Deep Fakes: We need to re-think the concept of ``real'' images.

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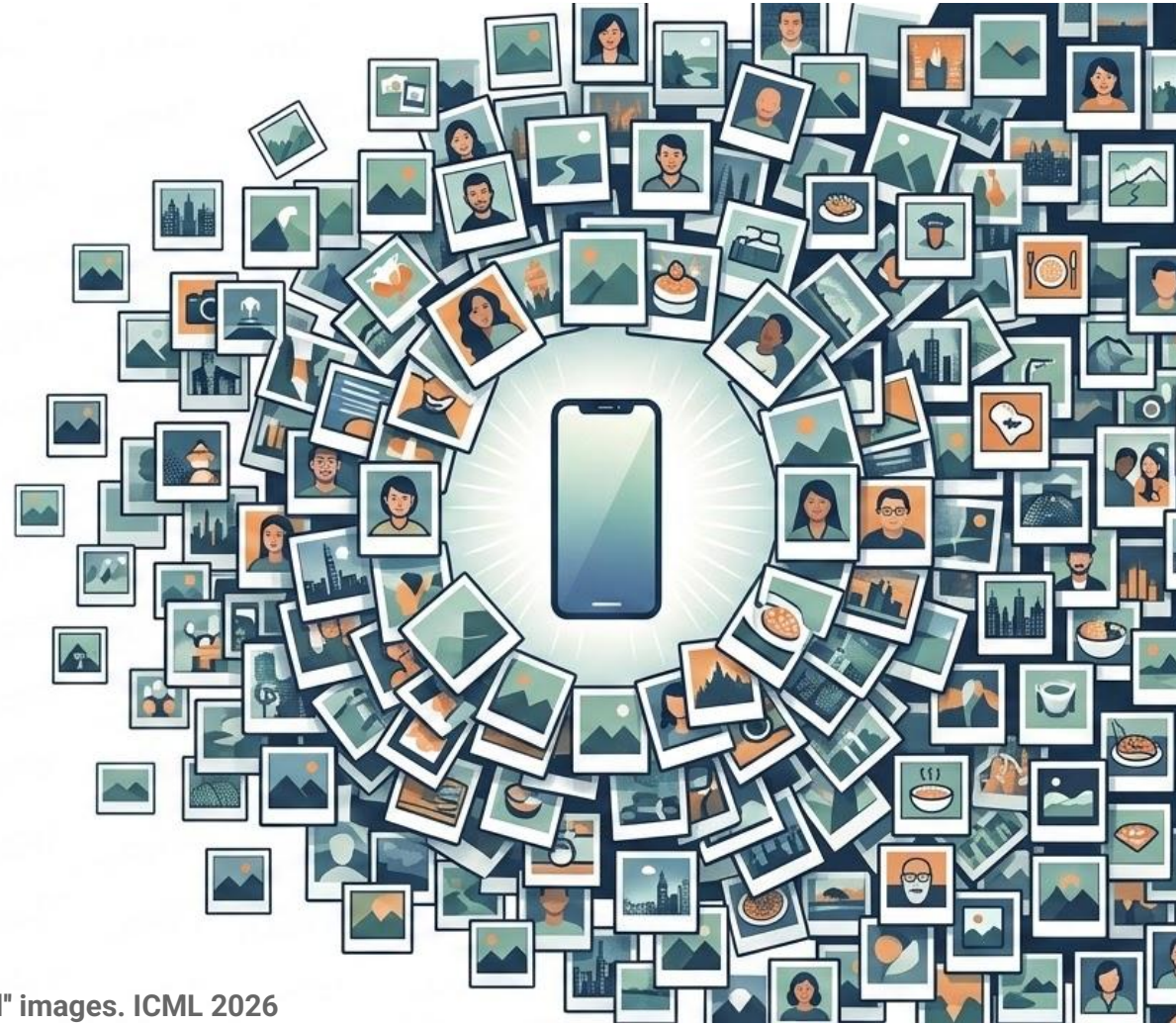
Position

If we want to find a technical solution towards Deep Fake detection, we need to re-think the concept of “real” images.

