Using Positive Matching Contrastive Loss with Facial Action Units to mitigate bias in Facial Expression Recognition

Varsha Suresh¹, Desmond C. Ong^{2,3}

¹Department of Computer Science, National University of Singapore ²Department of Psychology, The University of Texas at Austin ³Department of Information Systems and Analytics, National University of Singapore varshasuresh@u.nus.edu, desmond.ong@utexas.edu

Abstract-Machine learning models automatically learn discriminative features from the data, and are therefore susceptible to learn strongly-correlated biases, such as using protected attributes like gender and race. Most existing bias mitigation approaches aim to explicitly reduce the model's focus on these protected features. In this work, we propose to mitigate bias by explicitly guiding the model's focus towards task-relevant features using domain knowledge, and we hypothesize that this can indirectly reduce the dependence of the model on spurious correlations it learns from the data. We explore bias mitigation in facial expression recognition systems using facial Action Units (AUs) as the task-relevant feature. To this end, we introduce Feature-based Positive Matching Contrastive Loss which learns the distances between the positives of a sample based on the similarity between their corresponding AU embeddings. We compare our approach with representative baselines and show that incorporating task-relevant features via our method can improve model fairness at minimal cost to classification performance.

Index Terms—facial expression recognition, fairness, contrastive loss

I. INTRODUCTION

The performance of machine learning models depends on the quality of the dataset that they are trained on; any bias in the dataset will be learnt by the model [1], [2]. One example is dataset imbalance: if in a Facial Expression Recognition training dataset, there are more *Male* faces with *Angry* labels than *Female* faces, then given this spurious correlation, the model might learn to associate features associated with *Male* faces (which is task-irrelevant), with the output class *Angry*. Such task-irrelevant cues may be shortcuts that the model learns to achieve better performance, but which reduce generalizability to new data [3]–[5]. Moreover, for moral, ethical, and legal reasons, we may want to ensure that the model is unbiased with respect to certain **protected** attributes, such as race and gender.

Generally, there are two broad classes of approaches to mitigate bias in machine learning models. The first class of approaches require knowledge of the labels of the protected attribute. If one has labels of the protected attribute, one could try to compensate for the statistical distribution of the attribute [6], use the labels in contrastive-based approaches [4], or to "train out" the bias using adversarial-based approaches [7]–[10].

The second class of approaches do not require labels of the protected attribute during training (although for evaluating our bias mitigation techniques, we would still require labels). Most methods in this class use a helper model that is trained with the knowledge of the type of bias-causing features (such as texture biases in CNN models), and the information from these helper models is used to debias the main models [4], [11], [12]. Other approaches utilise the learning dynamics of neural networks, which have been shown to learn biased cues faster than task-relevant features [3], [5].

In this work, we propose a different approach to reducing bias. Instead of explicitly reducing the model's reliance on task-irrelevant features, we instead propose to guide the model to focus on a set of task-relevant features-and in doing so, reducing bias in the model. In particular, in the case of Facial Expression Recognition, we consider Facial Action Units (AUs) [13], which have been widely studied in Facial Expression Recognition research [14]-[17]. We introduce feature-based Positive Matching Contrastive Loss, which uses extracted AUs to compute similarities between faces with the same emotion label (i.e., among positive samples). We use these similarities in a contrastive loss to weigh the distances between each sample and its positive samples. We compare our work with representative baselines using two datasets (RAF-DB and IASLab), and find that, compared to existing approaches which do and do not use bias labels, our approach performs very well at reducing bias.

II. RELATED WORK

A. Bias mitigation for Machine Learning models

We review existing approaches based on whether they require explicit labels of the protected attribute (i.e., labels of the potential bias) during training.

This research is supported in part by the National Research Foundation, Singapore under its AI Singapore Programme (AISG Award No: AISG2-RP-2020-016), and by a Singapore Ministry of Education Academic Research Fund Tier 1 grant to DCO.

1) Bias mitigation with labels: One set of approaches makes the model aware of the bias such as by explicitly predicting bias labels in a multi-task setting [18], [19], compensating for the distributional statistics of the protected classes [6] or by incorporating the bias labels in the loss computation [4]. Alternatively, adversarial-based approaches explicitly try to make the model "blind" to the bias labels by using a confusion loss [7], [10] or gradient reversal techniques [9], [20]. Although most existing bias mitigation approaches use bias labels for mitigation, this may not always be practical as it is difficult to exhaustively list all the factors that may induce bias in real-life conditions. In addition, a majority of existing datasets do not contain bias label annotations, which may limit the utility of these approaches.

2) Bias mitigation without labels: Recently, there has been a shift in bias mitigation strategies towards debiasing the models without using bias labels. A majority of these approaches train an auxiliary model to debias the primary model [4], [11], [12]. The auxiliary model is generally trained to predict the task using biased features. For example, Convolutional Neural Networks(CNNs) are biased towards textures [21], and so one approach to debias object recognition models is to train an auxiliary model to use textures. For instance, [4] used the distance between samples from embedding space of the auxiliary model to weigh the positives samples in the contrastive objective of the primary model such that when two positives are closer in the embedding space, they should be weighed less in the primary model.

Another set of approaches harnesses the learning dynamics of neural networks to mitigate bias [3], [5]. If the dataset contains strong biases, then the model learns early on in training to differentiate samples based on these easier-to-learn bias features, which hampers the model's ability to learn task-relevant features [3], [5], [22], [23]. For example, [3] introduced Spectral Decoupling which uses a L2-regularisation penalty term to decouple the features from the learning dynamics of neural networks, which in turn gives the model a chance to learn from all the features. [5] used the observations from the model learning dynamics to select easy and hard samples for the main model with the help of an auxiliary model.

Our work does not require bias labels nor knowledge of the bias features. Instead of explicitly removing the dependence of the model on the task-irrelevant features, we aim to increase the importance of task-relevant features, obtained using domain knowledge. We hypothesize that doing so would in turn diminish the model's dependence on the bias features.

