.
- [78] M.-C. Chiu, P.-Y. Chen, and X. Ma, "Better may not be fairer: A study on subgroup discrepancy in image classification," in *ICCV*, 2023.
- [79] M. Jia, L. Tang, B.-C. Chen, C. Cardie, S. Belongie, B. Hariharan, and S.-N. Lim, "Visual prompt tuning," in *ECCV*, 2022.
- [80] Z. Li and C. Xu, "Discover the unknown biased attribute of an image classifier," in *ICCV*, 2021.
- [81] J. Choi, C. Gao, J. C. Messou, and J.-B. Huang, "Why can't I dance in the mall? Learning to mitigate scene bias in action recognition," *NeurIPS*, 2019.
- [82] Y. Zhai, Z. Liu, Z. Wu, Y. Wu, C. Zhou, D. Doermann, J. Yuan, and G. Hua, "SOAR: scene-debiasing open-set action recognition," in *ICCV*, 2023.
- [83] R. Vera-Rodriguez, M. Blazquez, A. Morales, E. Gonzalez-Sosa, J. C. Neves, and H. Proença, "Face-

- [84] GenderID: exploiting gender information in dcnn face recognition systems," in *CVPRW*, 2019.
- [85] N. Quadrianto, V. Sharmanska, and O. Thomas, "Discovering fair representations in the data domain," in *CVPR*, 2019.
- [86] A. Domnich and G. Anbarjafari, "Responsible AI: gender bias assessment in emotion recognition," *arXiv preprint arXiv:2103.11436*, 2021.
- [87] P. Dhar, J. Gleason, A. Roy, C. D. Castillo, and R. Chellappa, "Pass: protected attribute suppression system for mitigating bias in face recognition," in *ICCV*, 2021.
- [88] S. Gong, X. Liu, and A. K. Jain, "Mitigating face recognition bias via group adaptive classifier," in *CVPR*, 2021.
- [89] J. Ma, Z. Yue, K. Tomoyuki, S. Tomoki, K. Jayashree, S. Pranata, and H. Zhang, "Invariant feature regularization for fair face recognition," in *ICCV*, 2023.
- [90] H. Liang, P. Perona, and G. Balakrishnan, "Benchmarking algorithmic bias in face recognition: An experimental approach using synthetic faces and human evaluation," in *ICCV*, 2023.
- [91] S. Dooley, R. Sukthanker, J. Dickerson, C. White, F. Hutter, and M. Goldblum, "Rethinking Bias Mitigation: fairer architectures make for fairer face recognition," *NeurIPS*, 2024.
- [92] Y. Chen and J. Joo, "Understanding and mitigating annotation bias in facial expression recognition," in *ICCV*, 2021.
- [93] A. Chouldechova, S. Deng, Y. Wang, W. Xia, and P. Perona, "Unsupervised and semi-supervised bias benchmarking in face recognition," in *ECCV*, 2022.
- [94] P. Terhörst, J. N. Kolf, M. Huber, F. Kirchbuchner, N. Damer, A. M. Moreno, J. Fierrez, and A. Kuijper, "A comprehensive study on face recognition biases beyond demographics," *IEEE Transactions on Technology and Society*, vol. 3, no. 1, pp. 16–30, 2021.
- [95] M. Georgopoulos, J. Oldfield, M. A. Nicolaou, Y. Panagakis, and M. Pantic, "Mitigating demographic bias in facial datasets with style-based multi-attribute transfer," *International Journal of Computer Vision*, vol. 129, no. 7, pp. 2288–2307, 2021.
- [96] J. Li and W. Abd-Almageed, "CAT: controllable attribute translation for fair facial attribute classification," in *ECCV*, 2022.
- [97] S. Gong, X. Liu, and A. K. Jain, "Jointly de-biasing face recognition and demographic attribute estimation," in *ECCV*, 2020.
- [98] M. Wang and W. Deng, "Mitigating bias in face recognition using skewness-aware reinforcement learning," in *CVPR*, 2020.
- [99] B. Liu, W. Deng, Y. Zhong, M. Wang, J. Hu, X. Tao, and Y. Huang, "Fair Loss: margin-aware reinforcement learning for deep face recognition," in *ICCV*, 2019.
- [100] G. Balakrishnan, Y. Xiong, W. Xia, and P. Perona, "Towards causal benchmarking of bias in face analysis algorithms," *Deep Learning-Based Face Analytics*, pp. 327–359, 2021.
- [101] V. H. Maluleke, N. Thakkar, T. Brooks, E. Weber, T. Darrell, A. A. Efros, A. Kanazawa, and D. Guillary, "Studying bias in gans through the lens of race," in *ECCV*, 2022.
- [102] S. Tan, Y. Shen, and B. Zhou, "Improving the fairness of deep generative models without retraining," *arXiv preprint arXiv:2012.04842*, 2020.
- [103] C. H. Wu, S. Motamed, S. Srivastava, and F. D. De la Torre, "Generative visual prompt: Unifying distributional control of pre-trained generative models," *NeurIPS*, 2022.
- [104] N. Yu, K. Li, P. Zhou, J. Malik, L. Davis, and M. Fritz, "Inclusive GAN: improving data and minority coverage in generative models," in *ECCV*, 2020.