90% of all “Photos” are

taken by Smartphones



Traditonal Camera

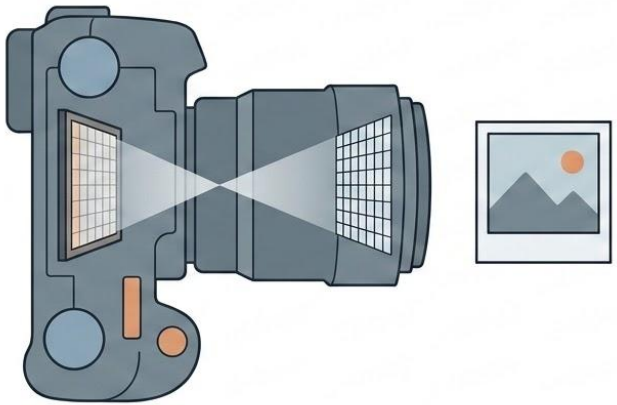


Photo = 3D -> 2D lens projection

Smartphone:

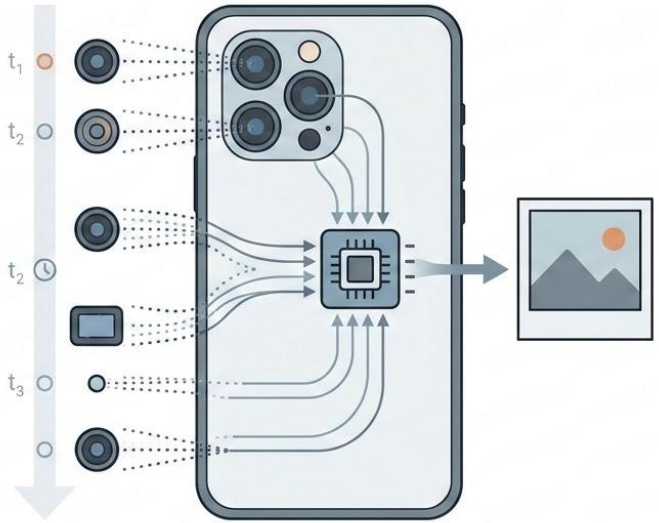


Photo = algorithmic fusion of multiple Sensors at multiple points in time

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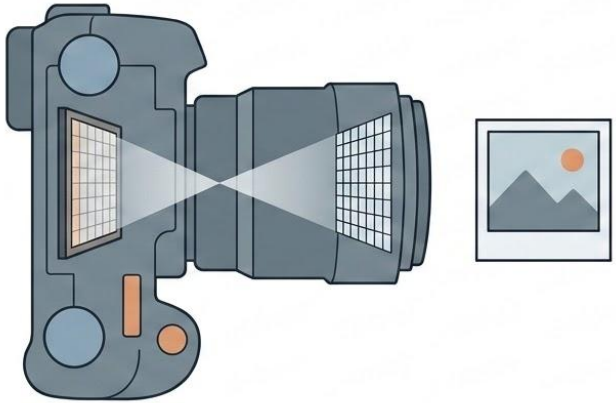

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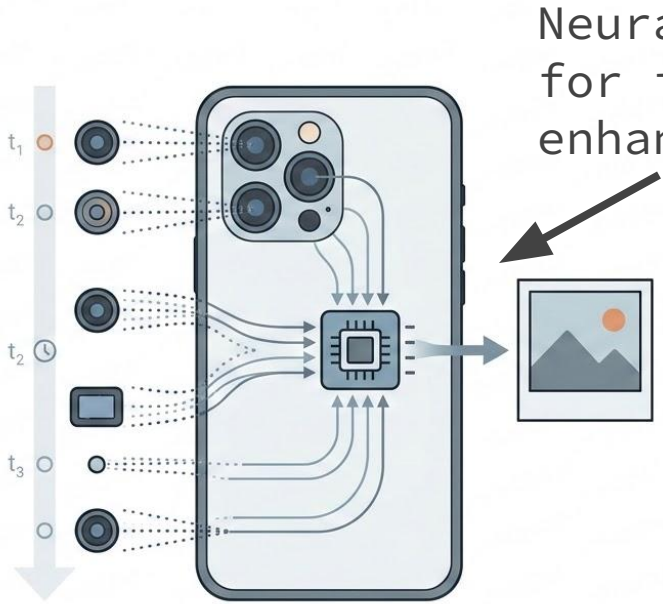
Smartphone:



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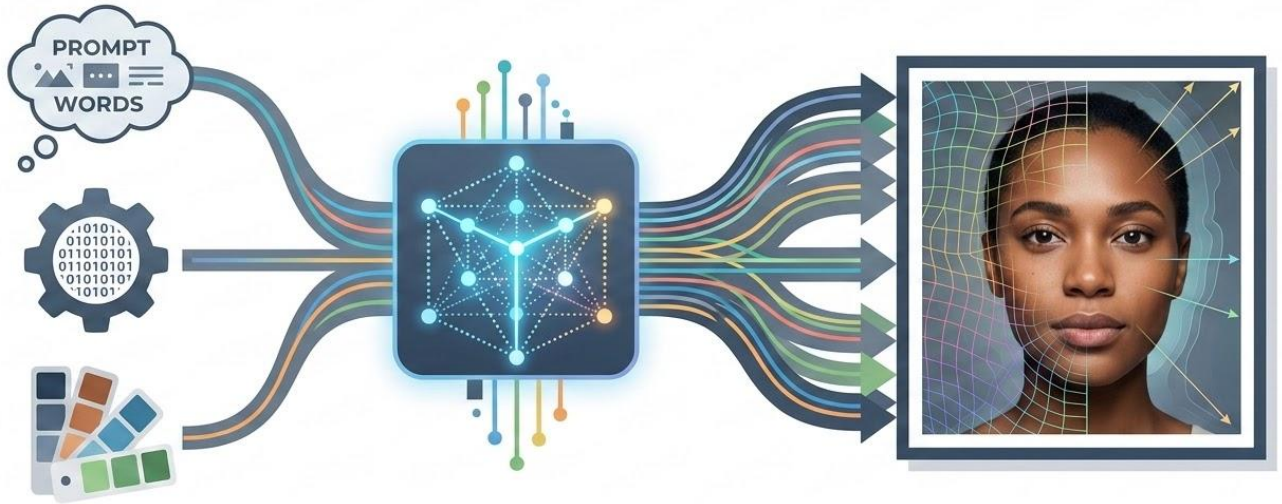
Central Question:



If ALL images are generated, how do we define REAL images?

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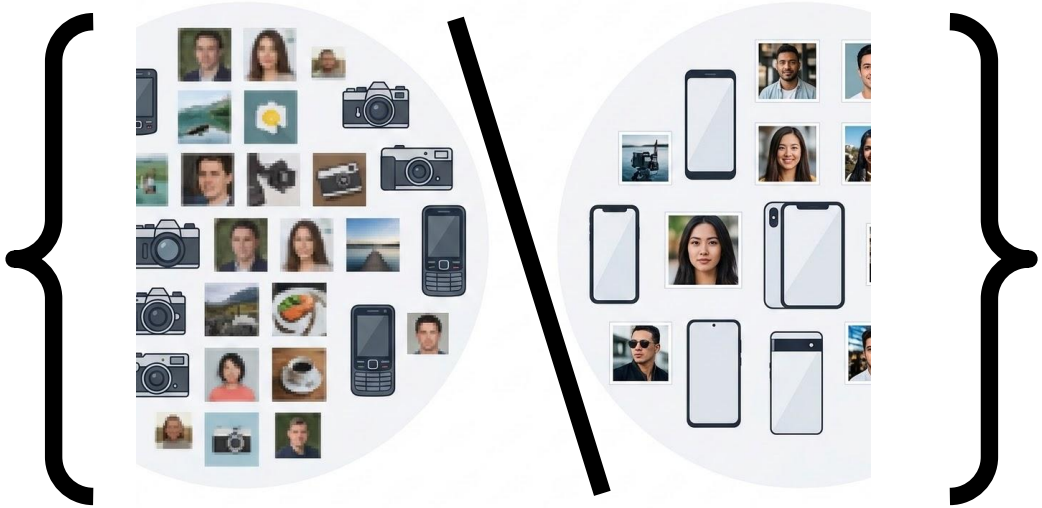
Data Analysis
“Real” data used in Deep Fake papers + benchmarks

Current Deep Fake Detection datasets mostly contain older, low resolution images.

