Discovering Transferable Forensic Features for CNN-generated Images Detection

European Conference on Computer Vision (ECCV) 2022 Oral

Keshigeyan Chandrasegaran Ngoc-Trung Tran Alexander Binder Ngai-Man Cheung




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CNN-generated images (Deepfakes / counterfeits) have become indistinguishable from real images

Samples generated using Zero-Insertion based Upsampling Architectural Variant (Chandrasegaran et al., 2021) of Progressive Growing of GAN (Karras et al., 2018)

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With rapid improvements in generative modelling, detecting such counterfeits is increasingly becoming challenging and critical.

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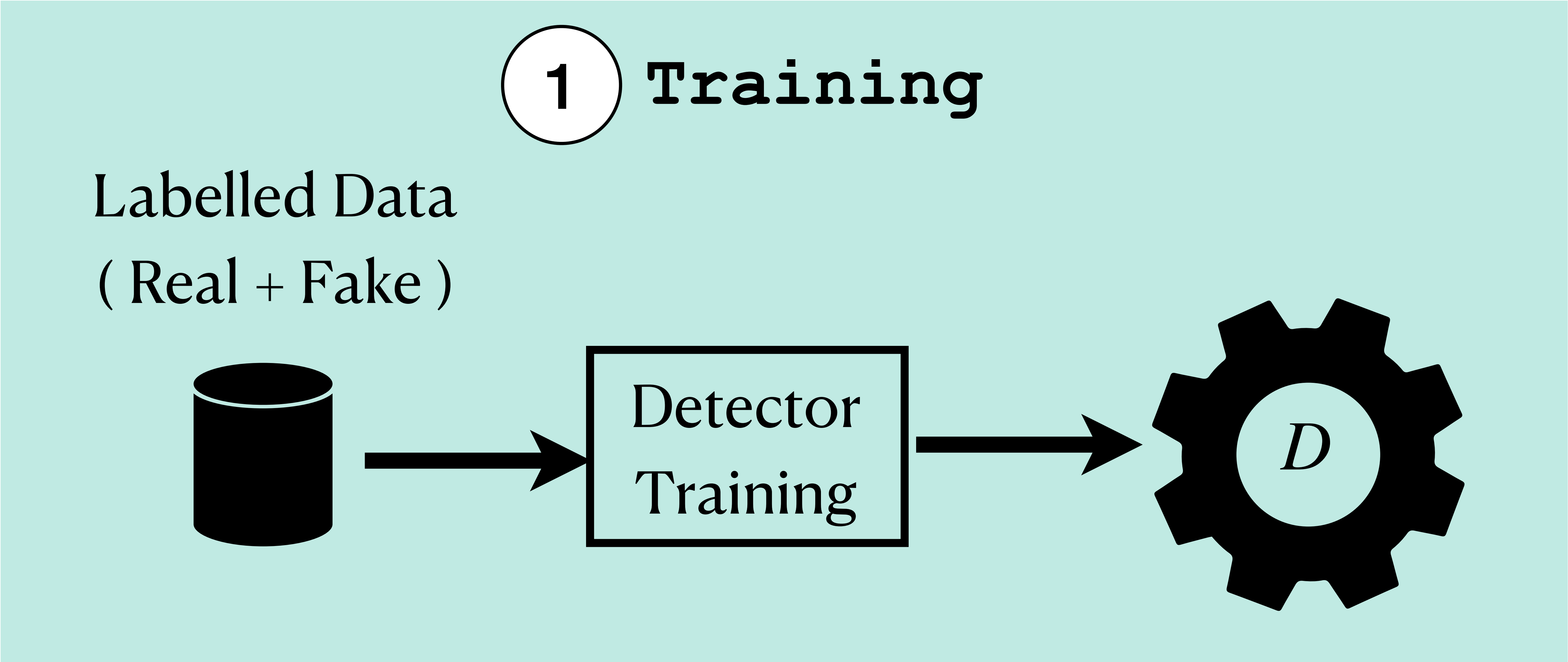
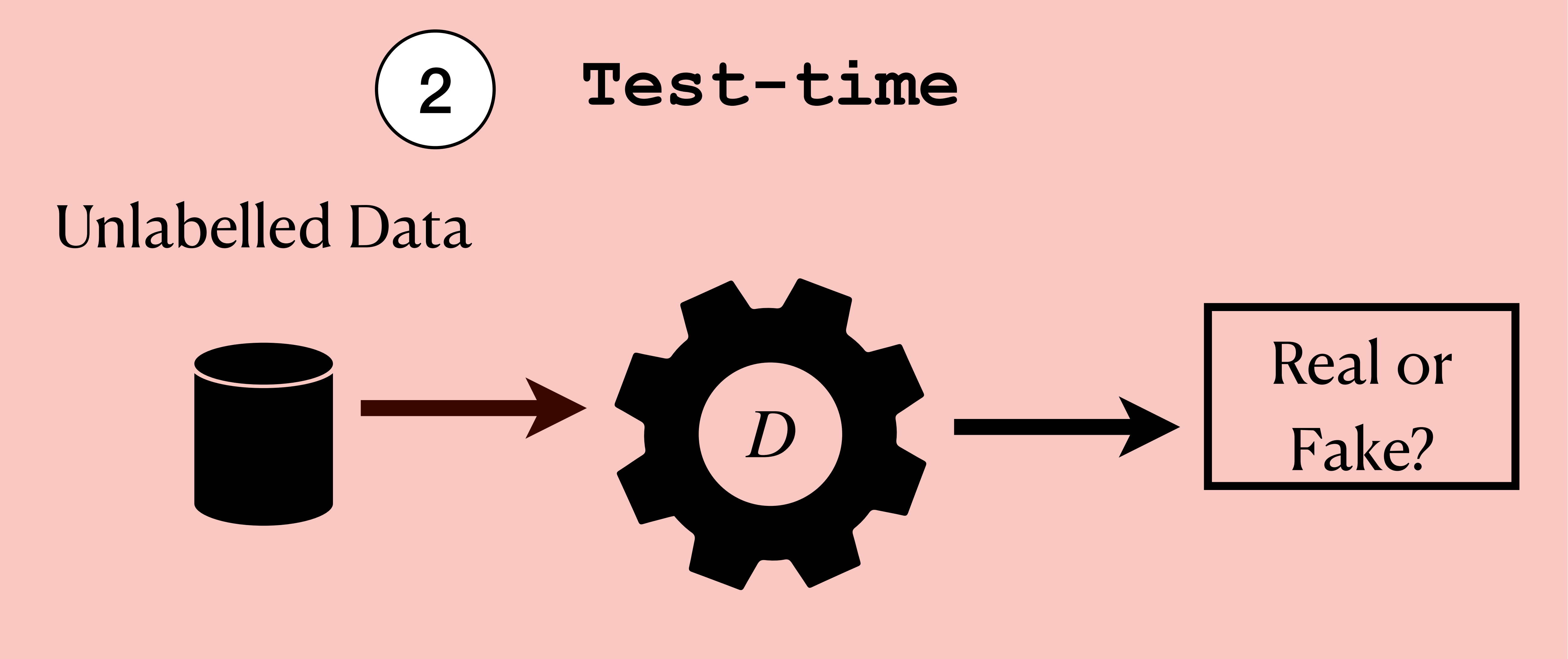
Out-Of-Distribution (OOD) counterfeit detection is challenging