- [105] S. Zhao, H. Ren, A. Yuan, J. Song, N. Goodman, and S. Ermon, "Bias and generalization in deep generative models: An empirical study," *NeurIPS*, 2018.
- [106] D. Xu, S. Yuan, L. Zhang, and X. Wu, "FairGAN: Fairness-aware generative adversarial networks," in *IEEE BigData*, 2018.
- [107] C. E. Karakas, A. Dirik, E. Yalçinkaya, and P. Yarnardag, "FairStyle: debiasing stylegan2 with style channel manipulations," in *ECCV*. Springer, 2022.
- [108] K. Choi, A. Grover, T. Singh, R. Shu, and S. Ermon, "Fair generative modeling via weak supervision," in *ICML*, 2020.
- [109] A. Jalal, S. Karmalkar, J. Hoffmann, A. Dimakis, and E. Price, "Fairness for image generation with uncertain sensitive attributes," in *ICML*, 2021.
- [110] P. J. Kenfack, K. Sabbagh, A. R. Rivera, and A. Khan, "RepFair-GAN: mitigating representation bias in gans using gradient clipping," *arXiv preprint arXiv:2207.10653*, 2022.
- [111] S. Sudhakar, V. Prabhu, O. Russakovsky, and J. Hoffman, "ICON2: reliably benchmarking predictive inequity in object detection," *arXiv preprint arXiv:2306.04482*, 2023.
- [112] B. Wilson, J. Hoffman, and J. Morgenstern, "Predictive inequity in object detection," *arXiv preprint arXiv:1902.11097*, 2019.
- [113] F. Kong, S. Yuan, W. Hao, and R. Henao, "Mitigating test-time bias for fair image retrieval," *NeurIPS*, 2024.
- [114] S. Chu, D. Kim, and B. Han, "Learning debiased and disentangled representations for semantic segmentation," *NeurIPS*, 2021.
- [115] N. Garcia, Y. Hirota, Y. Wu, and Y. Nakashima, "Uncurated image-text datasets: Shedding light on demographic bias," in *CVPR*, 2023.
- [116] B. A. Biswas and Q. Ji, "Probabilistic debiasing of scene graphs," in *CVPR*, 2023.
- [117] K. Tang, Y. Niu, J. Huang, J. Shi, and H. Zhang, "Unbiased scene graph generation from biased training," in *CVPR*, 2020.
- [118] J. Li, Y. Wong, Q. Zhao, and M. S. Kankanhalli, "Dual-glance model for deciphering social relationships," in *ICCV*, 2017.
- [119] I. Krasin, T. Duerig, N. Alldrin, V. Ferrari, S. Abu-El-Haija, A. Kuznetsova, H. Rom, J. Uijlings, S. Popov,

- A. Veit *et al.*, "OpenImages: a public dataset for large-scale multi-label and multi-class image classification," *Dataset available from https://github.com/openimages*, vol. 2, no. 3, p. 18, 2017.
- [121] Z. Liu, P. Luo, X. Wang, and X. Tang, "Deep learning face attributes in the wild," in *ICCV*, 2015.
- [122] U. Schimmack, "The implicit association test: A method in search of a construct," *Perspectives on Psychological Science*, vol. 16, no. 2, pp. 396–414, 2021.
- [123] S. Sagawa, P. W. Koh, T. B. Hashimoto, and P. Liang, "Distributionally robust neural networks for group shifts: On the importance of regularization for worst-case generalization," *arXiv preprint arXiv:1911.08731*, 2019.
- [124] X. Zhang, Y. He, R. Xu, H. Yu, Z. Shen, and P. Cui, "NICO++: towards better benchmarking for domain generalization," in *CVPR*, 2023.
- [125] A. Krizhevsky, G. Hinton *et al.*, "Learning multiple layers of features from tiny images," *Toronto, ON, Canada*, 2009.
- [126] D. Hendrycks and T. Dietterich, "Benchmarking neural network robustness to common corruptions and perturbations," in *ICLR*, 2019.
- [127] J. Nam, H. Cha, S. Ahn, J. Lee, and J. Shin, "Learning from failure: De-biasing classifier from biased classifier," *NeurIPS*, 2020.
- [128] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *CVPR*, 2019.
- [129] R. Rothe, R. Timofte, and L. Van Gool, "Deep expectation of real and apparent age from a single image without facial landmarks," *International Journal of Computer Vision*, vol. 126, no. 2, pp. 144–157, 2018.
- [130] Z. Zhang, Y. Song, and H. Qi, "Age progression/regression by conditional adversarial autoencoder," in *CVPR*, 2017.
- [131] Y. He, Z. Shen, and P. Cui, "Towards non-iid image classification: A dataset and baselines," *Pattern Recognition*, vol. 110, p. 107383, 2021.
- [132] D. Hendrycks, K. Zhao, S. Basart, J. Steinhardt, and D. Song, "Natural adversarial examples," in *CVPR*, 2021.
- [133] M. Yurochkin, A. Bower, and Y. Sun, "Training individually fair ml models with sensitive subspace robustness," *ICLR*, 2020.