No modern Smartphone data!



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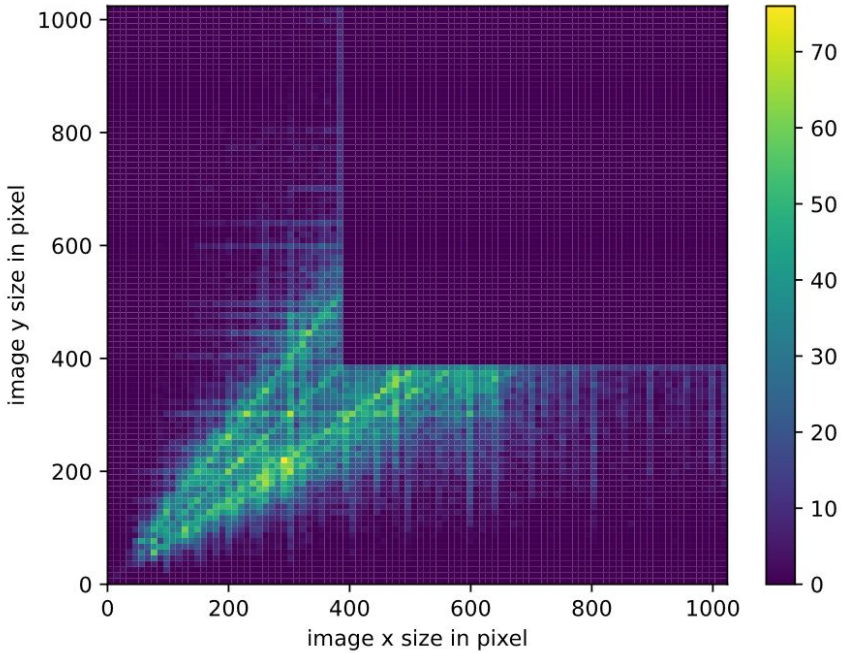