Detect similar fake images ✓



Detect similar fake images ✓

Detect Unseen fake images ✗

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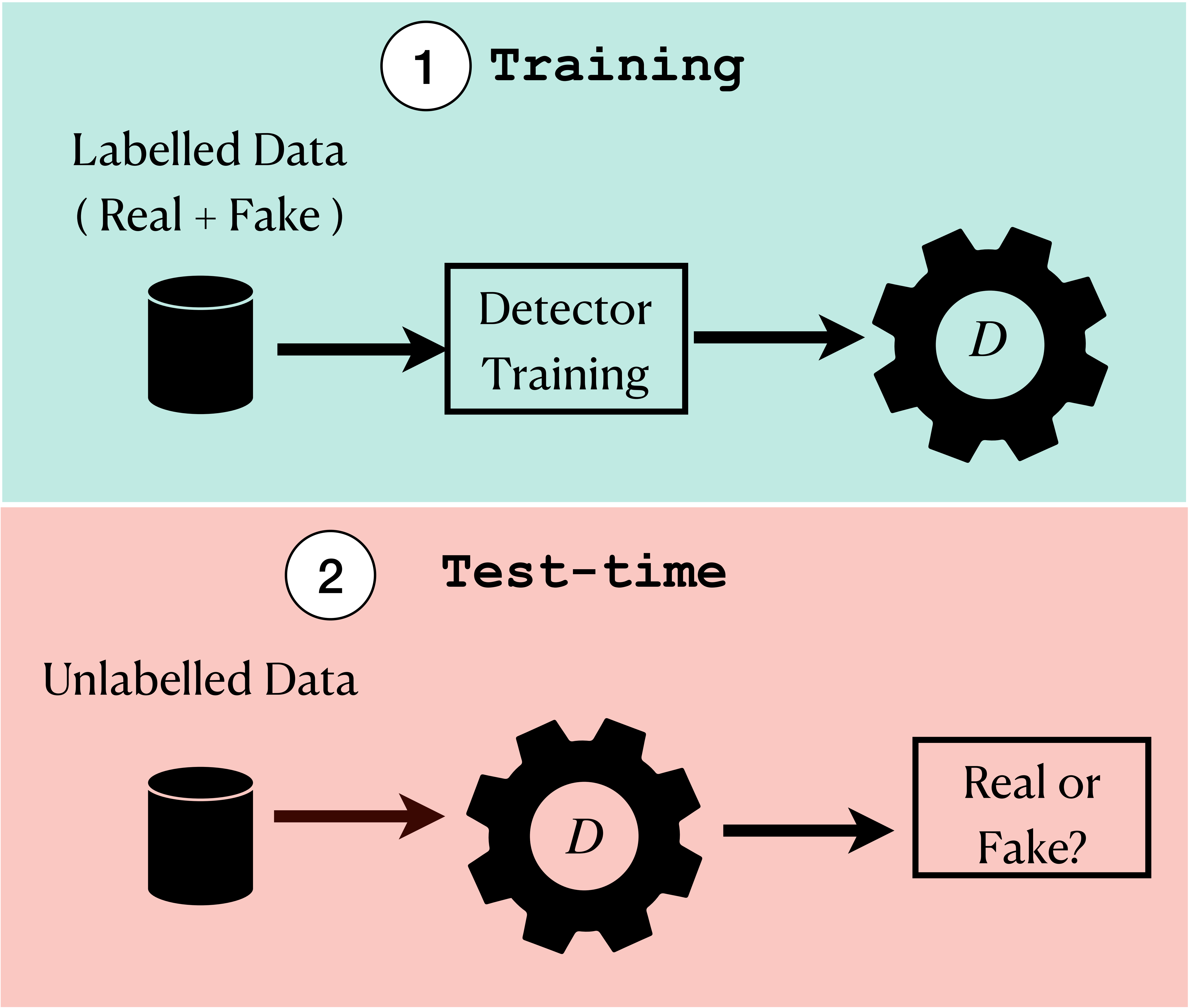

Detect similar fake images ✓

Detect similar fake images ✓

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Unsuccessful forensic transfer

However, a recent class of forensic detectors known as *universal detectors* (Wang et al., 2020) can surprisingly spot counterfeits regardless of generator architectures, loss functions, datasets or resolutions.

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This *universal detector (ResNet-50)* is trained on a large-scale dataset that consists *solely* of ProGAN-generated images and real images (Wang et al., 2020)

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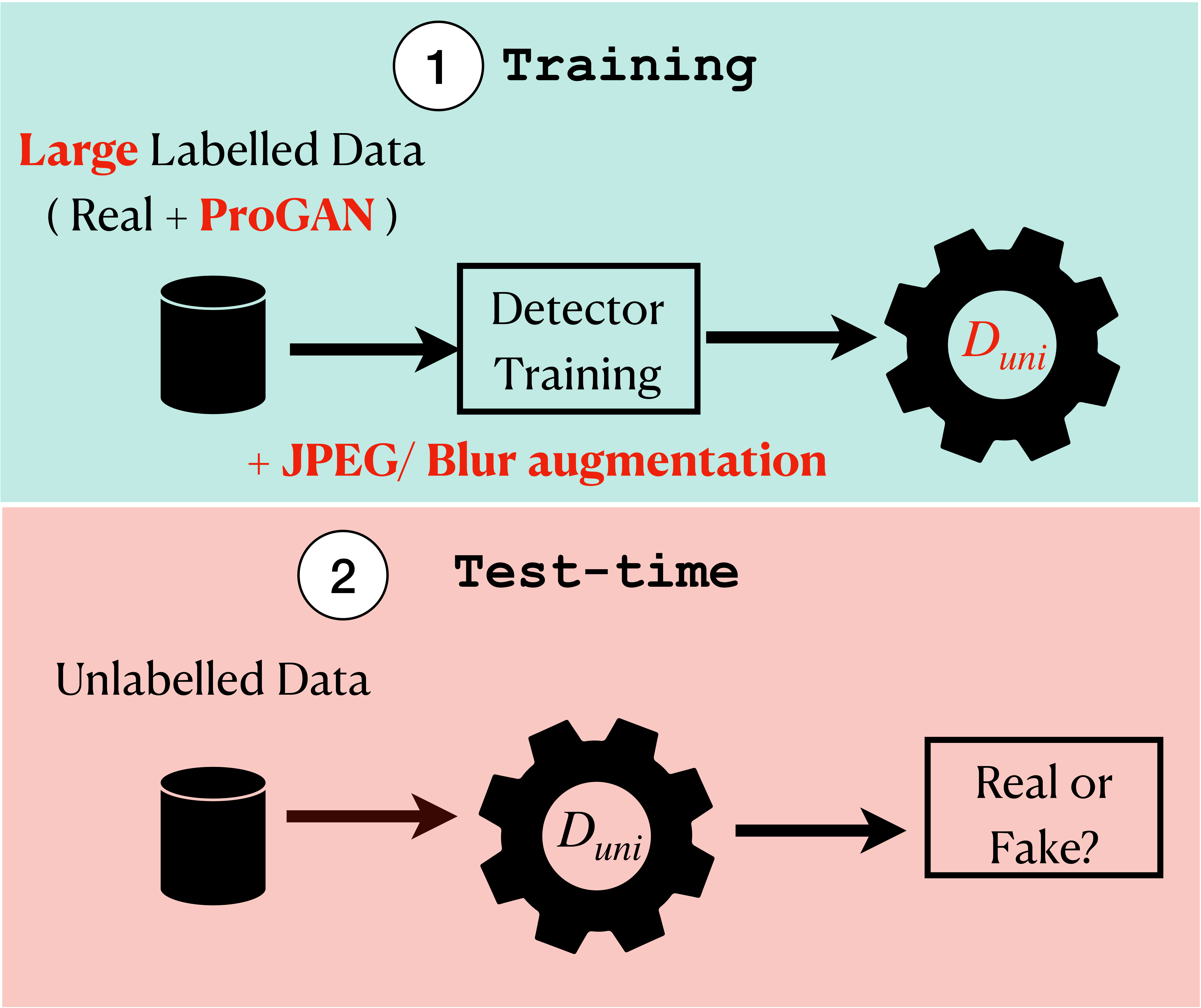
Universal Detector is a promising direction for OOD counterfeit detection



Detect ProGAN (fake) images

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Detect StyleGAN2 (fake) images