- [134] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, "Labeled faces in the wild: A database for studying face recognition in unconstrained environments," University of Massachusetts, Amherst, Tech. Rep. 07-49, October 2007.
- [135] W. A. G. Rojas, S. Diamos, K. R. Kini, D. Kanter, V. J. Reddi, and C. Coleman, "The dollar street dataset: Images representing the geographic and socioeconomic diversity of the world," in *NeurIPS*, 2022.
- [136] V. V. Ramaswamy, S. Y. Lin, D. Zhao, A. Adcock, L. van der Maaten, D. Ghadiyaram, and O. Russakovsky, "GeoDE: a geographically diverse evaluation dataset for object recognition," *NeurIPS*, 2024.
- [137] M. Arjovsky, L. Bottou, I. Gulrajani, and D. Lopez-Paz, "Invariant risk minimization," *arXiv preprint arXiv:1907.02893*, 2019.
- [138] W. Cukierski, "Dogs vs. cats," 2013. [Online]. Available: <https://kaggle.com/competitions/dogs-vs-cats>
- [139] F. Wang, L. Chen, C. Li, S. Huang, Y. Chen, C. Qian, and C. C. Loy, "The devil of face recognition is in the noise," in *ECCV*, 2018.
- [140] H. Caesar, J. Uijlings, and V. Ferrari, "COCO-Stuff: thing and stuff classes in context," in *CVPR*, 2018.
- [141] J. Peyre, I. Laptev, C. Schmid, and J. Sivic, "Weakly-supervised learning of visual relations," in *ICCV*, 2017.
- [142] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, "DeepFashion: powering robust clothes recognition and retrieval with rich annotations," in *CVPR*, 2016.
- [143] Y. Xian, C. H. Lampert, B. Schiele, and Z. Akata, "Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, no. 9, pp. 2251–2265, 2018.
- [144] S. Escalera, X. Baró, H. J. Escalante, and I. Guyon, "ChaLearn looking at people: A review of events and resources," in *IJCNN*, 2017.
- [145] J. Angwin, J. Larson, S. Mattu, and L. Kirchner, "There's software used across the country to predict future criminals and it's biased against blacks." 2020.
- [146] A. Georgiades, P. Belhumeur, and D. Kriegman, "From few to many: illumination cone models for face recognition under variable lighting and pose," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 6, pp. 643–660, 2001.
- [147] D. S. Ma, J. Correll, and B. Wittenbrink, "The chicago face database: A free stimulus set of faces and norming data," *Behavior Research Methods*, vol. 47, pp. 1122–1135, 2015.
- [148] K. Kärkkäinen and J. Joo, "FairFace: face attribute dataset for balanced race, gender, and age," *arXiv preprint arXiv:1908.04913*, 2019.
- [149] K. Soomro, A. R. Zamir, and M. Shah, "UCF101: a dataset of 101 human actions classes from videos in the wild," *arXiv preprint arXiv:1212.0402*, 2012.
- [150] H. Kuehne, H. Jhuang, E. Garrote, T. Poggio, and T. Serre, "Hmdb: A large video database for human motion recognition," in *ICCV*, 2011.
- [151] Y. Li, Y. Li, and N. Vasconcelos, "RESOUND: towards action recognition without representation bias," in *ECCV*, 2018.
- [152] Y.-G. Jiang, J. Liu, A. Roshan Zamir, G. Toderici, I. Laptev, M. Shah, and R. Sukthankar, "THUMOS challenge: Action recognition with a large number of classes," <http://crcv.ucf.edu/THUMOS14/>, 2014.
- [153] H. Jhuang, J. Gall, S. Zuffi, C. Schmid, and M. J. Black, "Towards understanding action recognition," in *ICCV*, 2013.
- [154] M. Monfort, A. Andonian, B. Zhou, K. Ramakrishnan, S. A. Bargal, T. Yan, L. Brown, Q. Fan, D. Gutfreund, C. Vondrick *et al.*, "Moments in time dataset: one million videos for event understanding," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 42, no. 2, pp. 502–508, 2019.
- [155] B. F. Klare, B. Klein, E. Taborsky, A. Blanton, J. Cheney, K. Allen, P. Grother, A. Mah, and A. K. Jain, "Pushing the frontiers of unconstrained face detection

- and recognition: Iarpa janus benchmark a," in *CVPR*, 2015.
- [156] E. Eidinger, R. Enbar, and T. Hassner, "Age and gender estimation of unfiltered faces," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 12, pp. 2170–2179, 2014.
- [157] M. Merler, N. Ratha, R. S. Feris, and J. R. Smith, "Diversity in faces," *arXiv preprint arXiv:1901.10436*, 2019.
- [158] L. Wolf, T. Hassner, and I. Maoz, "Face recognition in unconstrained videos with matched background similarity," in *CVPR*, 2011.
- [159] A. Nech and I. Kemelmacher-Shlizerman, "Level playing field for million scale face recognition," in *CVPR*, 2017.
- [160] B. Maze, J. Adams, J. A. Duncan, N. Kalka, T. Miller, C. Otto, A. K. Jain, W. T. Niggel, J. Anderson, J. Cheney, and P. Grother, "IARPA Janus Benchmark-C: face dataset and protocol," in *ICB*, 2018.