B. Bias mitigation strategies in Facial Expression Recognition

Facial expression recognition have been widely deployed in various commercial settings such as in automated candidate screening where companies use videos from applicants to filter candidates based on their facial expressions. Recently, these algorithms have come under scrutiny for reinforcing biases against certain groups of people, such as people with disabilities [24]. Similarly, Rhue [25] investigated two commercial expression recognition software, Face++ and Microsoft AI, and found that these two commercial offerings rated Black basketball players (in their professional website pictures) as displaying much more negative emotions than White players.

Yet, there are only a few papers that have focused on mitigating bias in the context of facial expression recognition. One example is [8], who investigated existing bias-mitigation techniques that use bias labels for gender- and race-bias mitigation in facial expression recognition of six basic emotions, and found promising results for adversarial approaches.

In a recent study, [26] used Facial Action Units to mitigate annotation bias, which occurs when human annotators extend their personal/social biases into the data annotation. In this work, while we are less concerned with annotation bias, we also use Facial Action Units as the task-relevant feature to develop fairer expression recognition models.

1) Facial Action Units for Facial Expression Recognition: We use the Facial Action Coding System (FACS) as the taskrelevant features for Facial Expression Recognition. FACS [13] is an anatomically-based coding system which codes facial muscular movements into a set of Action Units (AU), which gives a description of facial muscle movements. Action Units have been widely used in the study of facial expression and perception [27]–[29].

[14] used a FACS-based deep learning architecture to retrieve images that display similar facial expressions in FER2013, an in-the-wild facial expression dataset. Another detailed investigation by [15] found that there is activity in CNN-based FER models in the regions of the face corresponding to the locations of relevant Facial Action Units, which suggests a high correlation between the facial expressions and facial action units. Thus, there is literature to support the claim that these extracted AUs are meaningful indicators of facial expression, and hence we may be able to use these AU features as task-relevant features to guide the model towards these features, and away from task-irrelevant features.

III. APPROACH

A. Model Fairness

How do we measure if a model is "fair"? This is not a trivial question, and there have been different notions of fairness discussed in the literature [1], [30], [31]. In our context, let us consider a model trained to detect happiness (or not), $\hat{y} \in \{0, 1\}$, in a dataset containing the sensitive or protected attribute gender, male or female $\{a_m, a_f\} \in A$. We may desire for our model to have the same level of accuracy in predicting "truly" happy men and as it does for predicting "truly" happy women, or in other words, to have the same true positive detection rate (of happiness, y) across groups $a \in A$. This is in line with the notion of equality of opportunity [1], [30], where we ideally want:

$$P(\hat{y} = 1 | y = 1, A = a_f) = P(\hat{y} = 1 | y = 1, A = a_m) \quad (1)$$

where \hat{y} is the predicted label, y is the target label, for the protected classes $\{a_f, a_m\} \in A$. In this work, we focus on equality of opportunity as it maintains a balance in achieving

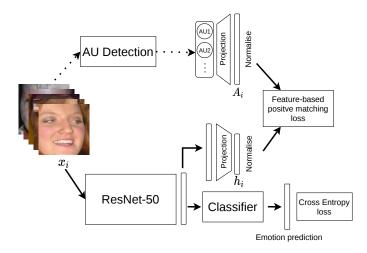


Fig. 1. An overview of our proposed Positive Matching Contrastive Loss. x_i is the input image, h_i is a latent embedding of the input image used to compute the contrastive loss, and A_i is AU embedding obtained after projection. Both h_i and A_i was normalised before computing the loss, in Eqn. 2. Dashed arrows represent *pre-processing* steps (extracting AU from input data) and solid arrows represents connections that are updated during model training. Images shown are taken from the RAF-DB dataset.

fairness by equalising the true positive rates amongst different protected groups [30].

B. Feature-based Positive Matching Loss

In standard supervised classification, the model learns input features that yields the best classification accuracy sometimes, some of these output-relevant features may correspond to protected attributes such as race and gender. For example, if the training dataset is imbalanced or has other types of bias in it, such that some protected attributes are more correlated with some output classes (e.g., White faces that tend to be labelled as Happy, compared to Black), then the model would learn to associate these attributes with the output (e.g., see [25] for an example for emotion classification and race).

In this work, we propose a different approach. How about if we guide the model to pay attention to certain types of input features that we know, from theory, relate to the output? In the case of emotion classification, there has been systematic research characterizing facial muscle movements, which has been formalized in the Facial Action Coding System [13], [27] and provides an informative set of features from which to infer emotions.

We introduce feature-based Positive Matching Contrastive Loss which provides extrinsic guidance to the model using task-relevant features, without the need for explicit bias labels. We hypothesize that such guidance will help the model focus on task-relevant similarities (such as facial muscle movements) over task-irrelevant features (that may be associated with race and/or gender).

Let the latent embedding of a sample *i* using a Convolutional Neural Network-based feature extractor be h_i , and let the embeddings of its positive samples (i.e., the other samples $\{p\} \in P_i$ that share the same output class as *i*) be

 $\{h_1, \dots, h_{P_i}\}$. We use a similarity function to calculate the pair-wise similarities between *i* and its positives $\{p\} \in P_i$, to obtain: $\{S(h_i, h_1), \dots, S(h_i, h_{P_i})\}$. Next, we repeat the same similarity calculations with the AU embeddings of sample *i*, A_i , along with its positives $\{A_1, \dots, A_{P_i}\}$, and we use these to weight the similarity scores of the *h* embeddings in the loss:

$$L_{\text{pos-match}} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{p=1}^{P_i} S(\boldsymbol{A}_i, \boldsymbol{A}_p) \cdot S(h_i, h_p)$$
(2)

where N is the total number of samples in a batch. We normalise both AU embeddings A_i and latent embeddings h_i , and we use cosine similarity for S(.,.).