Detect CycleGAN (fake) images

Detect BigGAN (fake) images

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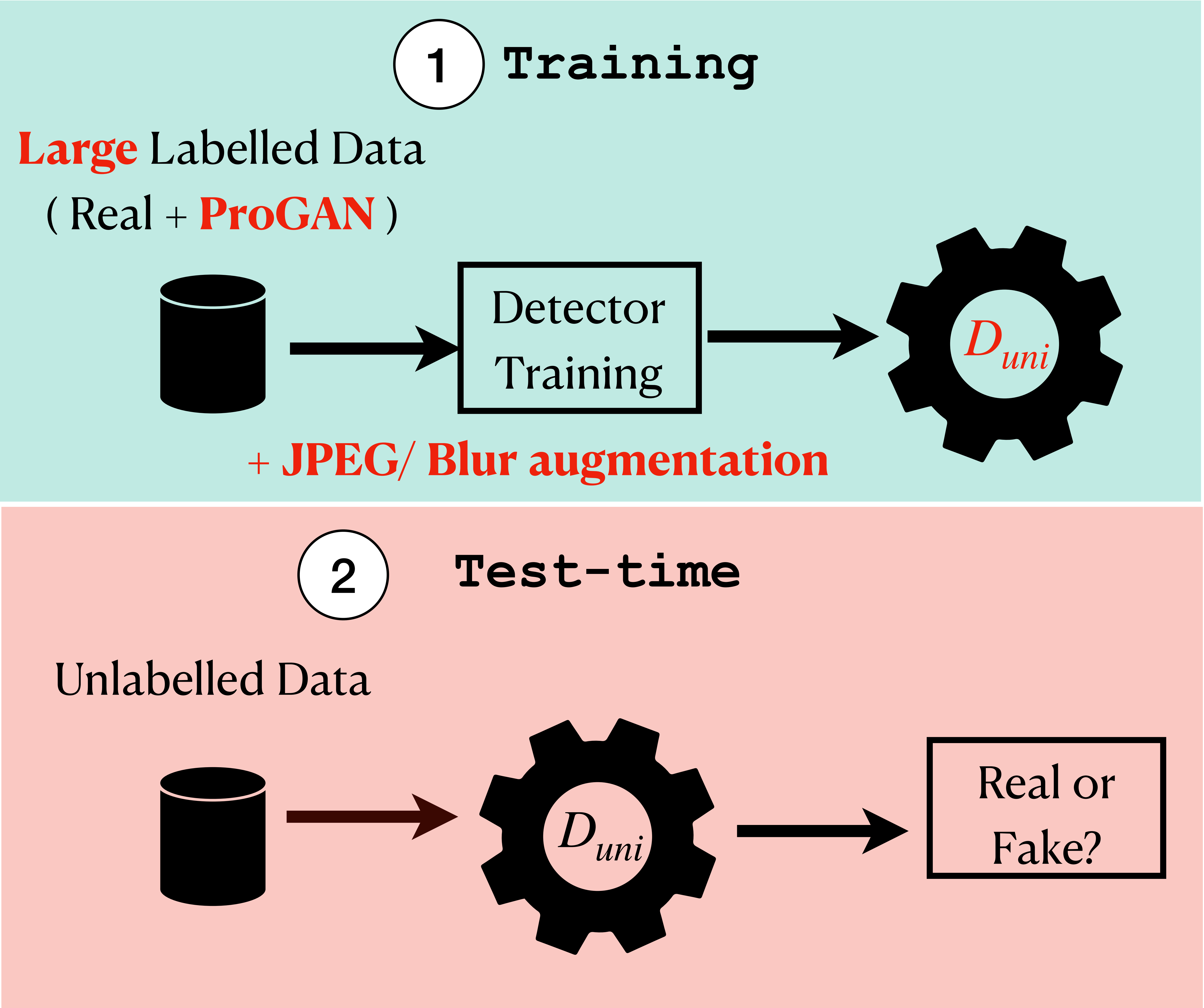

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Notable improvements in forensic transfer

This intriguing cross-model forensic transfer suggests the existence of *Transferable Forensic Features* (*T-FF*) in *universal detectors*.

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What *Transferable Forensic Features (T-FF)* are used by *universal detectors* for counterfeit detection?

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Our work conducts the *first* analytical study to *discover* & *understand* *Transferable Forensic Features (T-FF)* in *universal detectors*.

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Our Contributions/ Findings

- Existing interpretable AI methods are **not informative** to discover *T-FF*

- Develop an **explainable AI framework** to discover and understand *T-FF*
  - Forensic feature relevance statistic (FF-RS)
  - LRP-max visualization

- We discover that **color is a critical *T-FF*** in universal detectors for counterfeit detection.

- Propose a method to train **Color-Robust (CR) universal detectors**.

Are existing Interpretability methods capable of discovering *T-FF* ?

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Insights from a Model

Understanding the Model

Activation Maximization

Erhan 2009

[Deepdream] Olah 2015

Use model to Generate data

[RBM] Hinton 2006

[GAN] Goodfellow 2014

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Explaining single decision

Sensitivity w.r.t. inputs

Gevrey 2003

Baehrens 2010

[Sensitivity] Simonyan 2013

[Grad-CAM] Selvaraju 2016

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Local Linear Approximation

[LIME] Ribeiro 2016

Decomposition

[LRP] Bach 2015

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Source: SUTD Course 50.039 - Theory and Practice of Deep Learning (Lectures by Alexander Binder)

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    - Decomposition
      - **[LRP]** Bach 2015
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- We use Guided Grad-CAM
- Only positive explanations.

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- Both positive/ negative explanations.
- Relevance conservation property.

$$f(x) = \cdots = \sum_{d \in l+1} R_d^{(l+1)} = \sum_{d \in l} R_d^{(l)} = \cdots = \sum_{d} R_d^{(1)}$$

Decomposition

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ProGAN StyleGAN2 StyleGAN BigGAN CycleGAN

Image

$p_{counterfeit} \geq 95\ \%$

for all these counterfeits

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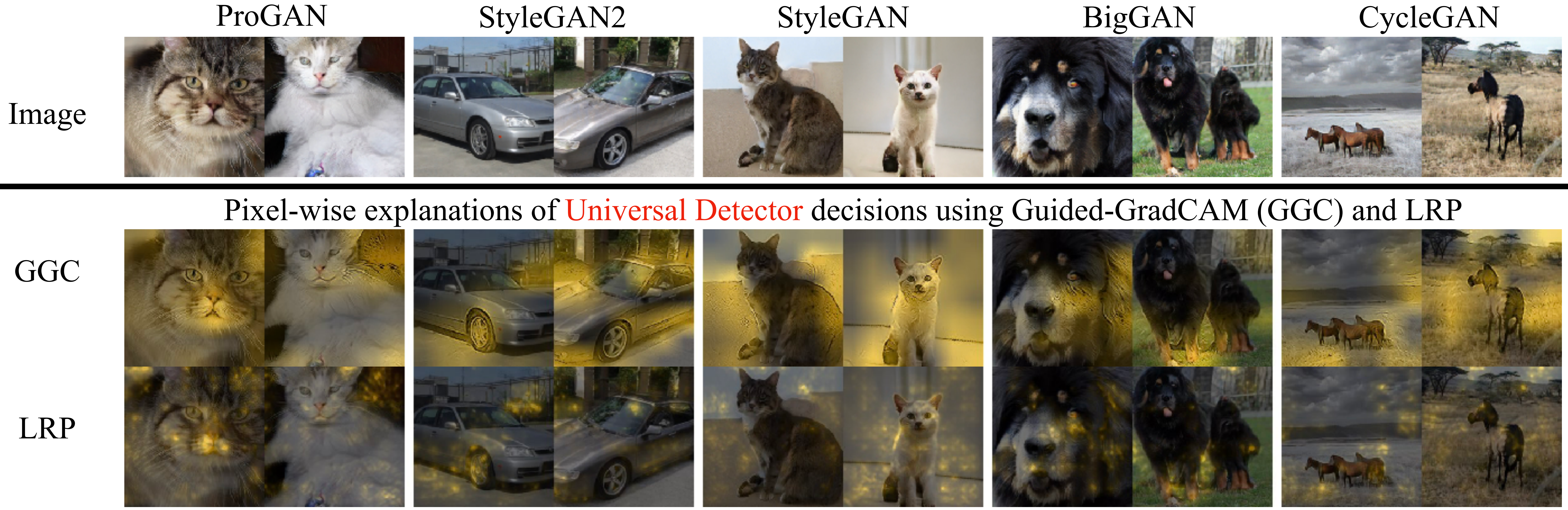

