KFC: Kinship Verification with Fair Contrastive Loss and Multi-Task Learning

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Introduction

- Goal
  - Boost **racial fairness**
  - Enhance **kinship verification** accuracy
  - Improve these two performance simultaneously
- Racial fairness
  - Fair contrastive loss function
  - Adversarial learning
- Kinship verification
  - Attention module
  - Multi-task learning

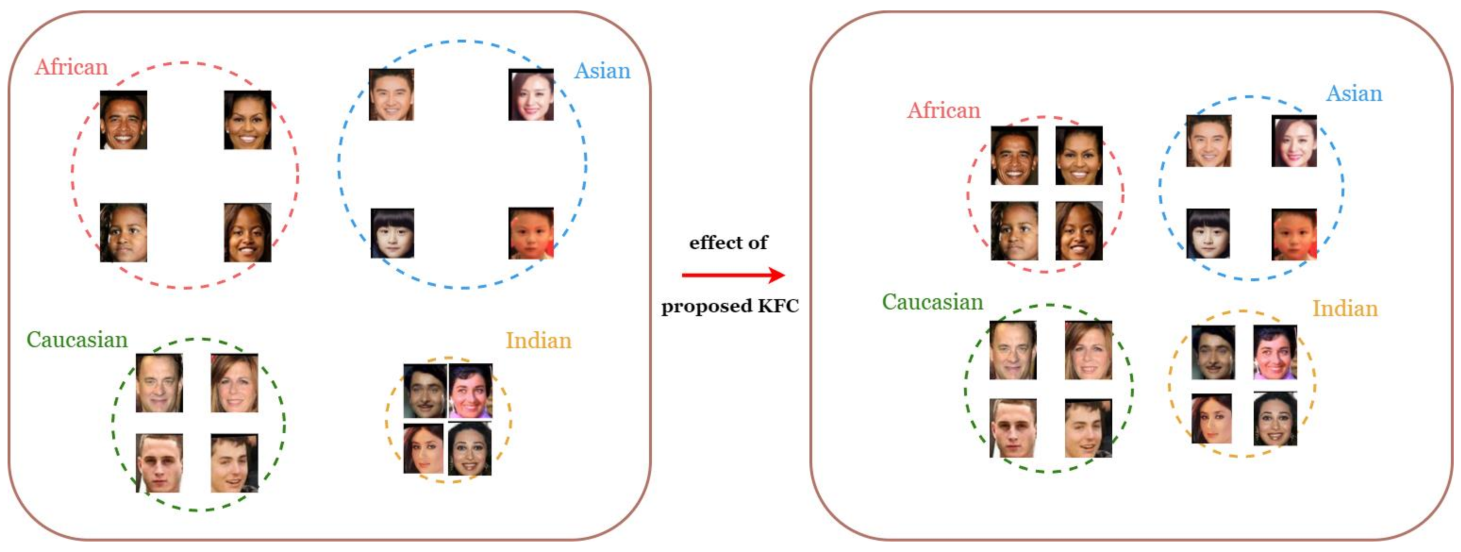


Figure 1: The schematic diagram for improving the fairness in kinship verification. Our method can effectively adjust the intra-class compactness and inter-class discrepancy in the feature space. We mitigate racial bias by balancing four races' intra-class and inter-class angle and making them as consistent as possible.

Dataset Construction

	African	Asian	Caucasian	Indian	sum
CornellKin	8	56	72	3	139
UBKinFace	18	192	173	0	383
KinFaceW-I	19	327	172	4	522
KinFaceW-II	55	96	788	35	974
Family101	5554	6540	82820	25374	120288
FIW(train)	8353	3841	59028	681	71903
FIW(val)	2087	1398	30147	0	33632
FIW(test)	1231	799	9665	97	11792
sum	17325	13249	182865	26194	239633
percent	7.23%	5.53%	76.31%	10.93%	100%

Table 1. The race distribution of our **KinRace** dataset. We combine 6 kinship datasets into one large kinship dataset. Moreover, we label the race of each identity to ensure racial fairness is taken into consideration.