To obtain the AU embeddings, we use the recentlyintroduced AU detection model, JAA-Net [32], to get the raw intensities for 12 AUs¹ in the range of 0 to 1. The AU extraction step is performed prior to the training of the CNNbased feature extractor. During training, each 12-dimensional raw AU vector is projected into a latent space using a nonlinear layer with a dimension of 32 with a ReLU activation. This network is trained along with the feature extractor to get the corresponding AU embedding A_i .

For feature extraction (Fig. 1), we fine-tune ResNet50 pretrained with VGGFace2 weights [33]–[35]. The output of the ResNet-50 network is further projected down to a latent space using a non-linear layer with a dimension of 128 with ReLU activation to obtain h_i which is used for computing $L_{\text{pos-match}}$ (Eqn. 2). For facial expression classification, as done in standard fine-tuning, the output from ResNet-50 is passed through a classification layer and trained using a Cross Entropy Loss. Therefore, the combined objective is given by:

$$09L_{\text{final}} = L_{\text{pos-match}} + L_{\text{CE}}$$
(3)
IV. EVALUATION

A. Datasets

We used two emotion-classification datasets with seven labels: {*happy, sad, angry, fear, surprise, disgust, and neutral*}.

- **RAF-DB** [36], [37] consists of crowd-sourced face images from the Internet. All the images are labelled with race, gender and age attributes, and we will consider mitigation of bias by **race** and **gender**². The train/validation/test split is 9816 / 2455 / 3068 samples respectively. We used the cropped and aligned version provided by the authors.
- **IASLab**³ is a lab-controlled dataset which comprises of posed expressions that also have **gender** annotations. In this dataset, all images are modified to have eyes centered in the same location⁴. We use a train/validation/test split

¹AU01: Inner brow raiser, AU02: Outer brow raiser, AU04: Brow lowerer, AU06: Cheek Raiser, AU07: Lid tightener, AU10: Upper Lip Raiser, AU12: Lip Corner Puller, AU14: Dimpler, AU15: Lip Corner Depressor, AU17: Chin Raiser, AU23: Lip Tightener, and AU24: Lip Pressor.

²In RAF-DB some samples are labelled "Unsure". Following previous works, for fairness evaluation we do not use these samples.

³Development of the Interdisciplinary Affective Science Laboratory (IASLab) Face Set was supported by the National Institutes of Health Director's Pioneer Award (DP10D003312) to Lisa Feldman Barrett.

⁴https://www.affective-science.org/face-set.shtml

Gender	Male	Female	Unsure
IASLab	414 (35.9%)	740 (64.1%)	-
RAF-DB	3,893 (40.2%)	5,179 (53.5%)	609 (6.3%)
Race	Caucasian	African-American	Asian
RAF-DB	7,420 (76.6%)	767 (7.9%)	1,494 (15.4%)
		TABLE I	

BREAKDOWN OF DATA BY RESPECT TO GENDER (TOP) AND RACE (BOTTOM). ONLY RAF-DB HAS RACE ANNOTATIONS.

of 1,151 / 144 / 145 samples.

B. Implementation Details

1) AU Detection: We use the $py-feat^5$ [38] package to implement JAA-Net for detecting AUs from training images. We first perform face detection using RetinaFace [39]. Samples with no faces detected are discarded and if multiple faces are detected then we take the largest face. Each image with a detected face will be passed through JAA-Net to obtain a 12-dimensional AU intensity vector.

2) Model Training: We trained our models using Stochastic Gradient Descent with a momentum of 0.9, a learning rate of 1e-03 and batch size of 32. We trained the models for 30 epochs using a step learning rate scheduler with step size of 10 and decay factor γ of 0.5, and did early stopping, choosing the best model based on validation accuracy. We resized the the shorter side of images to 256 pixels and perform center cropping of 224 × 224 pixels to shape the input to the feature-extractor [33]. The images are normalised using each respective dataset's mean and standard deviation. To prevent over-fitting, we augmented the datasets by performing horizontal flipping for a randomly-chosen 50% of the images.

C. Evaluation metric

1) Expression Classification: For classification performance, we use classification accuracy and weighted-F1 score.

2) Fairness measure: We use as our fairness measure the equality of opportunity [30] given in Eqn. 1. Following previous research [8], [31], we use the worst-case min-max ratio, which is the ratio of the minimum accuracy across all protected groups to the maximum accuracy across all protected groups. For example, if gender is the protected group and if the classification accuracy of emotions for males is lower than that for females, then the ratio would be the accuracy for males over the accuracy for females. The closer the min-max ratio is to unity, the smaller the disparity between the truepositive rate between protected groups, and hence the "more fair" the model is. Formally, if a_d is the protected group with the highest classification accuracy (for emotions):

$$a_d = \operatorname*{argmax}_{a \in K} \frac{1}{N_a} \sum_{i=1}^N \mathbb{1}_{(\hat{y_i} = y_i | A = a)}$$

where K is the number of group defined by the protected attribute, N is the total number of samples, N_a is the number of samples belonging to protected group a, and 1 is the

⁵https://py-feat.org/

	Fairness	by Gender		
	IASLab	Male Acc	Female Acc	Fairness
w/	Domain-aware	91.5 (2.3)	97.3 (1.0)	94.0 (2.8)
labels	Domain-unaware	89.4 (2.3)	94.7 (2.1)	94.4 (3.4)
-	Cross Entropy Baseline	90.2 (3.5)	96.1 (2.8)	93.8 (2.1)
w/o	Positive Matching (ours)	92.8 (1.0)	95.3 (1.7)	97.1 (2.3)
labels	Spectral Decoupling	89.4 (2.3)	92.4 (2.1)	95.5 (2.8)
	Spectral Decoupling + Ours	88.9 (0.9)	91.4 (2.7)	96.4 (2.1)
	RAF-DB	Male Acc	Female Acc	Fairness
w/	Domain-aware	82.1 (0.5)	85.6 (0.7)	95.9 (1.0)
labels	Domain-unaware	84.8 (0.5)	87.2 (0.3)	97.3 (0.5)
	Cross Entropy Baseline	84.7 (0.7)	87.4 (0.4)	96.9 (1.1)
w/o	Positive Matching (ours)	83.8 (0.7)	87.4 (0.5)	96.0 (1.1)
labels	Spectral Decoupling	81.8 (0.7)	85.0 (0.8)	96.3 (0.4)
	Spectral Decoupling + Ours	82.2 (0.8)	85.1 (0.6)	96.5 (1.5)