- [161] M. Wang, W. Deng, J. Hu, X. Tao, and Y. Huang, "Racial faces in the wild: Reducing racial bias by information maximization adaptation network," in *ICCV*, 2019.
- [162] J. Deng, J. Guo, X. An, Z. Zhu, and S. Zafeiriou, "Masked face recognition challenge: The insightface track report," in *ICCV*, 2021.
- [163] C. Whitelam, E. Taborsky, A. Blanton, B. Maze, J. Adams, T. Miller, N. Kalka, A. K. Jain, J. A. Duncan, K. Allen *et al.*, "IARPA Janus Benchmark-B Face Dataset," in *CVPRW*, 2017.
- [164] G. Bae, M. de La Gorce, T. Baltrušaitis, C. Hewitt, D. Chen, J. Valentin, R. Cipolla, and J. Shen, "DigiFace-1M: 1 million digital face images for face recognition," in *WACV*, 2023.
- [165] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "VGGFace2: a dataset for recognising faces across pose and age," in *FG*, 2018.
- [166] D. Lundqvist, A. Flykt, and A. Öhman, "Karolinska directed emotional faces," *PsycTESTS Dataset*, vol. 91, p. 630, 1998.
- [167] Z. Zhang, P. Luo, C.-C. Loy, and X. Tang, "Learning social relation traits from face images," in *ICCV*, 2015.
- [168] S. Li, W. Deng, and J. Du, "Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild," in *CVPR*, 2017.
- [169] A. Mollahosseini, B. Hasani, and M. H. Mahoor, "AffectNet: a database for facial expression, valence, and arousal computing in the wild," *IEEE Transactions on Affective Computing*, vol. 10, no. 1, pp. 18–31, 2017.
- [170] K. Ricanek and T. Tesafaye, "MORPH: a longitudinal image database of normal adult age-progression," in *FG*, 2006.
- [171] P. Terhörst, D. Fährmann, J. N. Kolf, N. Damer, F. Kirchbuchner, and A. Kuijper, "MAAD-Face: a massively annotated attribute dataset for face images," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 3942–3957, 2021.
- [172] B.-C. Chen, C.-S. Chen, and W. H. Hsu, "Cross-age reference coding for age-invariant face recognition and retrieval," in *ECCV*, 2014.
- [173] M. Georgopoulos, Y. Panagakis, and M. Pantic, "Investigating bias in deep face analysis: The kanface dataset and empirical study," *Image and Vision Computing*, vol. 102, p. 103954, 2020.
- [174] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "ArcFace: additive angular margin loss for deep face recognition," in *CVPR*, 2019.
- [175] Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao, "Ms-celeb-1m: A dataset and benchmark for large-scale face recognition," in *ECCV*. Springer, 2016, pp. 87–102.
- [176] Q. Meng, S. Zhao, Z. Huang, and F. Zhou, "Magface: A universal representation for face recognition and quality assessment," in *CVPR*, 2021, pp. 14225–14234.
- [177] S. Sengupta, J.-C. Chen, C. Castillo, V. M. Patel, R. Chellappa, and D. W. Jacobs, "Frontal to profile face verification in the wild," in *WACV*, 2016.
- [178] M. Kay, C. Matuszek, and S. A. Munson, "Unequal representation and gender stereotypes in image search results for occupations," in *ACM CHI*, 2015.
- [179] L. E. Celis and V. Keswani, "Implicit diversity in image summarization," *Proceedings of the ACM on Human-Computer Interaction*, vol. 4, no. CSCW2, pp. 1–28, 2020.
- [180] B. A. Plummer, L. Wang, C. M. Cervantes, J. C. Caicedo, J. Hockenmaier, and S. Lazebnik, "Flickr30k Entities: Collecting region-to-phrase correspondences for richer image-to-sentence models," in *ICCV*, 2015.
- [181] F. Yu, H. Chen, X. Wang, W. Xian, Y. Chen, F. Liu, V. Madhavan, and T. Darrell, "BDD100K: a diverse driving dataset for heterogeneous multitask learning," in *CVPR*, 2020.
- [182] Q. Yang, A. Wu, and W.-S. Zheng, "Person re-identification by contour sketch under moderate clothing change," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, no. 6, pp. 2029–2046, 2019.
- [183] X. Qian, W. Wang, L. Zhang, F. Zhu, Y. Fu, T. Xiang, Y.-G. Jiang, and X. Xue, "Long-term cloth-changing person re-identification," in *ACCV*, 2020.
- [184] S. Bhargava and D. Forsyth, "Exposing and correcting the gender bias in image captioning datasets and models," *arXiv preprint arXiv:1912.00578*, 2019.
- [185] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh, "VQA: Visual Question Answering," in *ICCV*, 2015.
- [186] V. Manjunatha, N. Saini, and L. S. Davis, "Explicit bias discovery in visual question answering models," in *CVPR*, 2019.
- [187] A. Agrawal, D. Batra, D. Parikh, and A. Kembhavi, "Don't just assume; look and answer: Overcoming priors for visual question answering," in *CVPR*, 2018.
