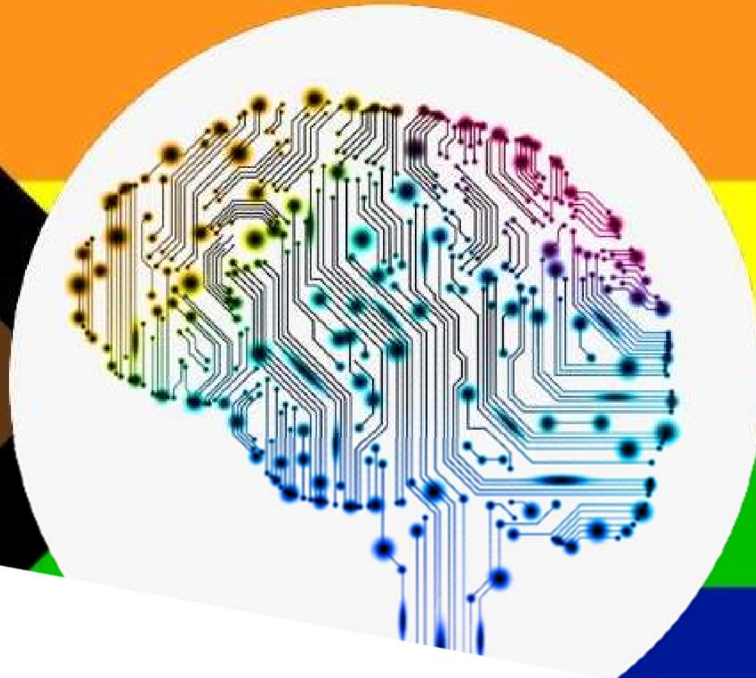

AI RECOGNITION OF PATIENT RACE IN MEDICAL IMAGING – A BRIEF SUMMARY

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OUTLINE

Prior studies in medical imaging shown a need for AI to detect a person's race; however, there is no correlation for race in medical images that is discernable to the human eye when interpreting the images.

METHODS

Using private and public datasets, experts:

(i) performed quantification of deep learning models in detecting race from medical images

(ii) assessed confounding anatomic and phenotypic population features and re-evaluated the deep learning models; and

(iii) By exploring the effect of image corruptions on model performance, they investigated the underlying reasons why AI models recognized race.

▸ METHOD

DATASET

	MXR	CXP	EMX	NLST	RSPECT (Stanford subset)	EM-CT	DHA	EM-Mammo	EM-CS
Data type	Chest x-ray	Chest x-ray	Chest x-ray	Chest CT	Chest CT (PE protocol)	Chest CT	Digital radiographyx-ray	Breast mammograms	Lateral c-spine x-ray
Number of patients (number of images)	53073 (228915)	65400 (223414)	90518 (227 872)	512 (198 475)	254 (72 329)	560 (187 513)	691 (691)	27160 (86669)	997 (10358)
Sex									
Female	27532 (51·9%)	29090 (44·5%)	48477 (53·6%)	184 (36·0%)	135 (53·1%)	286 (51·1%)	400 (49·2%)	27160 (100%)	535 (53·7%)
Male	25541 (48·1%)	36310 (55·5%)	42041 (46·4%)	328 (64·0%)	119 (46·9%)	274 (48·9%)	391 (56·6%)	0	462 (46·3%)
Race									
Black	8957 (16·9%)	3147 (4·8%)	42373 (46·8%)	241 (47·1%)	23 (9·1%)	403 (72·0%)	333 (48·2%)	13696 (50·4%)	247 (24·8%)
Asian	1935 (3·6%)	7096 (10·8%)	3293 (3·6%)	0	0	0	0	0	0
White	34035 (64·1%)	36765 (56·2%)	38071 (42·1%)	271 (53·0%)	231 (90·9%)	157 (28·0%)	358 (51·8%)	13464 (49·6%)	750 (75·2%)
Unknown	8146 (15·3%)	18420 (28·2%)	6781 (7·5%)	0	0	0	0	0	0
Dataset split									
Training, %	60·0%	60·0%	75·0%	78·0%	0	0	70·0%	60·0%	80·0%
Validation, %	10·0%	10·0%	12·5%	10·0%	0	0	10·0%	20·0%	10·0%
Test, %	30·0%	30·0%	12·5%	12·0%	100·0%	100·0%	20·0%	20·0%	10·0%

