

Any-Resolution AI-Generated Image Detection by Spectral Learning

Dimitrios Karageorgiou^{1,2} Symeon Papadopoulos¹ Ioannis Kompatsiaris¹ Efstratios Gavves^{2,3}

¹ Information Technologies Institute - CERTH, GR ² University of Amsterdam, NL ³ Archimedes/Athena RC, GR

<https://mever-team.github.io/spai>



CERTH
CENTRE FOR
RESEARCH & TECHNOLOGY
HELLAS



Information
Technologies
Institute



UNIVERSITY
OF AMSTERDAM



Too many GenAI models, too brittle artifacts!

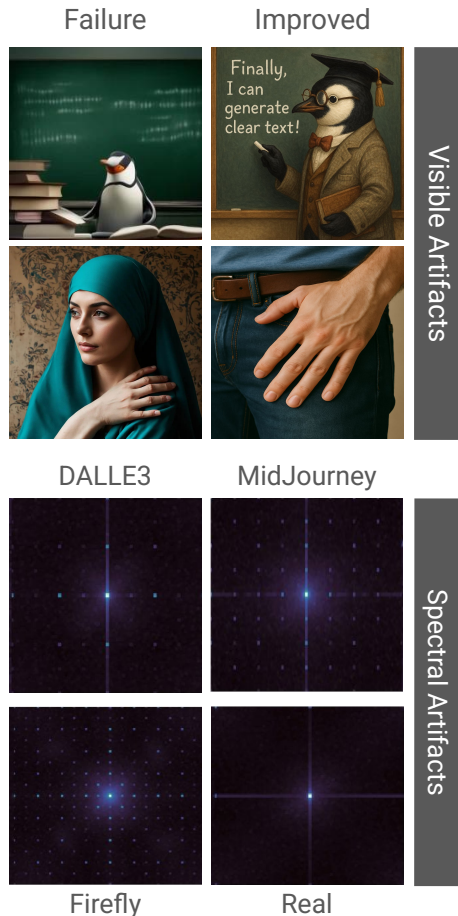
- An abundance of GenAI approaches is currently available. More get released daily!
 - LoRA finetunes → even more models!

Literature has established that generated images differ in some aspects from the real ones. **Yet, these aspects are totally unpredictable.**

- **Visible inconsistencies** are fixed in newer models. → Not very effective.
- **Spectral inconsistencies** → Significant discriminative power, but totally differ among different generative models (Bammey et al., 2023).

Key Issue

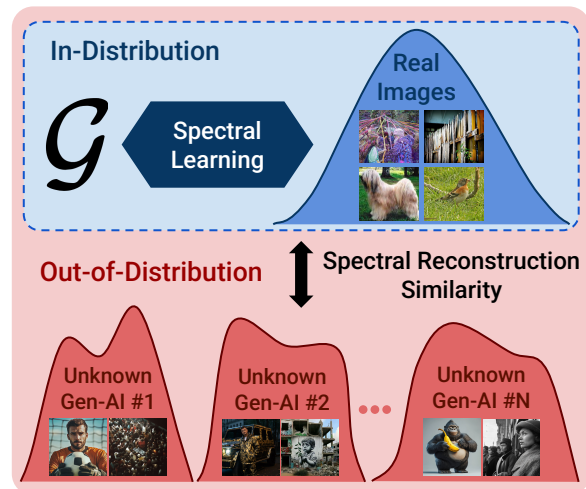
Any learned assumptions quickly become obsolete and detectors fail **to generalize on unseen generative approaches!**



SPAI: Any-Resolution AI-Generated Image Detection by Spectral Learning

Key Idea: The spectral distribution of real images constitutes an invariant and highly-discriminative pattern for the task of AI-Generated Image Detection.