- [188] G. Kv and A. Mittal, "Reducing language biases in visual question answering with visually-grounded question encoder," in *ECCV*, 2020.
- [189] Y. Goyal, T. Khot, D. Summers-Stay, D. Batra, and D. Parikh, "Making the V in VQA matter: Elevating the role of image understanding in visual question answering," in *CVPR*, 2017.
- [190] S. Park, S. Hwang, J. Hong, and H. Byun, "Fair-VQA: fairness-aware visual question answering through sensitive attribute prediction," *IEEE Access*, vol. 8, pp.

- 215 091–215 099, 2020.
- [191] R. R. Selvaraju, P. Tendulkar, D. Parikh, E. Horvitz, M. T. Ribeiro, B. Nushi, and E. Kamar, “Squinting at VQA models: Introspecting VQA models with sub-questions,” in *CVPR*, 2020.
- [192] V. Agarwal, R. Shetty, and M. Fritz, “Towards causal VQA: Revealing and reducing spurious correlations by invariant and covariant semantic editing,” in *CVPR*, 2020.
- [193] C. Kervadec, G. Antipov, M. Baccouche, and C. Wolf, “Roses are red, violets are blue... but should vqa expect them to?” in *CVPR*, 2021.
- [194] C. Dancette, R. Cadene, D. Teney, and M. Cord, “Beyond question-based biases: Assessing multimodal shortcut learning in visual question answering,” in *ICCV*, 2021.
- [195] Y. Zhu, O. Groth, M. Bernstein, and L. Fei-Fei, “Visual7W: grounded question answering in images,” in *CVPR*, 2016.
- [196] K. Marino, M. Rastegari, A. Farhadi, and R. Mottaghi, “OK-VQA: a visual question answering benchmark requiring external knowledge,” in *CVPR*, 2019.
- [197] R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma *et al.*, “Visual Genome: connecting language and vision using crowdsourced dense image annotations,” *International Journal of Computer Vision*, vol. 123, pp. 32–73, 2017.
- [198] Y. Hirota, Y. Nakashima, and N. Garcia, “Gender and racial bias in visual question answering datasets,” in *FAccT*, 2022.
- [199] C. Zhang, X. Chen, S. Chai, C. H. Wu, D. Lagun, T. Beeler, and F. De la Torre, “ITI-GEN: inclusive text-to-image generation,” in *ICCV*, 2023.
- [200] H. Feng, T. Bolkart, J. Tesch, M. J. Black, and V. Abrevaya, “Towards racially unbiased skin tone estimation via scene disambiguation,” in *ECCV*, 2022.
- [201] A. Torralba and A. A. Efros, “Unbiased look at dataset bias,” in *CVPR*, 2011.
- [202] R. Goyal, S. Ebrahimi Kahou, V. Michalski, J. Materzynska, S. Westphal, H. Kim, V. Haenel, I. Fründ, P. Yianilos, M. Mueller-Freitag *et al.*, “The “something something” video database for learning and evaluating visual common sense,” in *ICCV*, 2017.
- [203] J. Wang, Y. Liu, and X. E. Wang, “Are gender-neutral queries really gender-neutral? mitigating gender bias in image search,” *arXiv preprint arXiv:2109.05433*, 2021.
- [204] A. Birhane, V. Prabhu, S. Han, and V. N. Boddeti, “On hate scaling laws for data-swamps,” *arXiv preprint arXiv:2306.13141*, 2023.
- [205] A. Birhane, V. U. Prabhu, S. Han, V. N. Boddeti, and S. Luccioni, “Into the LAION’s Den: investigating hate in multimodal datasets,” *NeurIPS*, 2023.
- [206] Y. Du, F. Wei, Z. Zhang, M. Shi, Y. Gao, and G. Li, “Learning to prompt for open-vocabulary object detection with vision-language model,” in *CVPR*, 2022.
- [207] M. Zhang and C. Ré, “Contrastive adapters for foundation model group robustness,” *arXiv preprint arXiv:2207.07180*, 2022.
- [208] I. Misra, C. Lawrence Zitnick, M. Mitchell, and R. Girshick, “Seeing through the human reporting bias: Visual classifiers from noisy human-centric labels,” in *CVPR*, 2016.
- [209] T. De Vries, I. Misra, C. Wang, and L. Van der Maaten, “Does object recognition work for everyone?” in *CVPRW*, 2019.
- [210] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, “Coding facial expressions with gabor wavelets,” in *FG*, 1998.
- [211] M. J. Lyons, ““excavating ai” Re-excavated: Debunking a fallacious account of the JAFFE dataset,” *arXiv preprint arXiv:2107.13998*, 2021.
- [212] S. Singh and S. Benedict, “Indian semi-acted facial expression (iSAFE) dataset for human emotions recognition,” in *SIRS*, 2020.
- [213] A. Castelnovo, R. Crupi, G. Greco, D. Regoli, I. G. Penco, and A. C. Cosentini, “A clarification of the nuances in the fairness metrics landscape,” *Scientific Reports*, vol. 12, no. 1, p. 4209, 2022.
- [214] W. Fleisher, “What’s fair about individual fairness?” in *AIES*, 2021.