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Pixel-wise explanations of Universal Detector decisions using Guided-GradCAM (GGC) and LRP

GGC

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Explanations are random and do not reveal any meaningful visual features

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Pixel-wise explanations of ImageNet Classifier decisions using Guided-GradCAM (GGC) and LRP

GGC

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This is a control experiment

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Pixel-wise explanations of universal detector decisions are not informative to discover *T-FF*

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We study the *Feature Space* of universal detectors

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Forensic Feature Relevance Statistic (FF-RS) (ω)

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$$\boldsymbol{\omega} \text{ for a feature map quantifies } \frac{\textit{positive forensic relevance of the feature map}}{\textit{total unsigned forensic relevance of the entire layer}}$$

[Schematic Diagram] Forensic Feature Relevance Statistic (FF-RS) (ω)

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Algorithm 1: Calculate FF-RS (ω) (Non-vectorized)

Input:
forensics detector M,
data $D = \{x\}_{i=1}^{n}$, D is a large counterfeit dataset where x_i indicates the i^{th} counterfeit image.
Output:
$\omega(l_c)$ where l, c indicates the layer and channel index of forensic feature maps.
Every forensic feature map can be characterized by a unique set of l, c.

$R \leftarrow [\,]$; /*List to store feature map relevances*/
Set M to evaluation mode
for i *in* $\{0, 1, , ..., n\}$ **do**
  $f(x_i) \leftarrow M(x_i)$; /*logit output*/
  $r_i \leftarrow LRP(M, x_i, f(x_i))$; /*calculate LRP scores for counterfeits*/ ← Calculate relevance for all neurons using LRP
  for l' *in* $r_i.size(0)$ **do**
    for c' *in* $r_i.size(1)$ **do**
      $\boxed{r_i(l', c', h, w) \leftarrow \frac{max(0, r_i(l', c', h, w))}{\sum_{c,h,w} ||r_i(l', c, h, w)||}}$ ← Calculate $\boldsymbol{\omega}$ *for layer l, channel c*
      $R.append(r_i)$; /*r_i.size():(layer, channel, height, width)*/
    end
  end
end
$\boxed{\omega(l_c) \leftarrow \sum_{h,w} \frac{1}{N} \sum_{i}^{n} R_i(l, c, h, w)}$; /*forensic feature relevance*/ ← Spatially sum relevances
return $\omega(l_c)$

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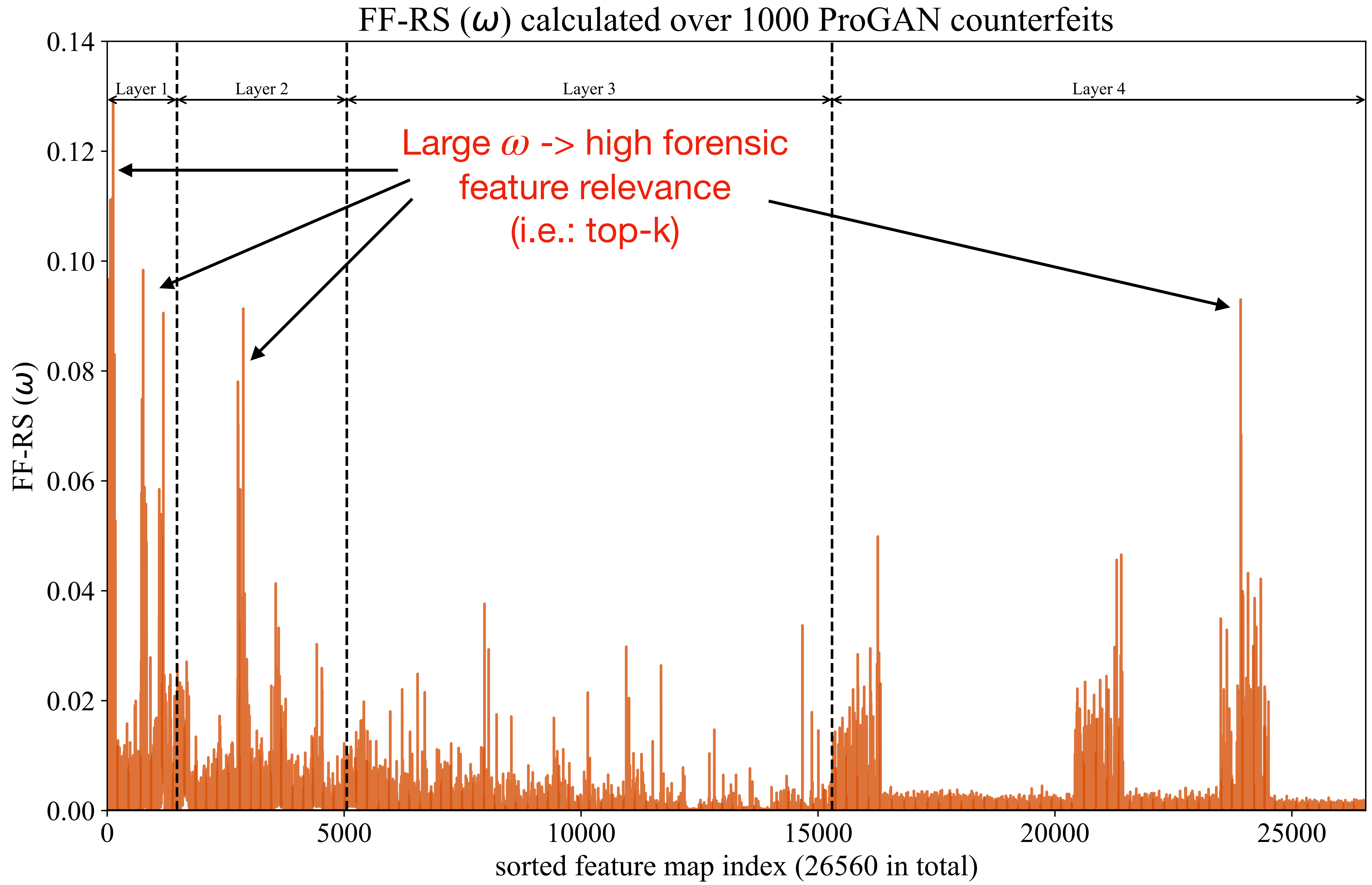
$\omega(l_c)$ where l, c indicates the layer and channel index of forensic feature maps.
Every forensic feature map can be characterized by a unique set of l, c.

$R \leftarrow [\,]$; /*List to store feature map relevances*/
Set M to evaluation mode
for i *in* $\{0, 1, , ..., n\}$ **do**
  $f(x_i) \leftarrow M(x_i)$; /*logit output*/
  $r_i \leftarrow LRP(M, x_i, f(x_i))$; /*calculate LRP scores for counterfeits*/
  for l' *in* $r_i.size(0)$ **do**
    for c' *in* $r_i.size(1)$ **do**
      $\boxed{r_i(l', c', h, w) \leftarrow \frac{max(0, r_i(l', c', h, w))}{\sum_{c,h,w} ||r_i(l', c, h, w)||}}$
      $R.append(r_i)$; /*r_i.size():(layer, channel, height, width)*/
    end
  end
end
$\boxed{\omega(l_c) \leftarrow \sum_{h,w} \frac{1}{N} \sum_i^n R_i(l, c, h, w)\ ;}$ /*forensic feature relevance*/
return $\omega(l_c)$



[Schematic Diagram] Forensic Feature Relevance Statistic (FF-RS) (ω)

$$\omega(l = 3,\ c = 1) = \frac{6}{21} = 0.29 \qquad \omega(l = 3,\ c = 2) = \frac{0}{21} = 0$$

Calculate FF-RS (ω)