CXP=CheXpert dataset. DHA=Digital Hand Atlas. EM-CS=Emory Cervical Spine radiograph dataset. EM-CT=Emory Chest CT dataset. EM-Mammo=Emory Mammogram dataset. EMX=Emory chest x-ray dataset. MXR=MIMIC-CXR dataset. NLST=National Lung Cancer Screening Trial dataset. RSPECT=RSNA Pulmonary Embolism CT dataset.

Table **1: Summary of datasets used for race prediction experiments**

▸ METHOD

RACE DETECTION IN RADIOLOGY IMAGING

	Area under the receiver operating characteristics curve
Race detection in radiology imaging	
Chest x-ray (internal validation)*	
MXR (Resnet34, Densenet121)	0·97, 0·94
CXP (Resnet 34)	0·98
EMX (Resnet34, Densenet121, EfficientNet-B0)	0·98, 0·97, 0·99
Chest x-ray (external validation)*	
MXR to CXP, MXR to EMX	0·97, 0·97
CXP to EMX, CXP to MXR	0·97, 0·96
EMX to MXR, EMX to CXP	0·98, 0·98
Chest x-ray (comparison of models)†	
MXR, CXP, EMX	Multiple results (appendix p 26)
CT chest (internal validation)*	
NLST (slice, study)	0·92, 0·96
CT chest (external validation)*	
NLST to EM-CT (slice, study)	0·80, 0·87
NLST to RSPECT (slice, study)	0·83, 0·90
Limb x-ray (internal validation)*	
DHA	0·91
Mammography*	
EM-Mammo (image, study)	0·78, 0·81
Cervical spine x-ray*	
EM-CS	0·92