- [215] C. Dwork, M. Hardt, T. Pitassi, O. Reingold, and R. Zemel, “Fairness through awareness,” in *ITCS*, 2012.
- [216] M. Hardt, E. Price, and N. Srebro, “Equality of opportunity in supervised learning,” *NeurIPS*, 2016.
- [217] M. J. Kusner, J. Loftus, C. Russell, and R. Silva, “Counterfactual fairness,” *NeurIPS*, 2017.
- [218] Z. Zuo, M. Khalili, and X. Zhang, “Counterfactually fair representation,” *NeurIPS*, 2023.
- [219] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: a large-scale hierarchical image database,” in *CVPR*, 2009.
- [220] C. Schuhmann, R. Beaumont, R. Vencu, C. Gordon, R. Wightman, M. Cherti, T. Coombes, A. Katta, C. Mullis, M. Wortsman *et al.*, “LAION-5B: An open large-scale dataset for training next generation image-text models,” *NeurIPS*, 2022.
- [221] G. Ilharco, M. Wortsman, R. Wightman, C. Gordon, N. Carlini, R. Taori, A. Dave, V. Shankar, H. Namkoong, J. Miller, H. Hajishirzi, A. Farhadi, and L. Schmidt, “OpenCLIP,” 2021.
- [222] R. Wightman, “Pytorch image models,” <https://github.com/rwightman/pytorch-image-models>, 2019.
- [223] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, F. A. Wichmann, and W. Brendel, “Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness,” *arXiv preprint arXiv:1811.12231*, 2018.
- [224] P. Zhang, Y. Goyal, D. Summers-Stay, D. Batra, and D. Parikh, “Yin and Yang: balancing and answering binary visual questions,” in *CVPR*, 2016.
- [225] A. Khosla, T. Zhou, T. Malisiewicz, A. A. Efros, and A. Torralba, “Undoing the damage of dataset bias,” in *ECCV*, 2012.
- [226] R. Cadene, C. Dancette, M. Cord, D. Parikh *et al.*, “RUBi: reducing unimodal biases for visual question answering,” *NeurIPS*, 2019.
- [227] H. Bahng, S. Chun, S. Yun, J. Choo, and S. J. Oh, “Learning de-biased representations with biased rep-

- resentations," in *ICML*, 2020.
- [228] K. Burns, L. A. Hendricks, K. Saenko, T. Darrell, and A. Rohrbach, "Women also snowboard: Overcoming bias in captioning models," *arXiv preprint arXiv:1803.09797*, 2018.
- [229] Y. Hirota, Y. Nakashima, and N. Garcia, "Model-agnostic gender debiased image captioning," in *CVPR*, 2023.
- [230] D. Zhao, A. Wang, and O. Russakovsky, "Understanding and evaluating racial biases in image captioning," in *ICCV*, 2021.
- [231] Y. Hirota, Y. Nakashima, and N. Garcia, "Quantifying societal bias amplification in image captioning," in *CVPR*, 2022.
- [232] P. Esposito, P. Atighehchian, A. Germanidis, and D. Ghadiyaram, "Mitigating stereotypical biases in text to image generative systems," *arXiv preprint arXiv:2310.06904*, 2023.
- [233] F. Friedrich, M. Brack, L. Struppek, D. Hintersdorf, P. Schramowski, S. Luccioni, and K. Kersting, "Fair Diffusion: instructing text-to-image generation models on fairness," *arXiv preprint arXiv:2302.10893*, 2023.
- [234] R. He, C. Xue, H. Tan, W. Zhang, Y. Yu, S. Bai, and X. Qi, "Debiasing text-to-image diffusion models," *arXiv preprint arXiv:2402.14577*, 2024.
- [235] S. Luccioni, C. Akiki, M. Mitchell, and Y. Jernite, "Stable Bias: evaluating societal representations in diffusion models," *NeurIPS*, 2024.
- [236] J. Cho, A. Zala, and M. Bansal, "DALL-Eval: probing the reasoning skills and social biases of text-to-image generation models," in *ICCV*, 2023.
- [237] H. Bansal, D. Yin, M. Monajatipoor, and K.-W. Chang, "How well can text-to-image generative models understand ethical natural language interventions?" *arXiv preprint arXiv:2210.15230*, 2022.
- [238] J. Wang, X. G. Liu, Z. Di, Y. Liu, and X. E. Wang, "T2IAT: measuring valence and stereotypical biases in text-to-image generation," *arXiv preprint arXiv:2306.00905*, 2023.
- [239] A. Chinchure, P. Shukla, G. Bhatt, K. Salij, K. Hosanagar, L. Sigal, and M. Turk, "TIBET: identifying and evaluating biases in text-to-image generative models," *arXiv preprint arXiv:2312.01261*, 2023.
- [240] N. Ruiz, Y. Li, V. Jampani, Y. Pritch, M. Rubinstein, and K. Aberman, "DreamBooth: fine tuning text-to-image diffusion models for subject-driven generation," in *CVPR*, 2023.
- [241] Z. Liu, P. Schaldenbrand, B.-C. Okogwu, W. Peng, Y. Yun, A. Hundt, J. Kim, and J. Oh, "SCoFT: self-contrastive fine-tuning for equitable image generation," *arXiv preprint arXiv:2401.08053*, 2024.