Methodology

Model Structure

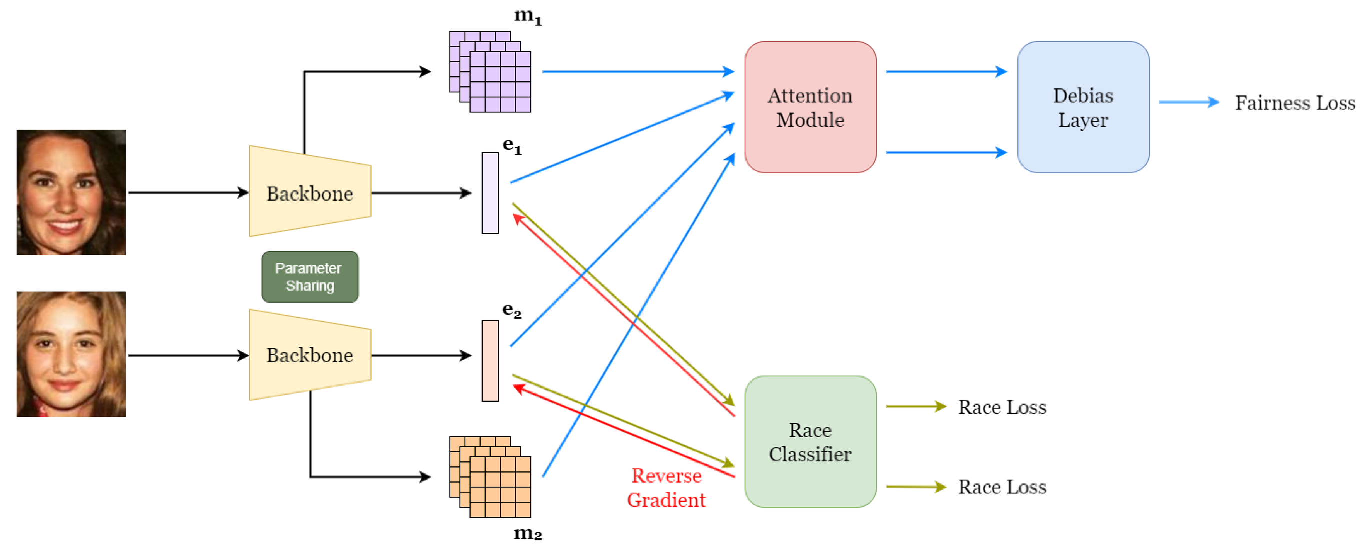


Figure 2: Overview of the proposed KFC model structure.

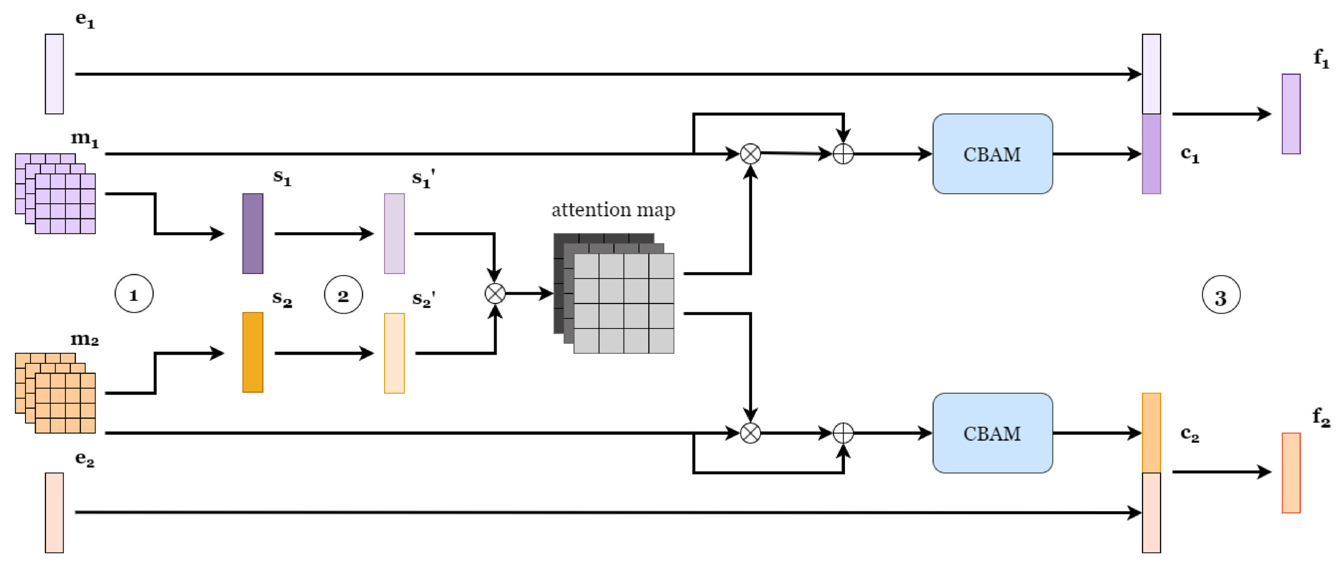


Figure 3: Overview of the proposed attention module.
① : average pooling. ② : 1x1 Conv with ReLU. ③ : 2 layers of 1x1 Conv with ReLU

Loss Function

Supervised contrastive loss

$$L_c(x_i, y_i) = -log \frac{e^{s(x_i,y_i)/\tau}}{\sum_{j=1}^{n}[e^{s(x_i,x_j)/\tau} + e^{s(x_i,y_j)/\tau}]}$$

Bias term

$$b = cos(M(f_m), M(f_i))^2 - cos(M(f_m), M(f_j))^2$$

Wang et al. proposed a bias term to indicate the model focuses more on identity *i* or *j*. f_i , f_j means the feature vector of *i*, *j*; f_m means the average feature vector between f_i and f_j. They assume b is positive if model focuses more on *i* while b is negative if model focuses on *j*.