TABLE II

Overall gender fairness measure for IASLab (top) and RAF-DB dataset (bottom). Values are averaged over 5 runs with standard deviation in parenthesis. Best scores amongst the approaches without bias labels are given in bold.

indicator function, then this worst-case ratio, the Fairness Score, is given by:

$$F = \min_{a_k \in K \setminus \{a_d\}} \left\{ \frac{\frac{1}{N_{a_k}} \sum_{i=1}^N \mathbb{1}_{(\hat{y}_i = y_i | A = a_k)}}{\frac{1}{N_{a_d}} \sum_{i=1}^N \mathbb{1}_{(\hat{y}_i = y_i | A = a_d)}} \right\}$$
(4)

D. Comparison Methods

We compare our approach with two classes of approaches: mitigation approaches that require labels of the protected attribute like race and gender, and mitigation approaches that do not require these labels. We note that our Positive Matching Contrastive Loss method does not require these labels.

- 1) Mitigation approaches that require bias-labels:
- **Domain-aware**. Instead of a (# of class)-way classifier, this approach trains a (# of classes \times # of groups)-way classifier to make the model aware of the bias labels ("fairness by awareness" [18], [40]). We replace the final classification layer of the vanilla model to accommodate for the increased classification categories. In the case of IASLab, this becomes a 14-class classification (7 emotion classes \times 2 gender groups), while in the case of RAF-DB, this becomes a 42-class classification (7 emotion classes \times 2 gender groups⁶ \times 3 races).
- **Domain-unaware**. We follow [7] and use gradient reversal on the domain classification to make the model unlearn the domain features. For IASLab, we classify the gender (2-way classification) and RAF-DB we classify both gender-race combined labels (6-way classification⁶).
- 2) Mitigation approaches that do not require bias-labels:
- Baseline (Cross Entropy Loss). This is the standard baseline, which uses a Cross-Entropy Loss to predict facial expressions L_{CE} . This is also our approach without the Positive Matching Loss (Eqn. 3 without $L_{\text{pos-match}}$).
- **Spectral Decoupling**. This method [3] mitigates bias without the need of bias labels. A L2 penalty is added

⁶RAF-DB has an "unsure" category for gender, but to be in-line with existing approaches, we only consider male and female.

		Fairnes	s by Gender, I	broken down	by Emotion			
	IASLab	Neutral	Anger	Disgust	Fear	Happiness	Sadness	Surprise
	# of training samples	159	155	162	170	170	172	166
	Female : Male ratio	66:34	64:36	66 : 34	64:36	64:36	66 : 34	59:41
w/	Domain-aware	100.0 (0.0)	81.1 (9.7)	93.8 (4.7)	82.6 (11.8)	100.0 (0.0)	91.5 (5.4)	98.6 (2.9)
labels	Domain-unaware	95.4 (6.2)	72.1 (19.5)	87.8 (9.6)	83.4 (10.1)	96.7 (6.7)	90.2 (3.3)	95.7 (5.7)
-	Cross Entropy Baseline	96.9 (3.8)	77.3 (15.9)	86.0 (8.0)	95.1 (6.1)	100.0 (0.0)	87.3 (6.3)	97.1 (3.5)
w/o	Positive Matching (ours)	96.9 (3.8)	87.1 (10.7)	91.8 (3.6)	80.1 (7.0)	100.0 (0.0)	91.5 (5.4)	97.1 (3.5)
labels	Spectral Decoupling	90.8 (3.1)	80.0 (10.0)	84.0 (13.6)	90.3 (10.2)	100.0 (0.0)	88.9 (7.8)	84.3 (8.3)
	Spectral Decoupling + Ours	92.3 (0.0)	81.1 (9.7)	78.0 (4.0)	91.8 (6.2)	100.0 (0.0)	95.1 (4.1)	84.3 (11.4)
	RAF-DB							
	# of training samples	1979	538	569	208	3831	1536	1020
	Female : Male ratio	50:46	65:33	58:39	57:41	59:38	53:28	48:41
w/	Domain-aware	96.9 (2.1)	91.9 (5.5)	86.6 (6.7)	79.8 (7.8)	96.9 (0.6)	92.4 (3.2)	91.7 (2.3)
labels	Domain-unaware	96.4 (0.8)	92.2 (4.2)	95.3 (4.0)	81.0 (10.8)	97.6 (0.9)	93.8 (1.7)	94.3 (3.2)
	Cross Entropy Baseline	97.6 (1.7)	89.4 (2.4)	90.6 (4.1)	79.9 (8.0)	96.7 (0.8)	95.0 (3.8)	92.9 (1.5)
w/o	Positive Matching (ours)	97.5 (1.0)	92.7 (3.7)	90.8 (3.4)	82.9 (6.4)	96.8 (1.2)	95.3 (2.4)	91.1 (1.1)
labels	Spectral Decoupling	96.1 (2.8)	89.4 (3.1)	93.9 (2.9)	75.8 (8.4)	96.5 (1.0)	93.3 (3.7)	87.6 (1.1)
	Spectral Decoupling + Ours	95.2 (2.7)	85.4 (3.8)	87.6 (7.5)	68.5 (13.5)	96.6 (1.1)	92.4 (1.7)	87.6 (1.7)