- [242] A. Basu, R. V. Babu, and D. Pruthi, "Inspecting the geographical representativeness of images from text-to-image models," in *ICCV*, 2023.
- [243] Y. Niu, K. Tang, H. Zhang, Z. Lu, X.-S. Hua, and J.-R. Wen, "Counterfactual VQA: A cause-effect look at language bias," in *CVPR*, 2021.
- [244] Z. Wen, G. Xu, M. Tan, Q. Wu, and Q. Wu, "Debiased visual question answering from feature and sample perspectives," *NeurIPS*, 2021.
- [245] J. W. Cho, D.-J. Kim, H. Ryu, and I. S. Kweon, "Generative bias for robust visual question answering," in *CVPR*, 2023.
- [246] A. Basu, S. Addepalli, and R. V. Babu, "RMLVQA: a margin loss approach for visual question answering with language biases," in *CVPR*, 2023.
- [247] V. Gupta, Z. Li, A. Kortylewski, C. Zhang, Y. Li, and A. Yuille, "SwapMix: diagnosing and regularizing the over-reliance on visual context in visual question answering," in *CVPR*, 2022.
- [248] H. Berg, S. M. Hall, Y. Bhagat, W. Yang, H. R. Kirk, A. Shtedritski, and M. Bain, "A prompt array keeps the bias away: Debiasing vision-language models with adversarial learning," *arXiv preprint arXiv:2203.11933*, 2022.
- [249] I. Alabdulmohsin, X. Wang, A. Steiner, P. Goyal, A. D'Amour, and X. Zhai, "CLIP the Bias: how useful is balancing data in multimodal learning?" *arXiv preprint arXiv:2403.04547*, 2024.
- [250] H. Phan, A. G. Wilson, and Q. Lei, "Controllable prompt tuning for balancing group distributional robustness," *arXiv preprint arXiv:2403.02695*, 2024.
- [251] C. Cui, Y. Zhou, X. Yang, S. Wu, L. Zhang, J. Zou, and H. Yao, "Holistic analysis of hallucination in GPT-4V(ision): bias and interference challenges," *arXiv preprint arXiv:2311.03287*, 2023.
- [252] H. Edwards and A. Storkey, "Censoring representations with an adversary," *arXiv preprint arXiv:1511.05897*, 2015.
- [253] Q. Xie, Z. Dai, Y. Du, E. Hovy, and G. Neubig, "Controllable invariance through adversarial feature learning," *NeurIPS*, 2017.
- [254] D. Madras, E. Creager, T. Pitassi, and R. Zemel, "Learning adversarially fair and transferable representations," in *ICML*, 2018.
- [255] E. Adeli, Q. Zhao, A. Pfefferbaum, E. V. Sullivan, L. Fei-Fei, J. C. Niebles, and K. M. Pohl, "Representation learning with statistical independence to mitigate bias," in *WACV*, 2021.
- [256] A. Gretton, O. Bousquet, A. Smola, and B. Schölkopf, "Measuring statistical dependence with hilbert-schmidt norms," in *ALT*, 2005.
- [257] B. Sadeghi, L. Wang, and V. N. Boddeti, "Adversarial representation learning with closed-form solvers," in *ECML PKDD*, 2021.
- [258] A. K. Menon and R. C. Williamson, "The cost of fairness in binary classification," in *FAccT*, 2018.
- [259] H. Zhao and G. J. Gordon, "Inherent tradeoffs in learning fair representations," *Journal of Machine Learning Research*, vol. 23, no. 57, pp. 1–26, 2022.
- [260] H. Wang, L. He, R. Gao, and F. Calmon, "Aleatoric and epistemic discrimination: Fundamental limits of fairness interventions," *NeurIPS*, 2024.
- [261] Y.-Y. Xu, C.-S. Lin, and Y.-C. F. Wang, "Bias-eliminating augmentation learning for debiased federated learning," in *CVPR*, 2023.
- [262] K. M. Collins, U. Bhatt, and A. Weller, "Eliciting and learning with soft labels from every annotator," in *HCOMP*, 2022.
- [263] P. Esser, S. Kulal, A. Blattmann, R. Entezari, J. Müller, H. Saini, Y. Levi, D. Lorenz, A. Sauer, F. Boesel *et al.*, "Scaling rectified flow transformers for high-

- resolution image synthesis," in *ICML*, 2024.
- [264] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, and S. Ganguli, "Deep unsupervised learning using nonequilibrium thermodynamics," in *ICML*, 2015.
- [265] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," *NeurIPS*, 2020.
- [266] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, and M. Chen, "Hierarchical text-conditional image generation with clip latents," *arXiv preprint arXiv:2204.06125*, 2022.
- [267] A. Ramesh, M. Pavlov, G. Goh, S. Gray, C. Voss, A. Radford, M. Chen, and I. Sutskever, "Zero-shot text-to-image generation," in *ICML*, 2021.
- [268] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *CVPR*, 2022.
- [269] L. Zhang, A. Rao, and M. Agrawala, "Adding conditional control to text-to-image diffusion models," in *ICCV*, 2023.