▸ METHOD

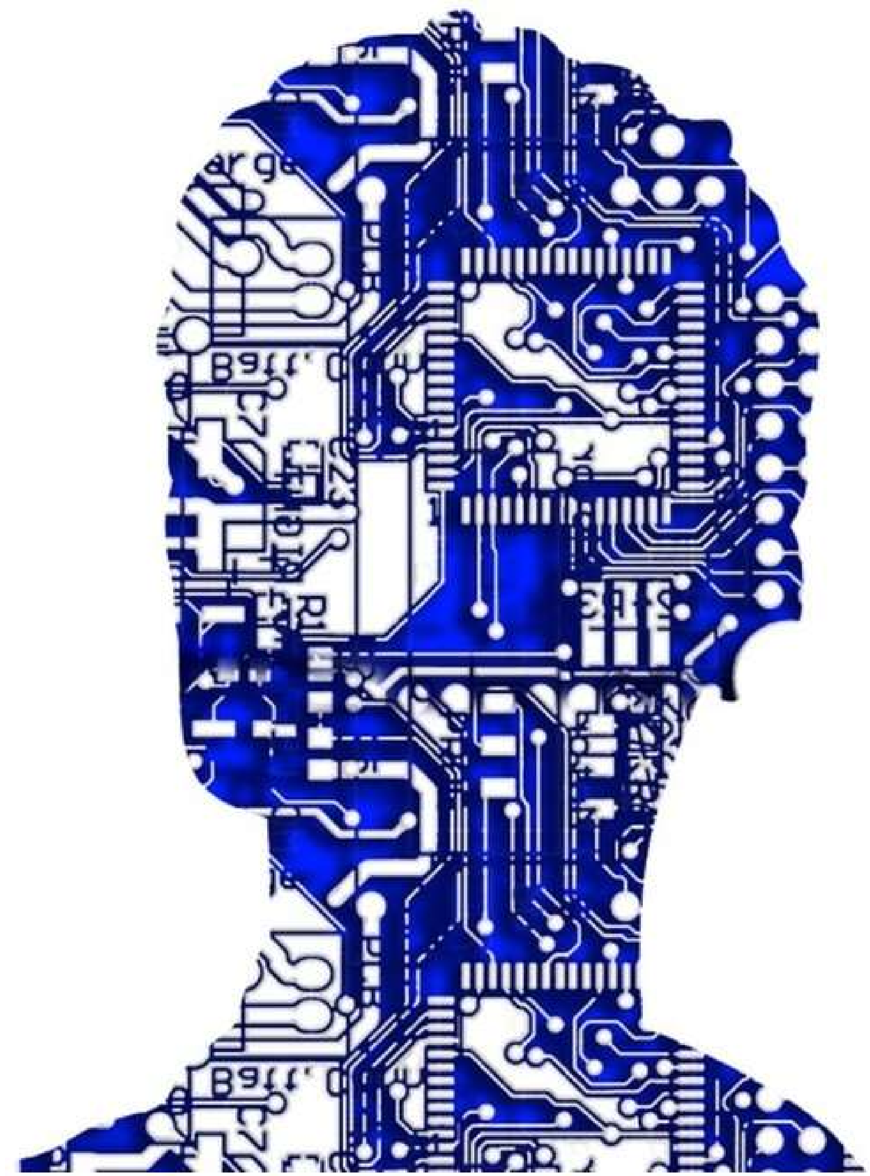
EXPERIMENTS ON ANATOMIC AND PHENOTYPIC CONFOUNDERS

Experiments on anatomic and phenotypic confounders	
BMI*	
CXP	0·55, 0·52
Image-based race detection stratified by BMI†	
EMX, MXR	Multiple results (appendix p 24)
Breast density*	
EM-Mammo	0·54
Breast density and age*	
EM-Mammo	0·61
Disease distribution*	
MXR, CXP	0·61, 0·57
Image-based race detection for the no finding class*	
MXR	0·94
Model prediction after training on dataset with equal disease distribution†	
MXR	0·75
Removal of bone density features*	
MXR, CXP	0·96, 0·94
Impact of average pixel thresholds†	
MXR	0·50
Impact of age†	
MXR	Multiple results (appendix p 27)
Impact of patient sex†	
MXR	Multiple results (appendix p 28)
Combination of age, sex, disease, and body habitus*	
EMX (logistic regression model, random forest classifier, XGBoost model)	0·65, 0·64, 0.64

(Table 2 continues in next column)

	Area under the receiver operating characteristics curve
(Continued from previous column)	
Experiments to evaluate the mechanism of race detection	
Frequency domain filtering	
High-pass filtering*	
MXR	Multiple results (appendix p 26)
Low-pass filtering*	
MXR	Multiple results (appendix p 26)
Notch filtering†	
MXR	Multiple results (appendix p 26)
Band-pass filtering†	
MXR	Multiple results (appendix p 25)
Image resolution and quality*	
MXR	Multiple results (appendix p 28)
Anatomical localisation	
Lung segmentation experiments†	
MXR	Multiple results (appendix p 29)
Saliency maps†	
MXR, CXP, EMX, NLST, DHA, EM-Mammo, EM-CS	Multiple results (appendix pp 13–18)
Occlusion experiments†	
MXR	Multiple results (appendix p 30)
Patch-based training*	
MXR	Multiple results (appendix p 30)
Image acquisition differences†	
EMX, EM-Mammo, ChexPhoto	Multiple results (appendix p 31)

Standard AI deep learning models can be trained to predict race from medical image, and that these models persisted over all anatomical regions of the human body.



