

OPEN-SET DEEPFAKE DETECTION TO FIGHT THE UNKNOWN

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CLOSED SET X OPEN SET

Closed Set Classification

Open Set Classification









CLOSED SET X OPEN SET





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To propose and investigate an open-set approach for deepfake detection in images.





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METHODOLOGY: FEATURE EXTRACTOR



Chenqi Kong, Baoliang Chen, Haoliang Li, Shiqi Wang, Anderson Rocha, and Sam Kwong, "**Detect and locate: Exposing face manipulation by semantic-and noise-level telltales**," *IEEE Transactions on Information Forensics and Security*, vol. 17, pp. 1741–1756, 2022 recod.ai



METHODOLOGY: FINE TUNING



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METHODOLOGY: CLUSTERING



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METHODOLOGY: OPEN-SET TRAINING











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DATA SET

Feature Extractor Training

Full FaceForensics ++ C23 and C40

Open-Set training and validation

Only Real images from FaceForensics ++ C40

Only Real images from DFD – DeepFake Detection (From Google & Jigsaw)



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1 – Baseline feature extractor and no Fine Tuning



Dataset	Classifier	Clusters	ACC	AUC	EER
	OCSVM	1	0.586	0.636	0.395
DFD	IF	1	0.629	0.647	0.380
	EVM	2	0.553	0.590	0.313
FF C40	OCSVM	1	0.775	0.852	0.228
	IF	1	0.785	0.872	0.194
	EVM	2	0.593	0.602	0.536







EXPERIMENTS AND RESULTS



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2 – Baseline feature extractor, Dimensionality reduction and no Fine Tuning



Dataset	Classifier	dim	clusters	ACC	AUC	EER
	OCSVM	256	2	0.544	0.580	0.445
DFD	IF	128	3	0.542	0.561	0.449
	EVM	96	4	0.500	0.486	0.969
	OCSVM	16	3	0.560	0.750	0.068
FF C40	IF	32	3	0.559	0.689	0.048
	EVM	32	3	0.631	0.675	0.028







EXPERIMENTS AND RESULTS

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3 – Baseline feature extractor, no dimensionality reduction and Fine Tuning



Dataset	Classifier	ACC	AUC	EER
	OCSVM	0.554	0.554	0.559
DFD	IF	0.601	0.630	0.402
	EVM	0.450	0.430	0.800
	OCSVM	0.764	0.861	0.193
FF C40	IF	0.788	0.865	0.207
	EVM	0.531	0.558	0.901





EXPERIMENTS AND RESULTS





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4 –	Feature	extractor with	Triplet Loss,	Dimensionality	reduction
and	no Fine	Tuning			



Features Extractor	Fine Tuning	Clustering	
TRIPLET	→	$\rightarrow \underbrace{\bigcirc} \underbrace{\bigcirc} \underbrace{\bigcirc} \\ \bigcirc \\$	Open-Set Training
LOSS			

Baseline in closed set scenario

- DFD: AUC of 76.23 and an EER of 0.303
- FF C40: AUC of 99.46 and an EER of 0.29

Detect	Classifier	Classifier dim		HTL-C		HTL-NC	
Dataset	Classifier	unn	AUC	EER	AUC	EER	
	OCSVM	2,912	0.778	0.283	0.778	0.283	
	IF	2,912	0.804	0.267	0.807	0.271	
DED	EVM	2,912	0.617	0.670	0.704	0.518	
	OCSVM	256	0.695	0.251	0.489	0.504	
	IF	128	0.654	0.386	0.670	0.333	
	EVM	96	0.497	0.993	0.657	0.669	
FF C40	OCSVM	2,912	0.756	0.149	0.786	0.179	
	IF	2,912	0.882	0.194	0.882	0.224	
	EVM	2,912	*	*	*	*	
	OCSVM	16	0.548	0.463	0.724	0.269	
	IF	32	0.778	0.269	0.849	0.194	
	EVM	32	0.738	0.313	0.717	0.313	
	EVM	32	0.738	0.313	0.717	0.313	



CONCLUSION





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 The open-set approach to deepfake detection is more challenging, but it provides a more robust model against variations in the generation technique.

✓ By employing Triplet Loss with Hard mining during feature extractor training, we achieved better results than those obtained with the closed-set approach.

✓ Dimensionality reduction and fine-tuning did not yield benefits for our model.

✓ The proposed organizational chart can be evaluated using other methods of extraction, dimensionality reduction, clustering, and fine-tuning.

✓ Initializing feature extractor weights using self-supervised methods.





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OPEN TO QUESTIONS!