- [270] D. Podell, Z. English, K. Lacey, A. Blattmann, T. Dockhorn, J. Müller, J. Penna, and R. Rombach, "SDXL: improving latent diffusion models for high-resolution image synthesis," *arXiv preprint arXiv:2307.01952*, 2023.
- [271] C. Wu and F. De la Torre, "Contrastive prompts improve disentanglement in text-to-image diffusion models," *arXiv preprint arXiv:2402.13490*, 2024.
- [272] P. Dhariwal and A. Nichol, "Diffusion models beat gans on image synthesis," *NeurIPS*, 2021.
- [273] X. Liu, D. H. Park, S. Azadi, G. Zhang, A. Chopikyan, Y. Hu, H. Shi, A. Rohrbach, and T. Darrell, "More control for free! image synthesis with semantic diffusion guidance," in *WACV*, 2023.
- [274] A. Nichol, P. Dhariwal, A. Ramesh, P. Shyam, P. Mishkin, B. McGrew, I. Sutskever, and M. Chen, "GLIDE: towards photorealistic image generation and editing with text-guided diffusion models," *arXiv preprint arXiv:2112.10741*, 2021.
- [275] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark *et al.*, "Learning transferable visual models from natural language supervision," in *ICML*, 2021.
- [276] J.-B. Alayrac, J. Donahue, P. Luc, A. Miech, I. Barr, Y. Hasson, K. Lenc, A. Mensch, K. Millican, M. Reynolds *et al.*, "Flamingo: a visual language model for few-shot learning," *NeurIPS*, 2022.
- [277] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A. C. Berg, W.-Y. Lo *et al.*, "Segment anything," in *ICCV*, 2023.
- [278] S. Agarwal, G. Krueger, J. Clark, A. Radford, J. W. Kim, and M. Brundage, "Evaluating CLIP: towards characterization of broader capabilities and downstream implications," *arXiv preprint arXiv:2108.02818*, 2021.
- [279] G. Ruggeri, D. Nozza *et al.*, "A multi-dimensional study on bias in vision-language models," in *ACL*, 2023.
- [280] X. Zhai, B. Mustafa, A. Kolesnikov, and L. Beyer, "Sigmoid loss for language image pre-training," in *ICCV*, 2023.
- [281] Y.-F. Zhang, W. Yu, Q. Wen, X. Wang, Z. Zhang, L. Wang, R. Jin, and T. Tan, "Debiasing large visual language models," *arXiv preprint arXiv:2403.05262*, 2024.
- [282] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat *et al.*, "GPT-4 technical report," *arXiv preprint arXiv:2303.08774*, 2023.
- [283] H. Liu, C. Li, Q. Wu, and Y. J. Lee, "Visual instruction tuning," *NeurIPS*, 2023.



Sepehr Dehdashtian is a Ph.D. student in the Department of Computer Science and Engineering at Michigan State University. He received a MSc degree in Electrical Engineering from Sharif University of Technology, Iran. His research interests are in Responsible AI and Fairness in Multimodal and Generative models.



Ruozhen (Catherine) He is a Ph.D. Student in the Department of Computer Science at Rice University. She received a BSc degree (First Class Honors) from the City University of Hong Kong. Her primary research interests lie in computer vision, focusing on efficient algorithms for multimodal models under limited supervision.



Yi Li is a Ph.D. candidate in the Department of Electrical and Computer Engineering at the University of California San Diego. He received his B.Eng. degree (First Class Honors) from the Chinese University of Hong Kong. His research interests include representation learning and bias mitigation for computer vision and multimodal machine learning.



Guha Balakrishnan is an Assistant Professor of Electrical and Computer Engineering working in the fields of computer vision and graphics. He is interested in the theory, practical design, and downstream applications of generative models for complex visual data. He is particularly excited by their application to promote fairness and accountability in vision systems. He received a Ph.D. in EECS from MIT in 2018.



Nuno Vasconcelos (Fellow, IEEE) is a Professor of Electrical and Computer Engineering at the University of California, San Diego, where he heads the Statistical Visual Computing Laboratory. He has received an NSF CAREER award, a Hellman Fellowship, several best paper awards, and authored more than 200 peer-reviewed publications. He has been the Area Chair of multiple computer vision conferences and the Associate Editor of the IEEE Transactions on PAMI.



Vicente Ordóñez (Member, IEEE) is an Associate Professor in the Department of Computer Science at Rice University. His research interests are at the intersection of Computer Vision and Natural Language Processing. He received a Ph.D. in Computer Science from the University of North Carolina at Chapel Hill in 2015. He received the Marr Prize at ICCV 2013 and a Best Paper award at EMNLP 2017.



Vishnu Naresh Boddeti (Member, IEEE) is an Associate Professor in the Department of Computer Science and Engineering at Michigan State University. He received a Ph.D. in Electrical and Computer Engineering from Carnegie Mellon University. His research interests are Computer Vision, Pattern Recognition, and Machine Learning. Papers co-authored by him have received Best Paper Awards at BTAS 2013 and GECCO 2019 and Best Student Paper Awards at ACCV 2018, SMAIS 2022, IJCB 2022, and