FINDINGS

RESULTS

	Area under the receiver operating characteristics curve value for race classification		
	Asian (95% CI)	Black (95% CI)	White (95% CI)
Primary race detection in chest x-ray imaging			
MXR Resnet34	0·986 (0·984–0·988)	0·982 (0·981–0·983)	0·981 (0·979–0·982)
CXP Resnet34	0·981 (0·979–0·983)	0·980 (0·977–0·983)	0·980 (0·978–0·981)
EMX Resnet34	0·969 (0·961–0·976)	0·992 (0·991–0·994)	0·988 (0·986–0·989)
External validation of race detection models in chest x-ray imaging			
MXR Resnet34 to CXP	0·947 (0·944–0·951)	0·962 (0·957–0·966)	0·948 (0·945–0·951)
MXR Resnet34 to EMX	0·914 (0·899–0·928)	0·983 (0·981–0·985)	0·975 (0·973–0·978)
CXP Resnet34 to MXR	0·974 (0·971–0·977)	0·955 (0·952–0·957)	0·956 (0·954–0·958)
CXP Resnet34 to EMX	0·915 (0·901–0·929)	0·968 (0·965–0·971)	0·954 (0·951–0·958)
EMX Resnet34 to MXR	0·966 (0·962–0·969)	0·970 (0·968–0·972)	0·964 (0·962–0·965)
EMX Resnet34 to CXP	0·949 (0·946–0·952)	0·973 (0·970–0·977)	0·947 (0·945–0·950)
Race detection in non-chest x-ray imaging modalities: binary race detection (Black or White)			
NLST	0·92 (slice; 0·910–0·918), 0·96 (study; 0·926–0·982)	..	..
NLST to EM-CT	0·80 (slice; 0·796–0·800), 0·87 (study; 0·829–0·904)	..	..
NLST to RSPECT	0·83 (slice; 0·825–0·834), 0·90 (study; 0·836–0·958)	..	..
EM-Mammo	0·78 (slice; 0·773–0·786), 0·81 (study; 0·794–0·818)	..	..
EM-CS	0·913 (0·892–0·931)	..	..
DHA	0·87 (0·752–0·894)	..	..

Values reflect the area under the receiver operating characteristics curve for each model on the test set per slice and per study (by averaging the predictions across all slices). CXP=CheXpert dataset. DHA=Digital Hand Atlas. EM-CS=Emory Cervical Spine radiograph dataset. EM-CT=Emory Chest CT dataset. EM-Mammo=Emory Mammogram dataset. EMX=Emory CXR dataset. MXR=MIMIC-CXR dataset. NLST=National Lung Cancer Screening Trial dataset. RSPECT=RSNA Pulmonary Embolism CT dataset.

Table 3: **Performance of deep learning models to detect race from chest x-rays**