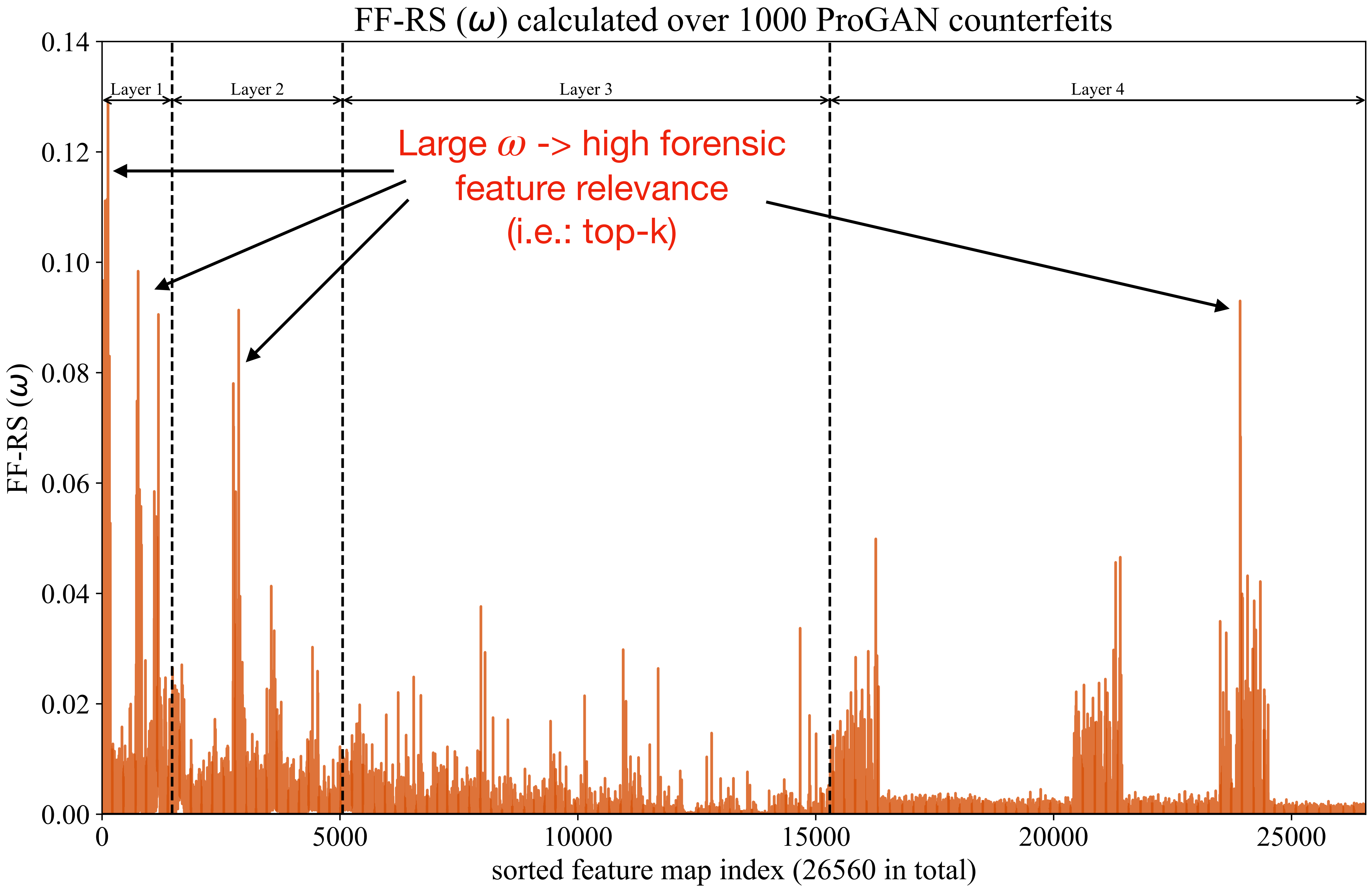
Rank all feature maps using ω values

Validation of our proposed *FF-RS* for discovering *T-FF*

top-k : Set of *T-FF* (top-ranked feature maps based on $\boldsymbol{\omega}$ values)

random-k : Set of random feature maps used as a control experiment

low-k : Set of low-ranked feature maps with very small $\boldsymbol{\omega}$ values



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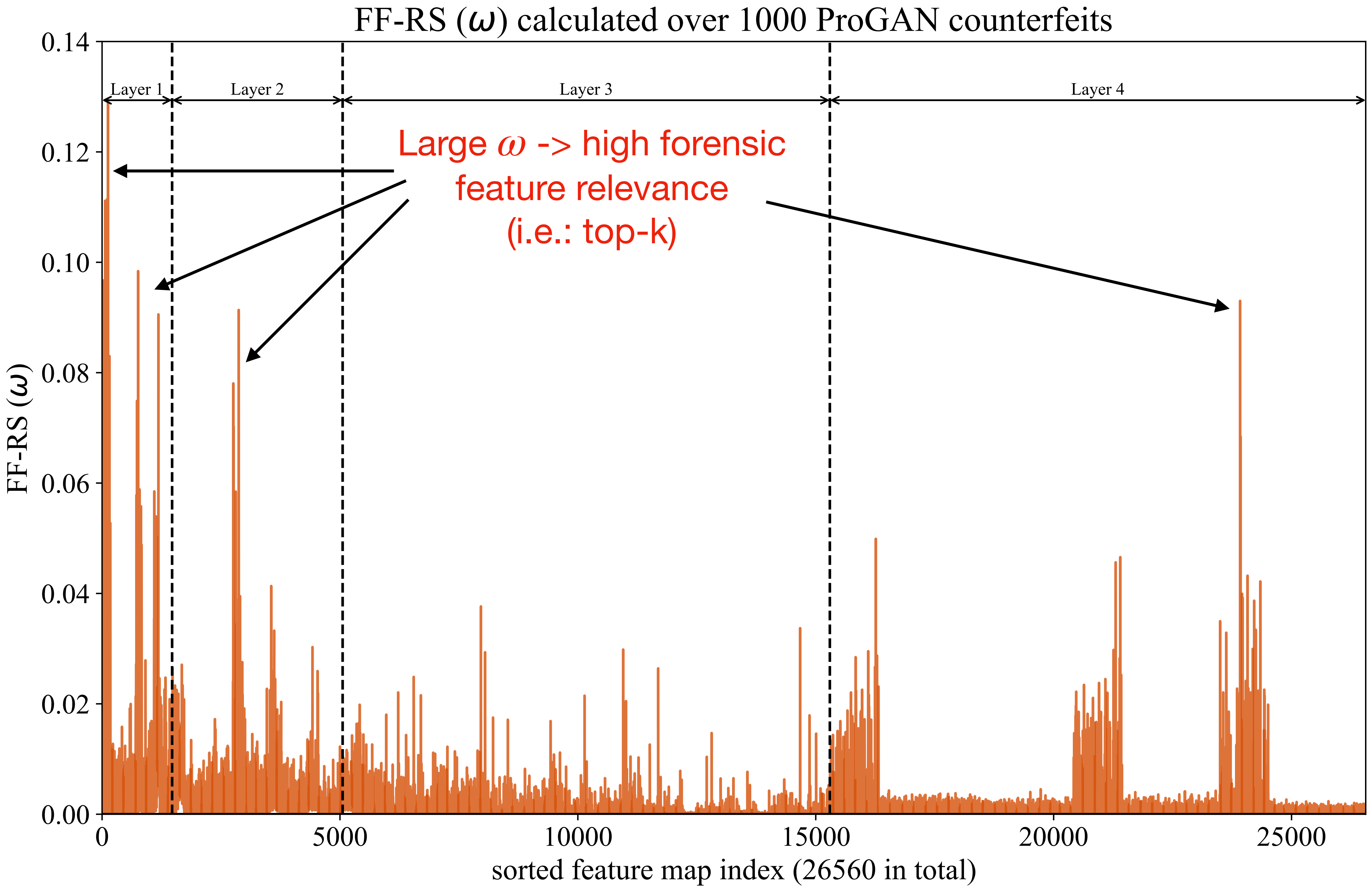

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ResNet-50 feature map dropout results (Sensitivity assessments)

AP / Acc	**ProGAN**			**StyleGAN2**			**StyleGAN**			**BigGAN**			**CycleGAN**			**StarGAN**			**GauGAN**		
k = 114	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**	**AP**	**Real**	**GAN**
baseline	100.0	100.0	100.0	99.1	95.5	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4