TABLE III

GENDER FAIRNESS MEASURE FOR EACH EMOTION CLASS FOR IASLAB (TOP) AND RAF-DB (BOTTOM). VALUES ARE AVERAGED OVER 5 RUNS WITH STANDARD DEVIATION IN PARENTHESIS. BEST SCORES AMONGST THE APPROACHES WITHOUT BIAS LABELS ARE GIVEN IN BOLD. RATIO VALUES CORRESPOND TO PERCENTAGE OF SAMPLES BELONGING TO THAT GROUP IN TRAINING DATASET.

to the loss term, and training is the same as the vanilla model. Hyper-parameters in this model are the penalty coefficient, set to 2e-05, and the annealing steps, set based on when the vanilla model overfits (400 steps for IASLab and 3,500 for RAF-DB). In addition, we also implemented Spectral Decoupling with our method (Spectral Decoupling + Positive Matching Loss).

V. RESULTS AND DISCUSSION

We first consider how the various methods perform on gender fairness, in Table II. Recall that the Fairness score (Eqn. 4) is the ratio of the minimum classification accuracy within each group to the maximum accuracy, and values closer to 1 indicate more similar performances across groups. To orient the reader, the baseline model using Cross Entropy Loss (i.e., with no bias mitigation), achieves a 90.2% accuracy for males and 96.1% accuracy for females on the IASLab dataset; the fairness score is thus 90.2/96.1 = 93.8%. Compared to this, our Positive Matching Contrastive Loss method yielded a greater fairness of 97.1%, and was the best performing of all methods. If we examined the fairness for specific emotion classes (Table III), our method also achieves the best fairness for 5 of the 7 classes, and for sadness, Spectral Decoupling plus our Positive Matching loss achieves the best fairness.

For gender fairness on the RAF-DB dataset, we find that neither our method, nor most of the other methods we tried (except for Domain-unaware), improved overall fairness beyond the Cross Entropy Baseline (96.9%). When we took a closer look at the performance on RAF-DB for specific emotion classes, in Table III, we find that out of the seven classes, our method yielded the best fairness for four classes (*anger, fear, happiness* and *sadness*).

If we next consider fairness by race (only in the RAF-DB dataset), in Table IV, the best performing method that does not use bias labels is the Spectral Decoupling of [3] augmented

with our Positive Matching Contrastive Loss, which achieves a Fairness of 98.6%. When we consider fairness for specific emotion classes, we again find that our approach achieves the best fairness on four of the seven classes, (*neutral, anger, disgust* and *fear*), and for *surprise*, Spectral Decoupling plus our Positive Matching loss achieves the best fairness.

One point of discussion is that the datasets do not have balanced gender and race ratios. For IASLab, the Female:Male ratio is 64:36 (Table I), while for RAF-DB it is a little closer at 57:43 (if we remove those with unknown labels), but still has more Female than Male faces. The racial distribution in the RAF-DB dataset is also heavily imbalanced, with almost 77% of the faces being Caucasian, 15% Asian, and only 8% African-American (and these are just three of many races). While overall the fairness scores seem high, these imbalances do translate to some troubling fairness values when we examine specific classes. For example, for race in RAF-DB and considering the classification of *fear*, the baseline cross entropy method achieves a Fairness Score of 49.5%, which suggests that the true positive rate for identifying *fear* in one race is half that of identifying fear in another. (Our method does not improve fairness for this particular class either).

Finally, we consider the impact of bias mitigation strategies on classification performance. Intuitively, we might expect that optimizing for two objectives (i.e., a fairness objective in addition to classification accuracy) may result in lower classification performance. We can see in Table V that this is indeed the case for RAF-DB, where all the bias mitigation strategies underperformed the cross entropy baseline on classification accuracy. The Domain-Unaware method overall had the smallest drop in accuracy (-0.3%), and our Positive Matching method had the smallest drop in accuracy among the strategies that do not require labels (-0.4%). For the IASLab dataset, we observed that, in fact, the Domain-Aware

				Fairness by	kace (RAF-D	В)			
				Caucasian Ac	c African-A	American Acc	Asian Acc	Fairness	
		# of training	samples	7420		767	1494	Fairness	
	w/	Domain-awar	e	84.2 (0.4)	84	.5 (1.2)	83.4 (0.9)	98.0 (0.6)	-
	labels	Domain-unaw	are	86.1 (0.3)	86	.8 (1.0)	86.2 (0.7)	98.6 (1.3)	
		Cross Entropy	Baseline	86.3 (0.3)	88	.6 (1.0)	86.5 (1.1)	96.9 (0.9)	-
	w/o	Positive Matc	hing (ours)	85.8 (0.2)	87	.8 (1.0)	87.0 (0.8)	97.6 (0.9)	
	labels			83.8 (0.8)	84	.7 (1.0)	84.4 (1.0)	97.7 (0.8)	
		Spectral Deco	oupling + Ours	84.0 (0.2)	84	.4 (1.0)	84.6 (0.5)	98.6 (0.4)	
			Neutral	Anger	Disgust	Fear	Happiness	Sadness	Surprise
	Ca:Af:As	ratio*	72:11:17	86:5:9	77:5:18	84:5:12	76:8:16	75:7:18	84:7:9
w/	Domain-awar	e	93.9 (3.2)	69.0 (10.6)	63.0 (9.8)	58.9 (13.6)	97.3 (0.9)	89.7 (4.0)	80.6 (11.8)
labels	Domain-unaw	are	94.4 (2.7)	69.9 (3.0)	66.9 (10.6)	48.8 (9.9)	98.1 (1.5)	84.5 (3.3)	83.3 (7.1)
	Cross Entropy	y Baseline	93.8 (2.6)	68.6 (7.2)	62.3 (7.6)	49.5 (6.8)	96.5 (1.7)	92.8 (4.9)	80.4 (3.8)
w/o	Positive Matc	hing (ours)	95.2 (3.2)	72.8 (8.9)	69.4 (15.2)	47.3 (9.6)	96.1 (1.5)	92.8 (3.0)	78.2 (3.9)
labels	Spectral Deco	oupling	93.5 (2.4)	64.0 (10.6)	60.9 (6.5)	36.6 (14.8)	96.9 (2.0)	90.0 (3.6)	76.5 (7.2)
	Spectral Deco	oupling + Ours	90.1 (3.7)	65.6 (7.4)	64.8 (7.6)	41.8 (9.3)	95.3 (2.1)	90.9 (2.1)	81.3 (7.5)