▸ FINDINGS

RESULTS

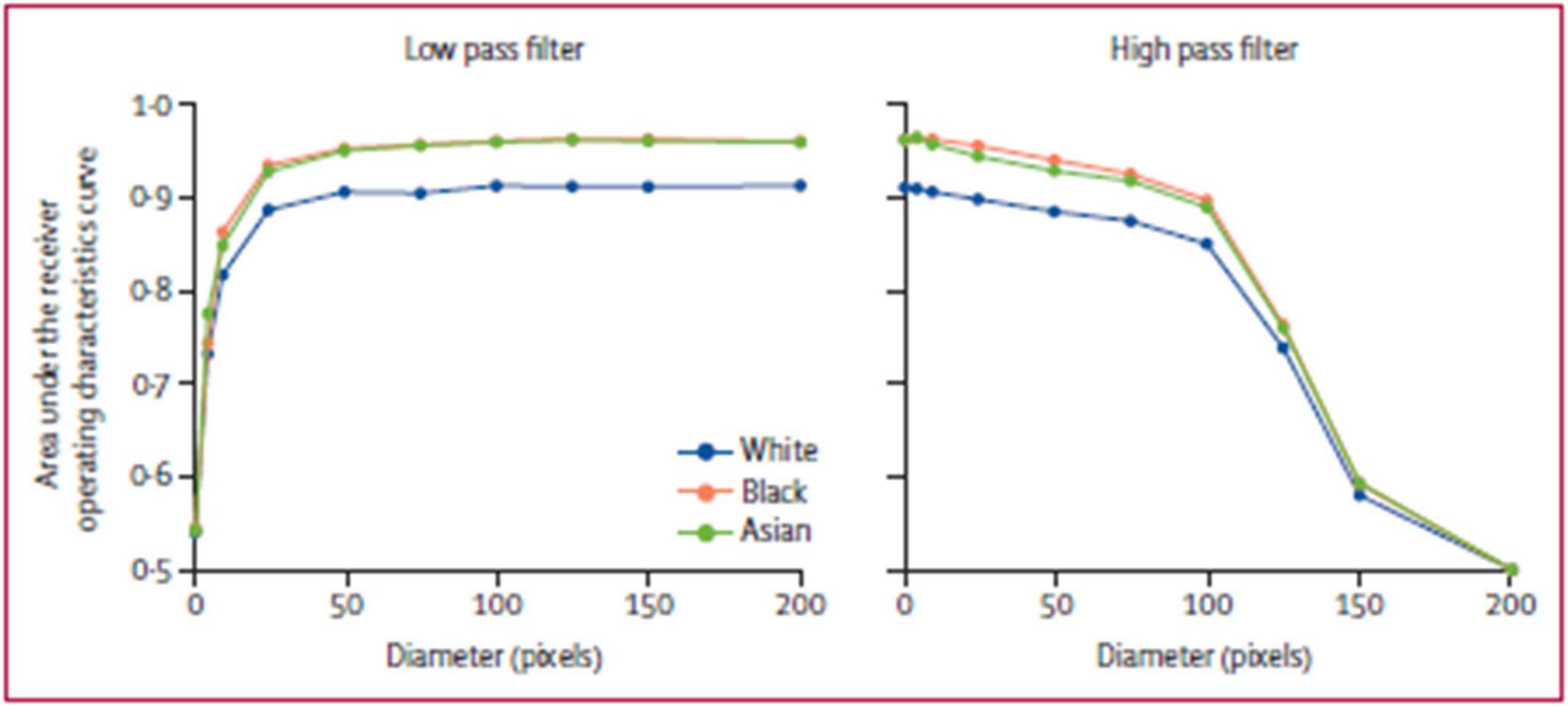
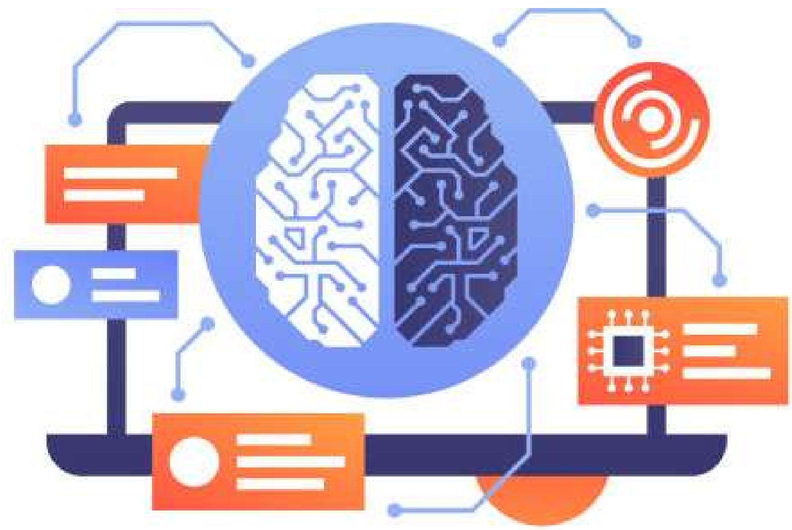


Figure 1: The effect on model performance of adding a low-pass filter and a high-pass filter for various diameters in the MXR dataset

MXR=MIMIC-CXR dataset.

▸ INTERPRETATION

AI can accurately predict self-reported race, even from corrupted, cropped, and otherwise unusable medical images, creates an enormous risk for all model deployments in medical imaging.



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QUESTIONS