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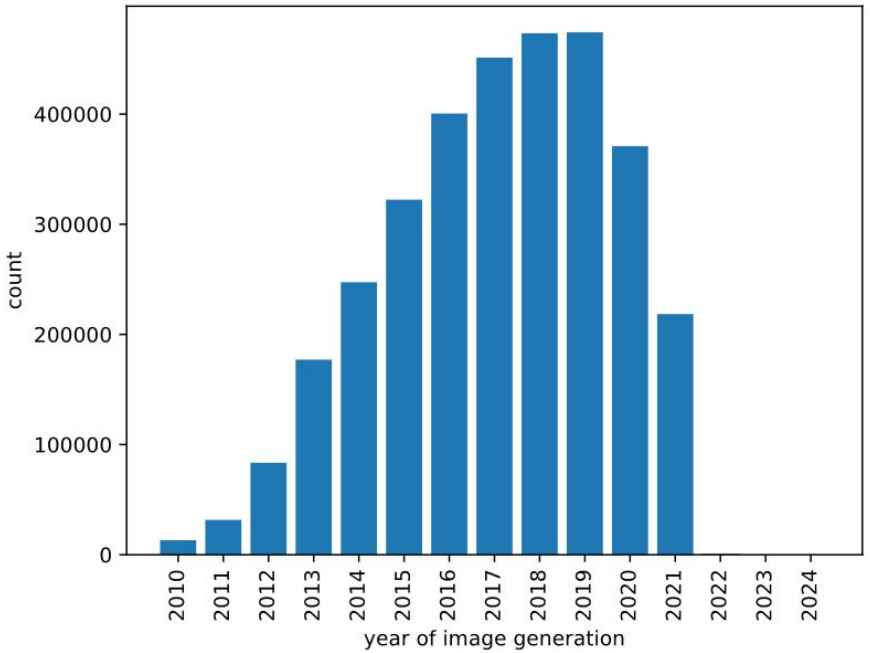
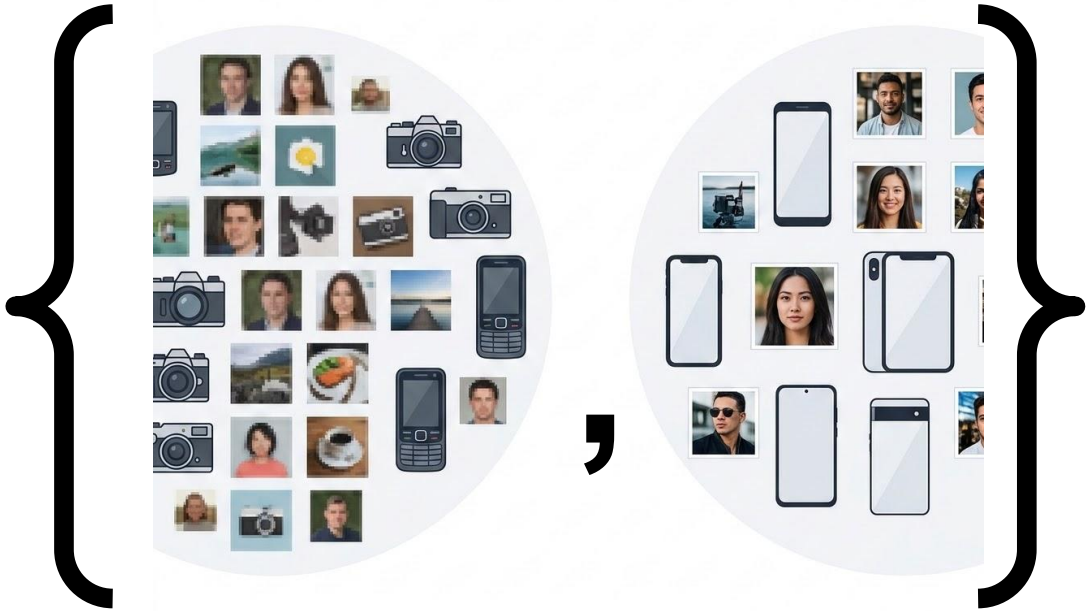


Conclusion #1

We need to curate new datasets containing modern Smartphone images



Proof of Problem: Low Level Features Fail

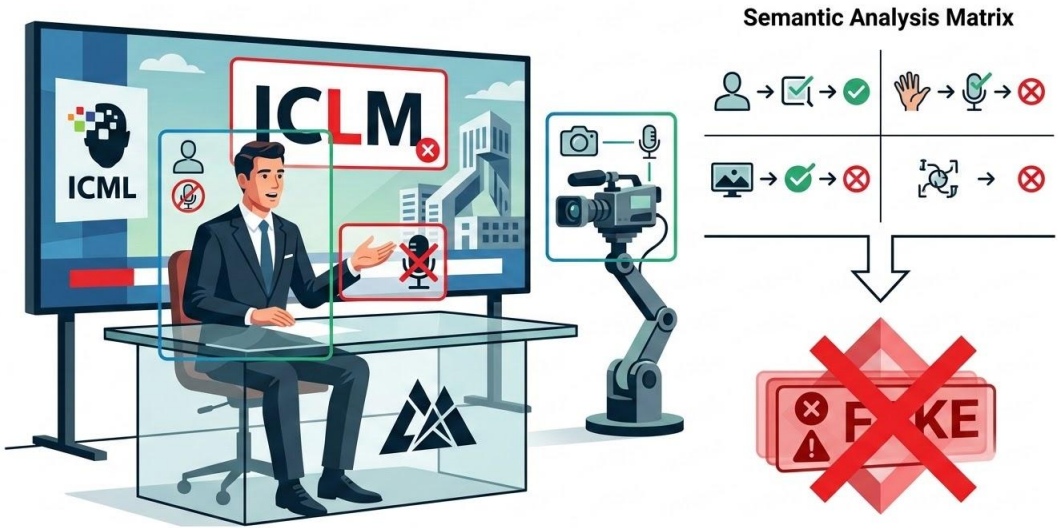
Evaluating SOTA Deep Fake Detectors on a small iPhone dataset. Images taken under different ambient light conditions.