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baseline	100.0	100.0	100.0	99.1	95.5	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4

k = 114 (<0.5%)

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baseline	100.0	100.0	100.0	99.1	95.5	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4
top-k	**69.8**	**99.4**	**3.2**	**55.3**	**89.4**	**11.3**	**56.6**	**90.6**	**13.7**	**55.4**	**86.4**	**18.3**	**61.2**	**91.4**	**17.4**	**72.6**	**89.4**	**35.9**	**71.0**	**95.0**	**18.8**

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baseline	100.0	100.0	100.0	99.1	95.5	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4
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random-k	100.0	99.9	96.1	98.6	89.4	96.9	98.7	91.4	96.1	88.0	79.4	85.1	96.6	81.0	96.2	97.0	88.0	91.7	98.7	91.9	97.1

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low-k	100.0	100.0	100.0	99.1	95.6	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4

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FF-RS (ω) successfully quantifies and discovers *T-FF*

k = 114	AP	Real	GAN	AP	Real	GAN	AP	Real	GAN	AP	Real	GAN	AP	Real	GAN	AP	Real	GAN	AP	Real	GAN
baseline	100.0	100.0	100.0	99.1	95.5	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4
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low-k	100.0	100.0	100.0	99.1	95.6	95.0	99.3	96.0	95.6	90.4	83.9	85.1	97.9	93.4	92.6	97.5	94.0	89.3	98.8	93.9	96.4

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Our Contributions/ Findings

- Existing interpretable AI methods are **not informative** to discover *T-FF* ✓
- Develop an **explainable AI framework** to discover and understand *T-FF*
  - Forensic feature relevance statistic (FF-RS) ✓
  - LRP-max visualization
- We discover that **color is a critical *T-FF*** in universal detectors for counterfeit detection.
- Propose a method to train **Color-Robust (CR) universal detectors**.

What *counterfeit properties* are detected by this set of *T-FF* discovered using *FF-RS?*

Samples generated using Zero-Insertion based Upsampling Architectural Variant (Chandrasegaran et al., 2021) of Progressive Growing of GAN (Karras et al., 2018)

Chandrasegaran, K., Tran, N. T., & Cheung, N. M. (2021). *A closer look at Fourier spectrum discrepancies for CNN-generated images detection*. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition
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Wang, S. Y., Wang, O., Zhang, R., Owens, A., & Efros, A. A. (2020). *CNN-generated images are surprisingly easy to spot... for now*. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition

What *counterfeit properties* are detected by this set of *T-FF?*

We introduce a novel pixel-wise visualization method — LRP-max — for visualizing which pixels in the input space correspond to maximum spatial relevance scores for each *T-FF*.

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We introduce a novel pixel-wise visualization method — LRP-max — for visualizing which pixels in the input space correspond to maximum spatial relevance scores for each *T-FF*.

Principal idea : Instead of back-propagating using detector logits, back-propagate from the maximum spatial relevance neuron for each *T-FF* independently.

[Schematic Diagram] Forensic Feature Relevance Statistic (FF-RS) (ω)

$$\omega(l = 3,\ c = 1) = \frac{6}{21} = 0.29$$

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Calculate FF-RS (ω)

Rank all feature maps using ω values

[Schematic Diagram] LRP-max

Calculate FF-RS (ω)

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Maximum spatial relevance neuron

Back-propagate from maximum spatial relevance neuron during LRP

Algorithm 2: Obtain LRP-max pixel-wise explanations (For a single feature map, for a single sample)

Input:
forensics detector M,
counterfeit image x where $x.size() = (3, x_{height}, x_{width})$,
forensic feature map l, c where l, c indicate layer and channel index respectively.

Output:
$\hat{E}_{l_c}(x)$ where E indicates the LRP-max pixel-wise explanations for sample x corresponding to forensic feature map at layer index l and channel index c.
Do note that $\hat{E}_{l_c}(x).size()$ is (x_{height}, x_{width}).
Every forensic feature map can be characterized by a unique set of l, c.

$z_{l_c}(x) \leftarrow LRP - FORWARD(M_{l_c}(x_i))$; `/*(h, w) relevance scores*/`
$h^*, w^* \leftarrow argmax(z_{l_c}(x))$; `/*find index of max relevance*/`
$z_{l_c}^{max}(x) \leftarrow z_{l_c}(x)[h^*, w^*]$; `/*LRP-max response neuron*/`
$E_{l_c}(x) \leftarrow LRP - BACKWARD(z_{l_c}^{max}(x))$; `/*explain LRP-max neuron*/`
$\hat{E}_{l_c}(x) \leftarrow \sum_{k=0}^{3}(E_{l_c}(x)(k, x_{height}, x_{width})$; `/*spatial LRP-max*/`
return $\hat{E}_{l_c}(x)$

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  - LRP-max visualization ✓

- We discover that **color is a critical *T-FF*** in universal detectors for counterfeit detection.

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Color is a critical *T-FF* (Qualitative Studies)

We introduce a novel pixel-wise visualization method — LRP-max — for visualizing which pixels in the input space correspond to maximum spatial relevance scores for each *T-FF*.

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ProGAN StyleGAN2 StyleGAN BigGAN CycleGAN StarGAN GauGAN

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Principal idea : Instead of back-propagating using detector logits, back-propagate from the maximum spatial relevance neuron for each *T-FF* independently.

We qualitatively discover that color is a critical *T-FF* in universal detectors for *cross-model forensic transfer*

Color is a critical *T-FF* (Quantitative Studies)

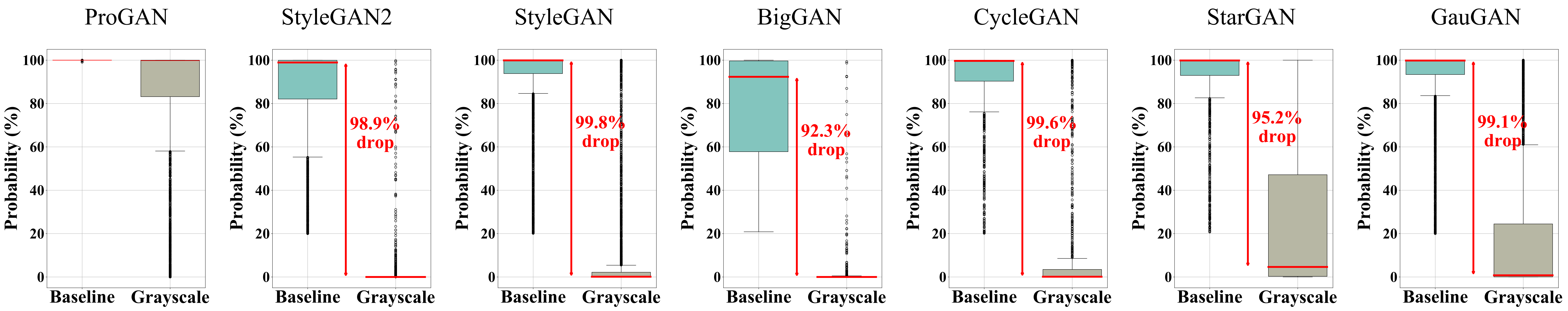
Median Counterfeit Probability Analysis based on Color Ablation

We study the change in median counterfeit probability when removing color information (grayscale) from counterfeits.