Proposed fair contrastive loss

$$L_{fairness} = -log \frac{e^{(cos(x_i,y_i)-b_i)/\tau}}{\sum_{j \neq i}^{N}[e^{cos(x_i,x_j)/\tau} + e^{cos(x_i,y_j)/\tau}] + e^{(cos(x_i,y_i)-b_i)/\tau}}$$

We combine bias term with contrastive loss, which creates an innovative fair contrastive loss. After subtracting the bias term in loss function, the greater gradients help each pair balances its unfairness situation, which can make the compactness degree of every race as consistent as possible. Furthermore, the temperature τ in the original contrastive loss can further tackle with the hard samples. Combining temperature τ with the debias term, we take into account both accuracy and fairness.

Experimental Results

Ablation Study

Methods%	African	Asian	Caucasian	Indian	Avg	Std
baseline	82.18	83.71	78.00	80.70	79.08	2.43
KFC(attention)	84.31	85.99	81.59	79.28	81.74	2.96
KFC(attention+multi-task)	85.03	84.39	87.01	78.95	85.82	3.45
KFC(attention+multi-task+debias layer)	85.16	84.94	86.67	81.32	**85.86**	**2.27**

Table 2. Ablation study on accuracy.

Methods%	African	Asian	Caucasian	Indian	Avg	Std
baseline	82.18	83.71	78.00	80.70	79.08	2.43
KFC(adversarial)	78.45	81.51	79.11	76.36	78.88	2.10
KFC(debias layer)	80.35	80.62	78.67	77.35	78.74	1.53
KFC(adversarial+debias layer)(acc best)	81.61	82.68	82.90	82.37	**82.74**	0.56
KFC(adversarial+debias layer)(std best)	81.28	81.29	80.83	80.80	80.88	**0.27**

Table 3. Ablation study on standard deviation. *acc best* refers to the epoch with the highest accuracy on validation dataset, and *std best* refers to the epoch with the lowest standard deviation on validation dataset.

Comparisons with SOTA Methods

Method	African	Asian	Caucasian	Indian	Avg	Std
Vuvko	71.13	73.32	72.61	76.19	72.96	3.40
Ustc-nelslip	76.05	77.07	75.54	63.98	74.33	6.15
TeamCNU	82.18	83.71	78.00	80.70	79.08	2.43
KFC(multi-task)	85.16	84.94	86.67	81.32	**85.86**	2.27
KFC(adversarial)	81.28	81.29	80.83	80.80	80.88	**0.27**

Table 4: Comparisons with SOTA methods on KinRace dataset

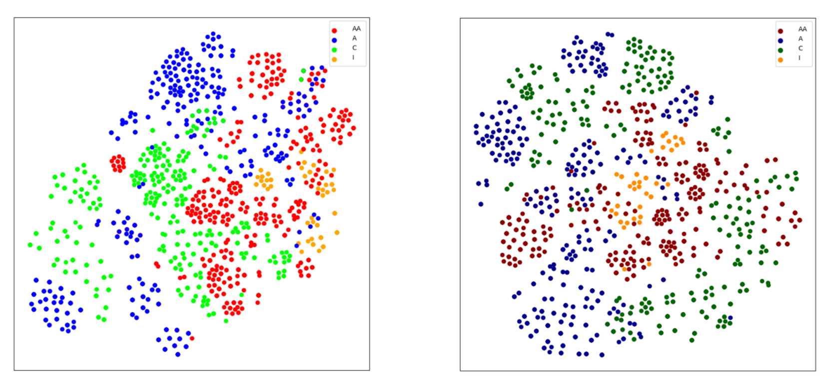
Method	C & YP	C & OP	Avg	Std
LPQ_ML	-	-	73.25	-
StatBIF-SIWEDA-WCCN	75.71	76.92	76.32	-
FAML	78.30	75.00	76.54	-
BC^2DA	83.28	**82.69**	83.30	-
KFC(multi-task)	**87.24**	81.00	**84.12**	1.36
KFC(adversarial)	82.71	77.75	80.23	**0.06**

Table 5: Comparisons with SOTA methods on UB KinFace dataset

Method	FD	MD	FS	MS	Std
Vuvko	75.00	78.00	81.00	74.00	-
Ustc-nelslip	76.00	75.00	82.00	75.00	-
TeamCNU	75.00	80.00	82.00	77.0	-
FaCoRNet(ArcFace)	77.30	80.40	82.60	78.80	-
FaCoRNet(AdaFace)	**79.50**	81.80	**84.80**	**80.20**	-
KFC(multi-task)	79.05	**83.61**	84.63	78.25	7.81
KFC(adversarial)	78.81	82.56	81.69	77.43	**5.57**

Table 6: Comparisons with SOTA methods on FIW dataset

Compactness Degree



(a) baseline (b) KFC

Figure 5: t-SNE visualizations. We randomly pick 400 pairs per race from KinRace dataset. AA for African, A for Asian, C for Caucasian, and I for Indian.

Methods		African	Asian	Caucasian	Indian	Std
baseline[46]	intra	17.21	18.32	15.36	10.08	3.68
	inter	46.85	52.34	40.85	44.20	4.85
ours	intra	12.21	16.59	15.65	11.36	**2.47**
	inter	41.35	49.93	41.04	42.80	**4.17**

Table 7: Intra-class and inter-class angle comparison. We randomly select 20 families per race from KinRace dataset.