Proof of Problem: Low Level Features Fail

DataSet	CNNSpot real	CNNSpot fake	DIRE real*	DIRE fake*	DCT real	DCT fake	Fusing real	Fusing fake	GRAM real	GRAM fake	LGRAD real	LGRAD fake
progan	1.00	1.00	0.95	0.95	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
stylegan	1.00	0.74	0.83	0.83	0.88	0.68	1.00	0.70	1.00	0.67	0.98	0.82
biggan	0.94	0.47	0.70	0.70	0.69	0.95	0.94	0.61	0.46	0.89	0.78	0.86
cyclegan	0.92	0.79	0.74	0.74	0.77	0.80	0.95	0.79	0.63	0.85	0.89	0.83
stargan	0.97	0.86	0.95	0.95	0.90	1.00	1.00	0.94	1.00	1.00	1.00	0.96
gaugan	0.93	0.65	0.67	0.67	0.68	0.93	0.92	0.62	0.20	0.96	0.64	0.97
stylegan2	1.00	0.69	0.75	0.75	0.92	0.40	1.00	0.67	1.00	0.72	0.99	0.73
whichfaceisreal	0.93	0.81	0.58	0.58	0.89	0.04	0.99	0.48	0.67	1.00	0.58	0.43
ADM	0.95	0.25	0.98	0.98	0.70	0.60	0.98	0.15	0.63	0.81	0.64	0.59
Glide	0.95	0.19	0.92	0.92	0.69	0.42	0.98	0.16	0.63	0.82	0.65	0.76
Midjourney	0.95	0.07	0.89	0.89	0.69	0.25	0.98	0.06	0.62	0.28	0.64	0.70
stable_diffusion_v_1_4	0.95	0.07	0.91	0.91	0.69	0.11	0.98	0.04	0.63	0.95	0.63	0.63
stable_diffusion_v_1_5	0.95	0.07	0.91	0.91	0.70	0.11	0.98	0.04	0.63	0.95	0.64	0.63
VQDM	0.95	0.15	0.91	0.91	0.69	0.89	0.98	0.12	0.63	0.80	0.64	0.73
wukong	0.95	0.07	0.90	0.90	0.69	0.14	0.98	0.06	0.62	0.87	0.63	0.53
DALLE2	0.95	0.06	0.92	0.92	0.38	0.31	0.99	0.07	0.44	0.97	0.45	0.93
AVG ACC	0.96	0.43	0.84	0.84	0.75	0.54	0.98	0.41	0.67	0.85	0.74	0.76
LAION 5B IPhone Images from 2010	0.99		0.00		0.88		1.00		0.84		0.73	
LAION 5B IPhone Images from 2021	0.99		0.00		0.89		1.00		0.97		0.78	
LAION 5B Images from iPhone4	0.99		0.00		0.85		1.00		0.91		0.62	
LAION 5B Images from iPhone12Pro	0.99		0.00		0.89		1.00		0.98		0.83	
AVG LAION iPhone	0.99		0.00		0.88		1.00		0.92		0.74	
IPhone 13mini good (iOS 18.4.1)	0.89		0.00		1.00		1.00		1.00		0.22	
IPhone 13mini poor (iOS 18.4.1)	1.00		0.00		0.50		1.00		1.00		0.40	
iPhone 15Pro (iOS 18.4.1)	1.00		0.00		0.00		0.00		0.60		0.20	
AVG iPhone RAW	0.96		0.00		0.50		0.67		0.87		0.27	

Limited # of samples

Conclusion #2



We need to move the definition of “real” to a semantic level.

BUT: How do we define a feasible threshold?

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