$p_{counterfeit} = 0.97$ $p_{counterfeit} = 0.96$ $p_{counterfeit} = 0.95$ $p_{counterfeit} = 0.97$ $p_{counterfeit} = ?$ $p_{counterfeit} = ?$ $p_{counterfeit} = ?$ $p_{counterfeit} = ?$

Color is a critical *T-FF* (Quantitative Studies I)

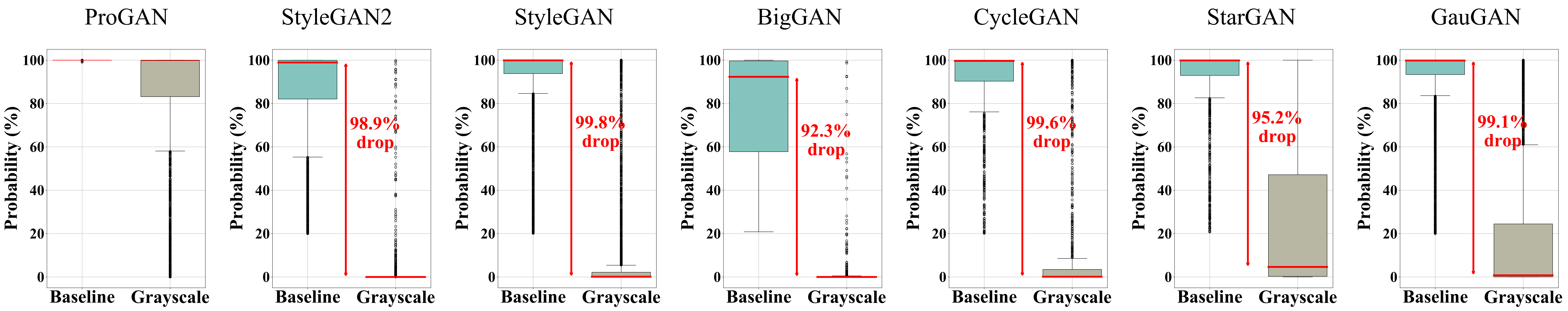
Median Counterfeit Probability Analysis based on Color Ablation



Color ablation causes the median probability predicted by universal detector to drop by > 89% across all unseen GANs

Color is a critical *T-FF* (Quantitative Studies II)

Median Counterfeit Probability Analysis based on Color Ablation



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% Color-conditional *T-FF* (Mood's median test) based on maximum spatial activation distributions

% Color-conditional	ProGAN	StyleGAN2	StyleGAN	BigGAN	CycleGAN	StarGAN	GauGAN
ResNet-50	?	?	?	?	?	?	?

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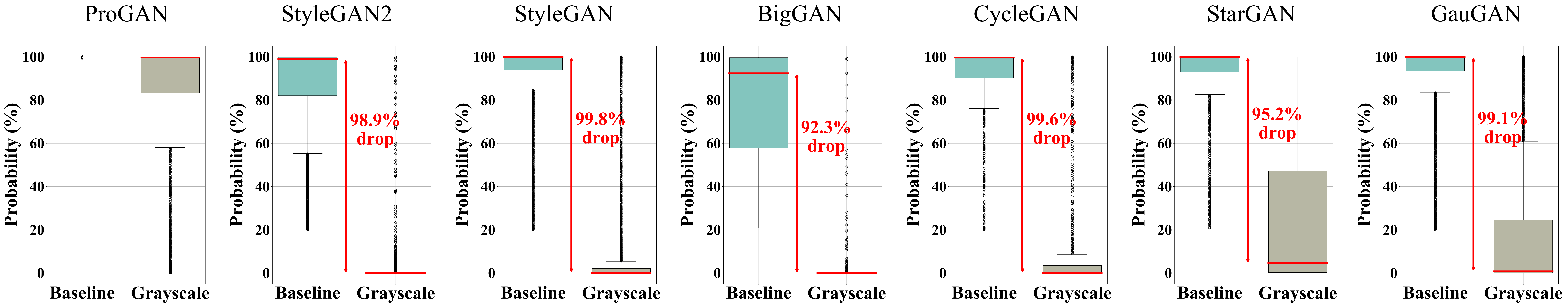

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ResNet-50	85.1	74.6	73.7	68.4	86.8	71.1	70.2

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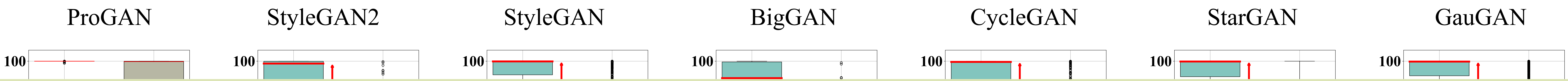

We quantitatively show that color is a critical *T-FF* in universal detectors for cross-model forensic transfer

$p_{counterfeit} = 0.97$ $p_{counterfeit} = 0.96$ $p_{counterfeit} = 0.95$ $p_{counterfeit} = 0.97$ $p_{counterfeit} = 0.04$ $p_{counterfeit} = 0.10$ $p_{counterfeit} = 0.00$ $p_{counterfeit} = 0.01$

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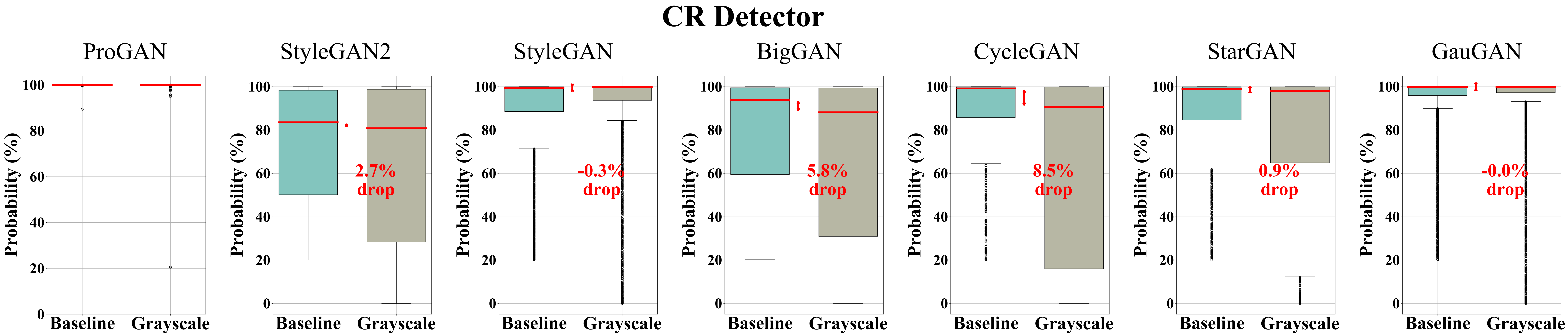
Our Contributions/ Findings

- Existing interpretable AI methods are **not informative** to discover *T-FF* ✓
- Develop an **explainable AI framework** to discover and understand *T-FF*
  - Forensic feature relevance statistic (FF-RS) ✓
  - LRP-max visualization ✓
- We discover that **color is a critical *T-FF*** in universal detectors for counterfeit detection. ✓
- Propose a method to train **Color-Robust (CR) universal detectors**.

Applications : Color-Robust (CR) Universal Detectors

Idea : Randomly remove color information from samples during training (both real and counterfeits) to manoeuvre detectors to learn *T-FF* that do not substantially rely on color information (Random Grayscaling).



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ResNet-50	85.1	74.6	73.7	68.4	86.8	71.1	70.2
CR-ResNet-50	**55.3**	**33.3**	**48.2**	**31.6**	**56.1**	**48.2**	**39.5**

T-FF in Color-Robust (CR) Universal Detectors

Largely correspond to patterns / artifacts

Faintly Colored

Notable patterns include wheels, stripes in zebras

T-FF in Color-Robust (CR) Universal Detectors

Largely correspond to patterns / artifacts

Faintly Colored

Notable patterns include wheels, stripes in zebras

Our explainable AI framework can identify different types of *T-FF* in addition to color.