Fairness by Daca (PAE DB)

TABLE IV

RACE FAIRNESS MEASURES FOR THE RAF-DB DATASET, ACROSS ALL CLASSES (TOP) AND BROKEN DOWN BY INDIVIDUAL CLASSES (BOTTOM). VALUES ARE AVERAGED OVER 5 RUNS WITH STANDARD DEVIATION IN PARENTHESIS. BEST SCORES AMONGST THE APPROACHES WITHOUT BIAS LABELS ARE GIVEN IN BOLD. *CA=CAUCASIAN, AF=AFRICAN-AMERICAN, AS=ASIAN. (THE RATIO VALUES FOR FEAR IS OVER 100 DUE TO ROUNDING.)

Overall Emotion Classification Performance	Overall	Emotion	Classification	Performance
--	---------	---------	----------------	-------------

	IASLab	Acc	F1	Δ_{CE}
w/	Domain-aware	95.4 (0.9)	95.4 (1.0)	+1.2
labels	Domain-unaware	93.0 (1.5)	93.0 (1.6)	-1.2
	Cross Entropy Baseline	94.2 (2.8)	94.2 (2.9)	-
w/o	Positive Matching (ours)	94.5 (0.9)	94.5 (0.9)	+0.3
labels	Spectral Decoupling	91.4 (1.2)	91.4 (1.2)	-2.8
	Spectral Decoupling + Ours	90.6 (1.8)	90.6 (1.8)	-3.6
	RAF-DB	Acc	F1	Δ_{CE}
w/	RAF-DB Domain-aware	Acc 84.1 (0.5)	F1 83.9 (0.5)	Δ_{CE} -2.4
w/ labels				-
,	Domain-aware	84.1 (0.5)	83.9 (0.5)	-2.4
,	Domain-aware Domain-unaware	84.1 (0.5) 86.2 (0.3)	83.9 (0.5) 85.9 (0.3)	-2.4
labels	Domain-aware Domain-unaware Cross Entropy Baseline	84.1 (0.5) 86.2 (0.3) 86.5 (0.3)	83.9 (0.5) 85.9 (0.3) 86.3 (0.3)	-2.4 -0.3

TABLE V

Overall emotion classification performance for IASLab (top) and RAF-DB (bottom) using accuracy and weighted F1 score. Values are averaged over 5 runs with standard deviation in parenthesis. Best scores amongst the approaches without bias labels are given in bold. Δ_{CE} denotes the accuracy

DIFFERENCE OF A GIVEN METHOD WITH THE CROSS ENTROPY BASELINE, WHICH HAS NO BIAS MITIGATION.

method increased classification accuracy by 1.2%, and our Positive Matching method had the largest increase in accuracy among the strategies that do not require labels (0.3%). Thus, especially compared to the other bias mitigation strategies that do not require labels, our proposed method not only increases fairness scores of the model, but also maintains classification performance compared to the standard (un-biasmitigated) classifier.

VI. LIMITATIONS AND FUTURE WORK

Our main premise is that a valid approach to bias mitigation is to guide the model to focus on a set of task-relevant features instead of protected attributes. In the specific case of facial expression recognition, we can appeal to many decades of work in psychology to suggest that there may be some desirable task-relevant features such as facial Action Units. However, there is evidence that socio-cultural variations exist within the expressions associated with similar emotions. For instance, [41] found significant differences in AU06 and AU12 intensities across gender, race, and age for happy emotion. Similarly, there is evidence that people across cultures regulate their display of emotions differently leading to variations in emotion intensities displayed [42], [43]. In the future, understanding the effects of these differences can help further reduce irrelevant intra-class variations leading to fairer models.

Also, generalising this approach to other domains would require tailored, specific domain knowledge, which may have to be hand-crafted, or perhaps extracted from external knowledge bases. There is plenty of evidence suggesting that incorporating domain-relevant context into deep-learning models leads to better performance [44]–[48], and in this work we show that using domain knowledge could also help build *fairer* models.

Future work could more deeply study the quality of the task-relevant features, for example by varying the type/number of the AUs used, or including other external knowledge sources. While we analyzed the performance of our method on specific emotion classes, another important future direction is to understand how we can extend this approach to optimize for fairness in specific classes, which is especially important in cases where we have larger number of classes that may be more closely confusable, such as in fine-grained emotion classification [49]–[52].

VII. CONCLUSION

In this work, we introduced feature-based Positive Matching Contrastive loss which reduces (equality of opportunity) bias in facial expression recognition models by explicitly guiding the model towards task-relevant features—Facial Action Units. Our method aims to bring the hidden representations of positive samples (samples with same emotion label) closer together according to their similarity in task-relevant features (Action Units). Our approach was able to improve fairness at minimal cost to classification performance when compared to existing bias mitigation methods in two commonly used facial expression recognition datasets. This work is a step towards developing fairer machine learning models which is in turn important for the ethical deployment of these models in society.

ETHICAL STATEMENT

Machine learning models have been widely deployed in multiple settings that directly affect peoples' lives, and has been shown to be biased by race for emotion recognition [25]. There is a pressing need to study bias mitigation strategies, especially in facial expression recognition. Our work is a step in this direction, by offering a way to improve fairness without the need to use labels of the protected attributes (such as race and gender labels), by guiding the model to focus on features that are directly relevant to the task at hand.