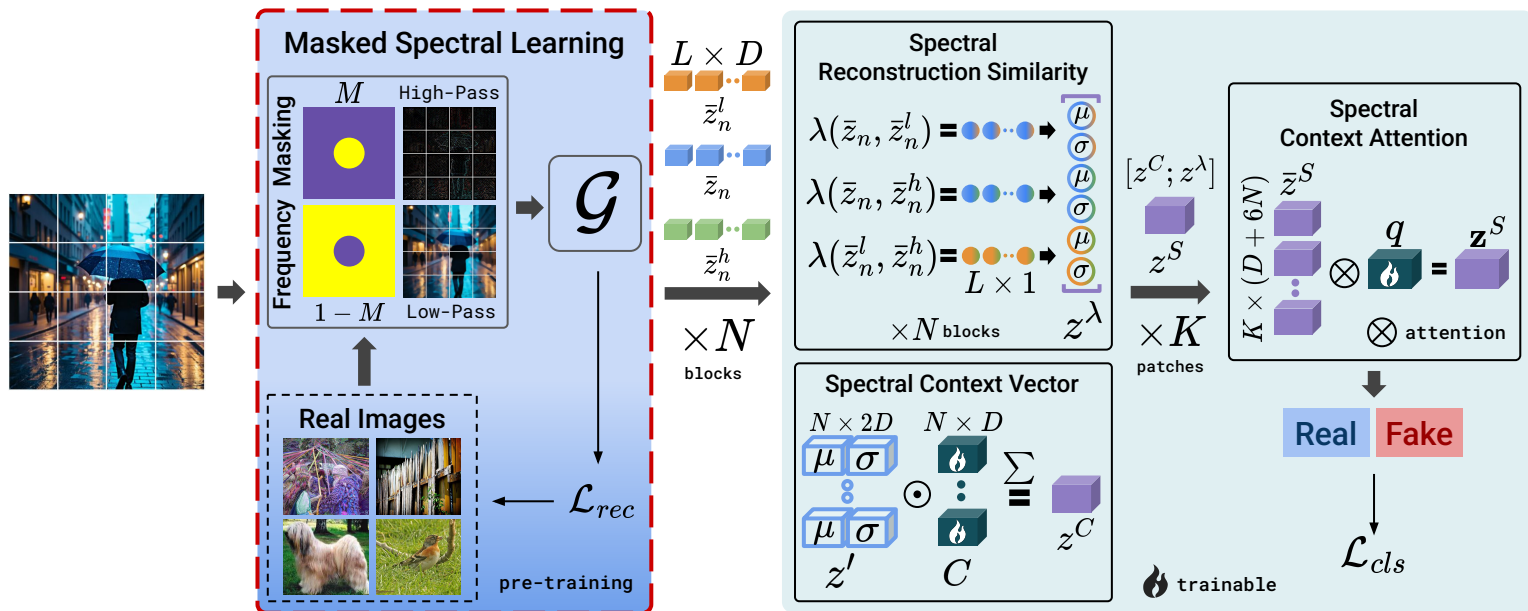
→ **Corollary:** Given a model of the spectral distribution of real images, AI-Generated images can be detected as Out-Of-Distribution (OOD) samples of this model.



Key Questions

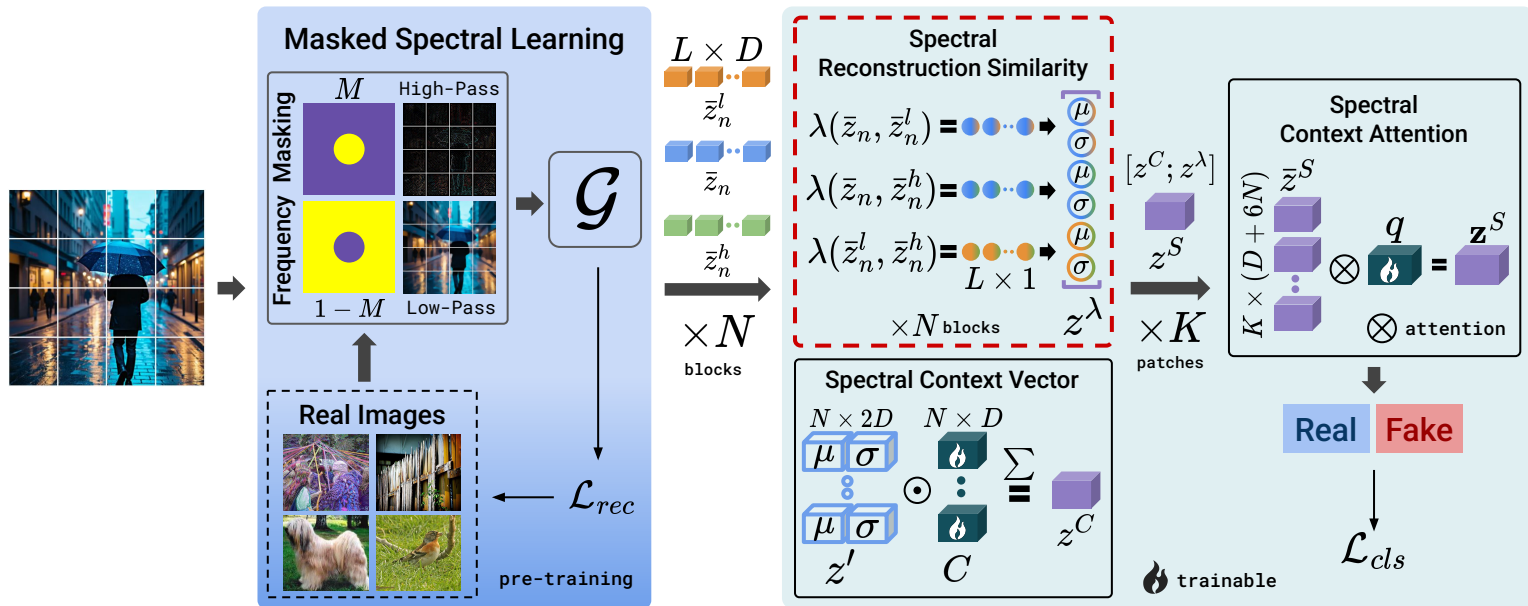
1. How can we craft a suitable spectral model of real images?
2. How can we detect its Out-Of-Distribution samples?