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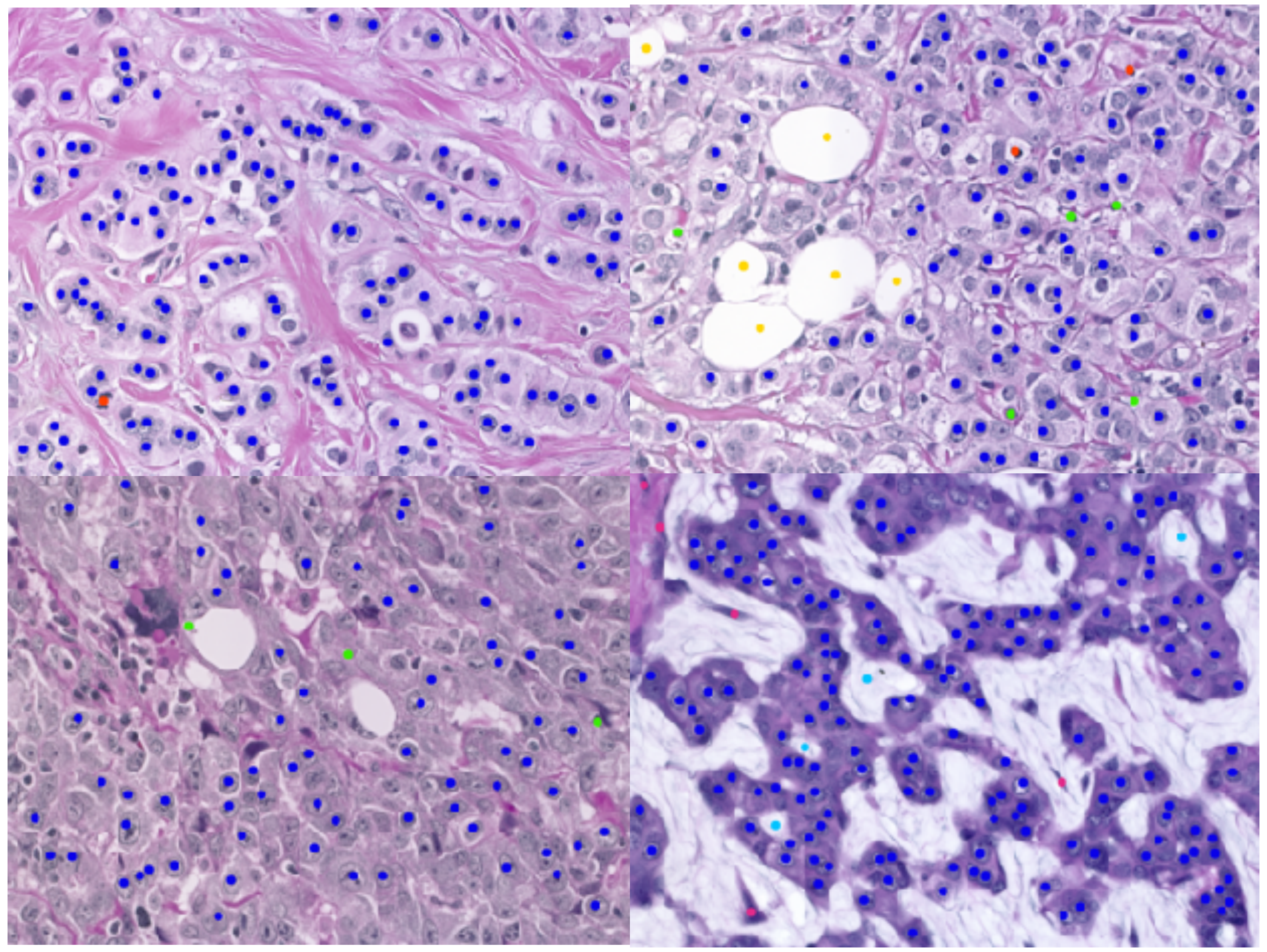
- We discover that **color is a critical *T-FF*** in universal detectors for counterfeit detection. ✓

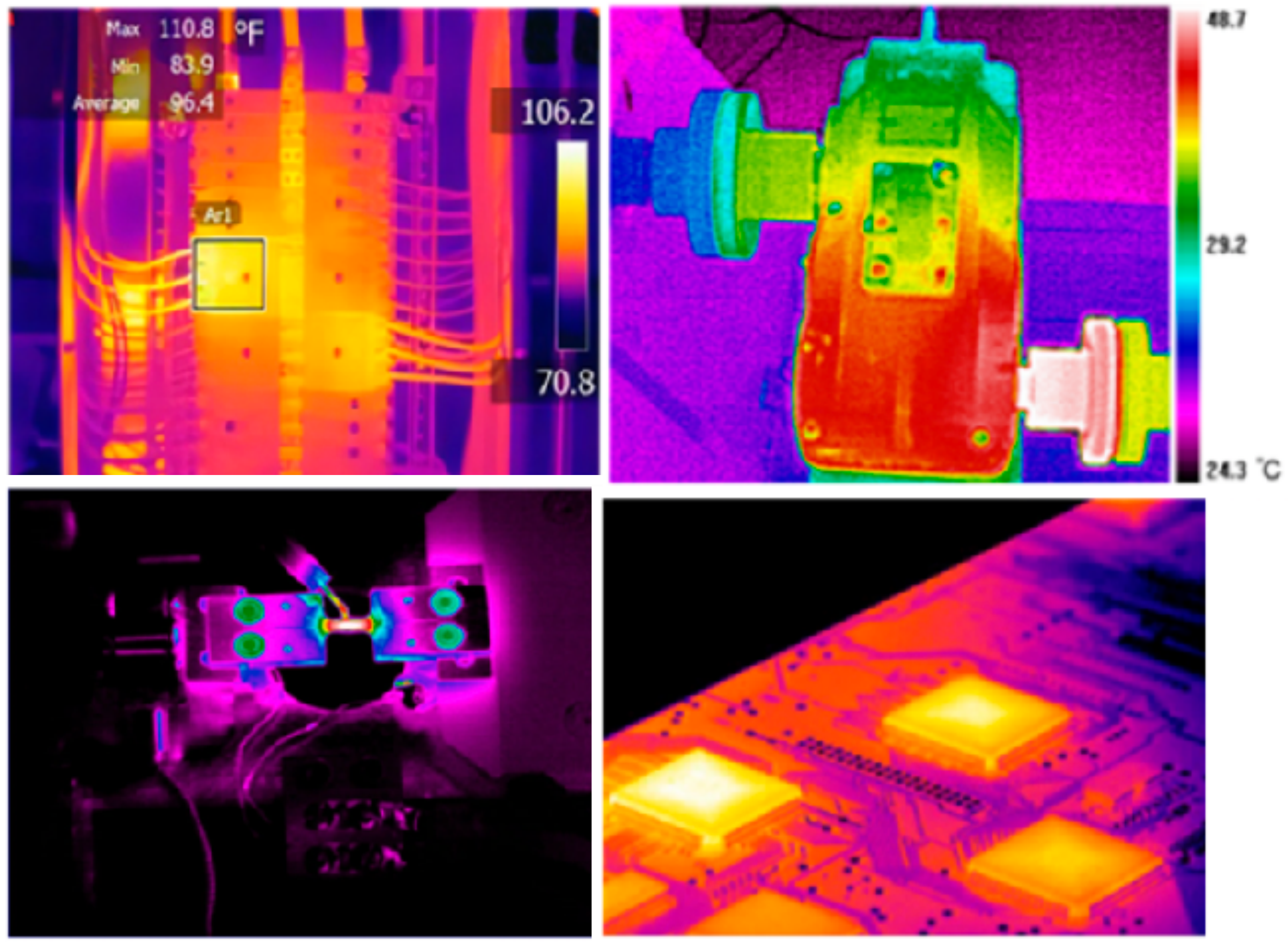
- Propose a method to train **Color-Robust (CR) universal detectors**. ✓

Deeper Question

Are CNN-based generative models struggling to accurately reproduce the color distribution of data?



Histopathology



Thermal Imaging
(Material Science/ Manufacturing)

Our Contributions/ Findings

- Existing interpretable AI methods are **not informative** to discover *T-FF* ✓
- Develop an **explainable AI framework** to discover and understand *T-FF*
  - Forensic feature relevance statistic (FF-RS) ✓
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Code / Pre-trained models: https://keshik6.github.io/transferable-forensic-features/

Summary

We propose a novel Forensic Feature Relevance Statistic (FF-RS) to quantify & discover Transferable Forensic Features *(T-FF)* in universal detectors for counterfeit detection.

We qualitatively (LRP-max) and quantitatively show that color is a critical Transferable Forensic Feature *(T-FF)* in universal detectors for counterfeit detection

Based on our findings, we propose a simple data augmentation scheme to train Color-Robust (CR) universal detectors

Code / Pre-trained models:
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