REFERENCES

- N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A survey on bias and fairness in machine learning," in *ACM Computing Surveys (CSUR)*, vol. 54, no. 6. ACM New York, NY, USA, 2021, pp. 1–35.
- [2] B. Hutchinson and M. Mitchell, "50 years of test (un) fairness: Lessons for machine learning," in *Proceedings of the Conference on Fairness*, *Accountability, and Transparency*, 2019, pp. 49–58.
- [3] M. Pezeshki, O. Kaba, Y. Bengio, A. C. Courville, D. Precup, and G. Lajoie, "Gradient starvation: A learning proclivity in neural networks," in *Advances in Neural Information Processing Systems*, vol. 34, 2021.
- [4] Y. Hong and E. Yang, "Unbiased classification through bias-contrastive and bias-balanced learning," in Advances in Neural Information Processing Systems, vol. 34, 2021.
- [5] J. Nam, H. Cha, S. Ahn, J. Lee, and J. Shin, "Learning from failure: De-biasing classifier from biased classifier," in *Advances in Neural Information Processing Systems*, vol. 33, 2020, pp. 20673–20684.
- [6] 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 *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 8919–8928.
- [7] B. H. Zhang, B. Lemoine, and M. Mitchell, "Mitigating unwanted biases with adversarial learning," in *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 2018, pp. 335–340.
- [8] T. Xu, J. White, S. Kalkan, and H. Gunes, "Investigating bias and fairness in facial expression recognition," in *European Conference on Computer Vision*. Springer, 2020, pp. 506–523.
- [9] D. Madras, E. Creager, T. Pitassi, and R. Zemel, "Learning adversarially fair and transferable representations," in *International Conference on Machine Learning*. PMLR, 2018, pp. 3384–3393.
- [10] M. Alvi, A. Zisserman, and C. Nellåker, "Turning a blind eye: Explicit removal of biases and variation from deep neural network embeddings," in *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, 2018, pp. 0–0.
- [11] H. Bahng, S. Chun, S. Yun, J. Choo, and S. J. Oh, "Learning de-biased representations with biased representations," in *International Conference* on Machine Learning. PMLR, 2020, pp. 528–539.
- [12] R. Cadene, C. Dancette, M. Cord, D. Parikh et al., "Rubi: Reducing unimodal biases for visual question answering," in Advances in Neural Information Processing Systems, vol. 32, 2019.
- [13] P. Ekman, W. V. Freisen, and S. Ancoli, "Facial signs of emotional experience." in *Journal of Personality and Social Psychology*, vol. 39, no. 6. American Psychological Association, 1980, p. 1125.
- [14] T. T. D. Pham, S. Kim, Y. Lu, S.-W. Jung, and C.-S. Won, "Facial action units-based image retrieval for facial expression recognition," in *IEEE Access*, vol. 7. IEEE, 2019, pp. 5200–5207.

- [15] P. Khorrami, T. Paine, and T. Huang, "Do deep neural networks learn facial action units when doing expression recognition?" in *Proceedings* of the IEEE International Conference on Computer Vision Workshops, 2015, pp. 19–27.
- [16] M. Valstar and M. Pantic, "Fully automatic facial action unit detection and temporal analysis," in 2006 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'06). IEEE, 2006, pp. 149– 149.
- [17] L. Yao, Y. Wan, H. Ni, and B. Xu, "Action unit classification for facial expression recognition using active learning and svm," in *Multimedia Tools and Applications*, vol. 80, no. 16. Springer, 2021, pp. 24287– 24301.
- [18] C. Dwork, M. Hardt, T. Pitassi, O. Reingold, and R. Zemel, "Fairness through awareness," in *Proceedings of the 3rd Innovations in Theoretical Computer Science Conference*, 2012, pp. 214–226.
- [19] Y. Wang, X. Wang, A. Beutel, F. Prost, J. Chen, and E. H. Chi, "Understanding and improving fairness-accuracy trade-offs in multi-task learning," in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2021, pp. 1748–1757.
- [20] A. Beutel, J. Chen, Z. Zhao, and E. H. Chi, "Data decisions and theoretical implications when adversarially learning fair representations," *arXiv preprint arXiv*:1707.00075, 2017.
- [21] Y. Li, Q. Yu, M. Tan, J. Mei, P. Tang, W. Shen, A. Yuille et al., "Shapetexture debiased neural network training," in *International Conference* on Learning Representations, 2020.
- [22] G. Parascandolo, A. Neitz, A. Orvieto, L. Gresele, and B. Schölkopf, "Learning explanations that are hard to vary," in *Ninth International Conference on Learning Representations (ICLR 2021)*, 2021.
- [23] E. Kim, J. Lee, and J. Choo, "Biaswap: Removing dataset bias with bias-tailored swapping augmentation," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 14992–15001.
- [24] M. Whittaker, M. Alper, C. L. Bennett, S. Hendren, L. Kaziunas, M. Mills, M. R. Morris, J. Rankin, E. Rogers, M. Salas *et al.*, "Disability, bias, and ai," in *AI Now Institute*, 2019.
- [25] L. Rhue, "Racial influence on automated perceptions of emotions," Available at SSRN 3281765, 2018.
- [26] Y. Chen and J. Joo, "Understanding and mitigating annotation bias in facial expression recognition," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 14980–14991.
- [27] J. F. Cohn, Z. Ambadar, and P. Ekman, "Observer-based measurement of facial expression with the facial action coding system," in *The Handbook* of *Emotion Elicitation and Assessment*, vol. 1, no. 3, 2007, pp. 203–221.
- [28] E. L. Rosenberg and P. Ekman, What the face reveals: Basic and applied studies of spontaneous expression using the Facial Action Coding System (FACS). Oxford University Press, 2020.
- [29] M. A. Sayette, J. F. Cohn, J. M. Wertz, M. A. Perrott, and D. J. Parrott, "A psychometric evaluation of the facial action coding system for assessing spontaneous expression," in *Journal of Nonverbal Behavior*, vol. 25, no. 3. Springer, 2001, pp. 167–185.
- [30] M. Hardt, E. Price, and N. Srebro, "Equality of opportunity in supervised learning," in Advances in Neural Information Processing Systems, vol. 29, 2016.
- [31] A. Ghosh, L. Genuit, and M. Reagan, "Characterizing intersectional group fairness with worst-case comparisons," in *Artificial Intelligence Diversity, Belonging, Equity, and Inclusion.* PMLR, 2021, pp. 22–34.
- [32] Z. Shao, Z. Liu, J. Cai, and L. Ma, "JAA-Net: joint facial action unit detection and face alignment via adaptive attention," in *International Journal of Computer Vision*, vol. 129, no. 2. Springer, 2021, pp. 321– 340.
- [33] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "VGGFace2: A dataset for recognising faces across pose and age," in 2018 13th IEEE International Conference on Automatic Face & Gesture recognition (FG 2018). IEEE, 2018, pp. 67–74.
- [34] S. T. Ly, N.-T. Do, G. Lee, S.-H. Kim, and H.-J. Yang, "Multimodal 2D and 3D for in-the-wild facial expression recognition." in *CVPR Workshops*, 2019, pp. 2927–2934.
- [35] Q. T. Ngo and S. Yoon, "Facial expression recognition based on weighted-cluster loss and deep transfer learning using a highly imbalanced dataset," in *Sensors*, vol. 20, no. 9. Multidisciplinary Digital Publishing Institute, 2020, p. 2639.
- [36] S. Li, W. Deng, and J. Du, "Reliable crowdsourcing and deep localitypreserving learning for expression recognition in the wild," in 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2017, pp. 2584–2593.