Masked Spectral Learning: Learning the spectral distribution of real images



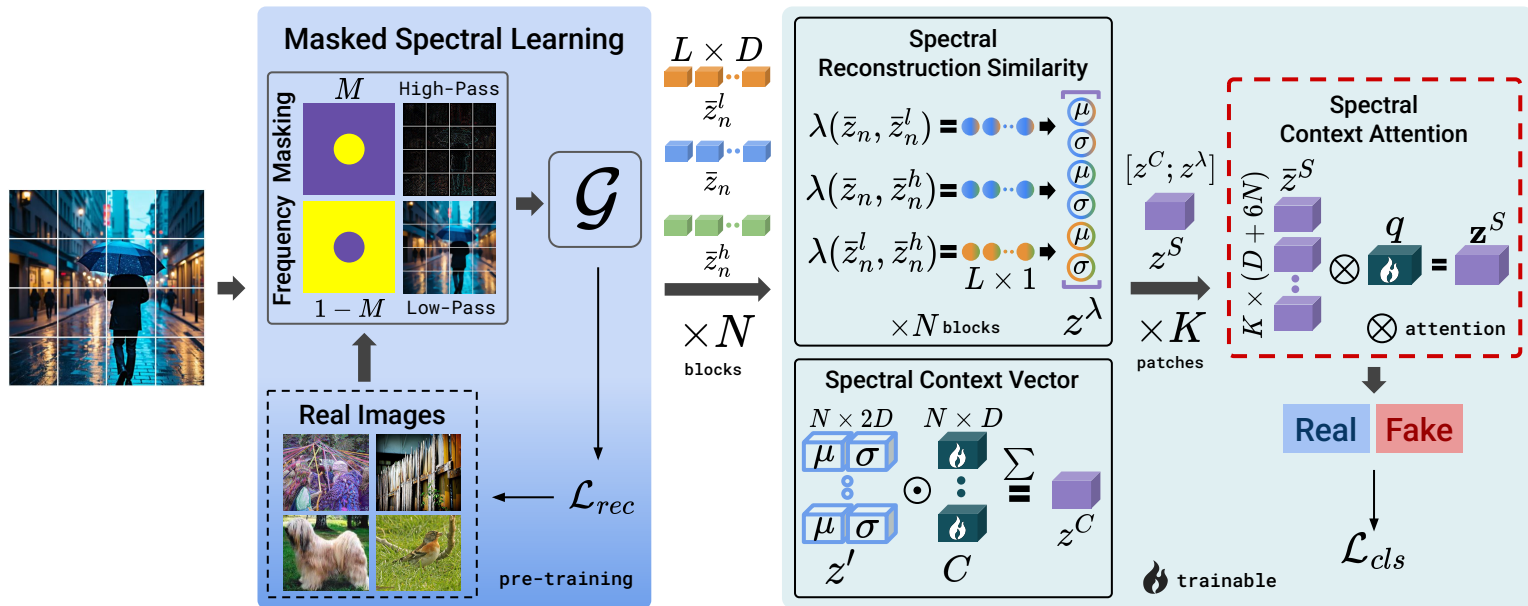
- **Self-supervised training on real images using the pre-text task of frequency reconstruction.**
- Inputs are generated by low/high frequency filtering. – Model reconstructs missing frequencies.
- Reconstruction loss is computed on the DFT domain.
- A vision transformer is used for the model \mathcal{G} .

Spectral Reconstruction Similarity (SRS): Detecting OOD images



- **Low- & high-pass filtered images** are embedded using the learned spectral model.
- Cosine similarity among the three pairs of original, low-pass and high-pass filtered images.
- Spectral reconstruction similarity is computed for the features of each transformer block of \mathcal{G} .

Spectral Context Attention: Embedding arbitrary resolution images



- Image is split into patches (ViT resolution – 224x224).
- The most discriminative SRS values according to the spectral context of each patch are considered.
- Subtle details are captured, as images are processed in their native resolution, with linear complexity.

Comparison against state-of-the-art

Generalization on generators of different architectures, resolution, image quality, open-source & commercial.

Image Size	< 0.5 MPixels			0.5 - 1.0 MPixels						> 1.0 MPixels				AVG
Approach	Glide	SD1.3	SD1.4	Flux	DALLE2	SD2	SDXL	SD3	GigaGAN	MJv5	MJv6.1	DALLE3	Firefly	
NPR [66]	72.2	89.6	60.5	19.8	3.9	12.5	18.1	60.6	83.2	15.3	19.8	97.1	38.0	45.4
Dire [72]	33.3	59.9	61.3	45.7	52.2	68.5	46.9	49.2	36.3	41.9	50.3	65.2	49.9	50.8
CNNDet. [71]	59.2	59.0	61.2	39.8	71.5	57.5	67.4	30.2	73.4	48.8	56.7	23.5	73.4	55.5
FreqDet. [23]	43.6	92.3	92.7	36.5	47.4	42.5	66.5	69.8	63.2	36.9	27.5	42.2	80.9	57.1
Fusing [34]	63.0	62.8	62.2	57.5	76.7	66.9	62.1	38.8	80.4	64.0	74.0	25.2	76.3	62.3
LGrad [65]	76.5	82.4	83.4	74.9	85.7	60.7	70.2	12.7	89.9	69.2	79.6	30.0	42.0	65.9
UnivFD [52]	63.3	80.8	81.2	36.3	91.4	84.3	78.3	28.6	86.2	57.1	60.5	31.0	95.5	67.3
GramNet [48]	78.2	83.9	84.3	78.6	85.2	66.7	77.8	19.2	85.0	63.8	84.9	42.9	38.0	68.4
DeFake [63]	86.1	64.2	63.6	90.5	41.4	66.2	52.3	87.7	71.7	67.0	87.5	93.3	39.4	70.1
PatchCr. [77]	78.4	95.7	96.2	86.9	81.8	95.7	96.7	33.8	98.0	79.0	96.1	28.1	79.1	80.4
DMID [7]	73.1	100.0	100.0	97.2	54.3	99.7	99.6	67.9	67.9	99.9	94.4	41.3	90.2	83.5
RINE [39]	95.6	99.9	99.9	93.0	93.0	96.6	99.3	39.1	92.9	96.4	81.2	41.8	82.9	85.5
SPAI (Ours)	90.2	99.6	99.6	83.0	91.1	96.5	97.4	75.9	85.4	94.5	84.0	90.2	96.0	91.0

While several detectors achieve high performance on specific Gen-AI models, they catastrophically fail to others.

□ **SPAI achieves consistent performance across Gen-AI models of different type!**

Beyond binary detection and Open Challenges

Spectral context attention natively provides a mechanism to understand which regions of the image were more important for the final decision.



6-fingers case correctly spotted Attending texture-rich regions.

Figure 4. Qualitative analysis of spectral context attention. A cool-warm overlay has been applied on each patch. Red color indicates significant patches for deciding whether the image is AI-generated (high attention values), while blue color indicates irrelevant patches (low attention values). The attention values have been normalized in $[0, 1]$.

AI-Generated content commonly appears online in the form of derivative images, i.e. screenshots of posts, photos of a screen etc.

The intermediate medium (digital or analog) heavily distorts the spectral distribution of the AI-generated images.

Detecting such images remains an open issue for any detector that relies on the image signal.



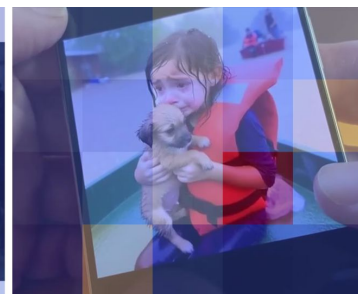
Detection: 86%



Detection: 79%



Detection: 0%



Detection: 2%



Greeks in AI 2025



We open-source SPAI's code, weights and data:

<https://mever-team.github.io/spai>

For any questions you can contact:

d.karageorgiou@uva.nl



CERTH
CENTRE FOR
RESEARCH & TECHNOLOGY
HELLAS



**Information
Technologies
Institute**



**UNIVERSITY
OF AMSTERDAM**