- [37] S. Li and W. Deng, "Reliable crowdsourcing and deep localitypreserving learning for unconstrained facial expression recognition," in *IEEE Transactions on Image Processing*, vol. 28, no. 1. IEEE, 2019, pp. 356–370.
- [38] J. H. Cheong, T. Xie, S. Byrne, and L. J. Chang, "Py-feat: Python facial expression analysis toolbox," in arXiv preprint arXiv:2104.03509, 2021.
- [39] J. Deng, J. Guo, E. Ververas, I. Kotsia, and S. Zafeiriou, "Retinaface: Single-shot multi-level face localisation in the wild," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 5203–5212.
- [40] K. Yang, K. Qinami, L. Fei-Fei, J. Deng, and O. Russakovsky, "Towards fairer datasets: Filtering and balancing the distribution of the people subtree in the imagenet hierarchy," in *Proceedings of the 2020 Conference* on Fairness, Accountability, and Transparency, 2020, pp. 547–558.
- [41] Y. Fan, J. C. Lam, and V. O. Li, "Demographic effects on facial emotion expression: an interdisciplinary investigation of the facial action units of happiness," *Scientific Reports*, vol. 11, no. 1, pp. 1–11, 2021.
- [42] D. Matsumoto, A. Olide, J. Schug, B. Willingham, and M. Callan, "Cross-cultural judgments of spontaneous facial expressions of emotion," *Journal of Nonverbal Behavior*, vol. 33, no. 4, pp. 213–238, 2009.
- [43] H. A. Elfenbein and N. Ambady, "On the universality and cultural specificity of emotion recognition: a meta-analysis." *Psychological Bulletin*, vol. 128, no. 2, p. 203, 2002.
- [44] Z. Cui, T. Song, Y. Wang, and Q. Ji, "Knowledge augmented deep neural networks for joint facial expression and action unit recognition," in *Advances in Neural Information Processing Systems*, vol. 33, 2020, pp. 14 338–14 349.
- [45] Y. Chen, J. Wang, S. Chen, Z. Shi, and J. Cai, "Facial motion prior networks for facial expression recognition," in 2019 IEEE Visual Communications and Image Processing (VCIP). IEEE, 2019, pp. 1–4.
- [46] V. Suresh and D. C. Ong, "Using knowledge-embedded attention to augment pre-trained language models for fine-grained emotion recognition," in *Proceedings of the 9th International Conference on Affective Computing and Intelligent Interaction (ACII 2021)*, 2021.
- [47] P. Zhong, D. Wang, and C. Miao, "Knowledge-enriched transformer for emotion detection in textual conversations," in *Proceedings of the* 2019 Conference on Empirical Methods in NLP and the 9th Intl. Joint Conference on NLP (EMNLP-IJCNLP), 2019, pp. 165–176.
- [48] A. Roy and S. Pan, "Incorporating extra knowledge to enhance word embedding," in *Proceedings of the 29th International Joint Conference* on Artificial Intelligence, IJCAI-20, 2020, pp. 4929–4935.
- [49] R. Panda, J. Zhang, H. Li, J.-Y. Lee, X. Lu, and A. K. Roy-Chowdhury, "Contemplating visual emotions: Understanding and overcoming dataset bias," in *Proceedings of the European Conference on Computer Vision* (ECCV), 2018.
- [50] V. Suresh and D. C. Ong, "Not all negatives are equal: Label-aware contrastive loss for fine-grained text classification," in *Proceedings of the* 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP), 2021.
- [51] D. Demszky, D. Movshovitz-Attias, J. Ko, A. Cowen, G. Nemade, and S. Ravi, "GoEmotions: A dataset of fine-grained emotions," in *Proceed*ings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, pp. 4040–4054.
- [52] L. Liang, C. Lang, Y. Li, S. Feng, and J. Zhao, "Fine-grained facial expression recognition in the wild," in *IEEE Transactions on Information Forensics and Security*, vol. 16. IEEE, 2020, pp. 482–494.