Looking into the dark: from image to video

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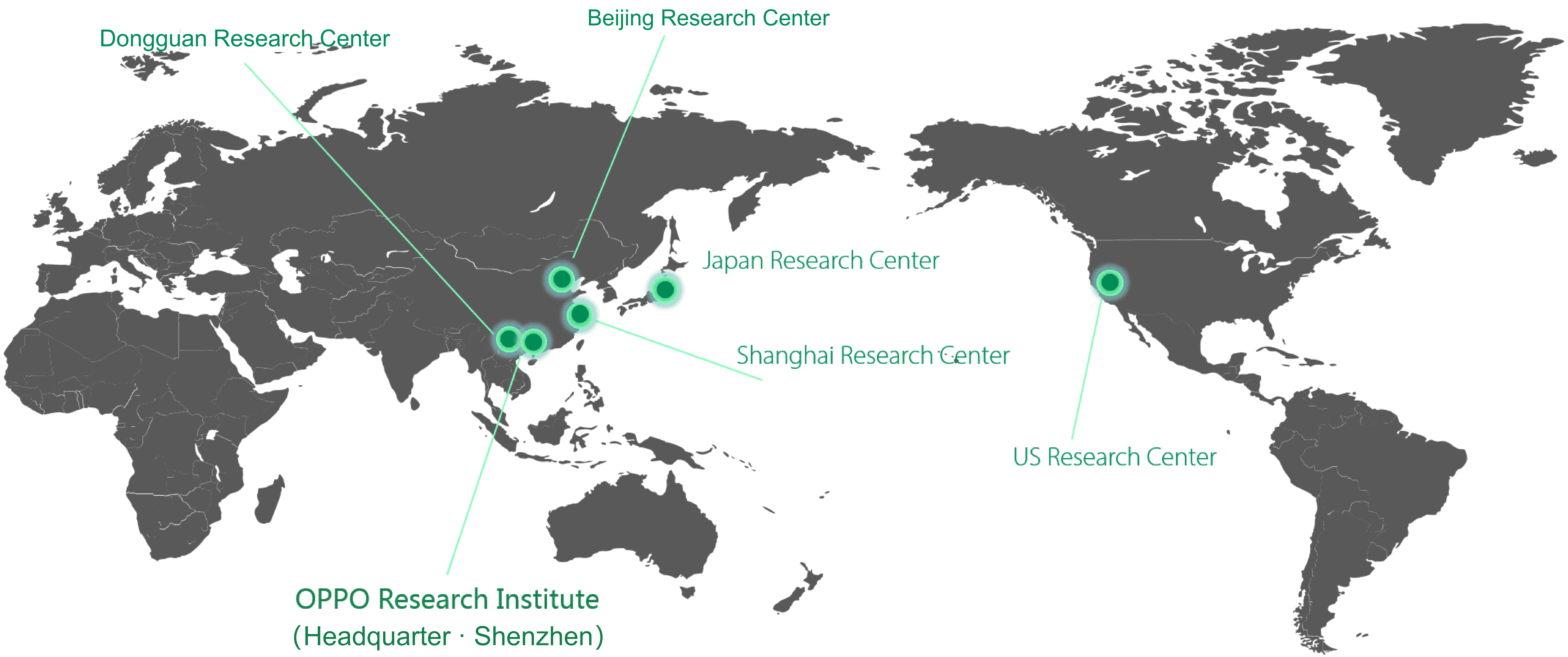
oppo

Entered **40+** markets

Ranked **#5** in 2020 Q1*

More than **350** million users

* https://www.counterpointresearch.com/global-smartphone-shipments-plummet-300mn/


Dongguan Research Center
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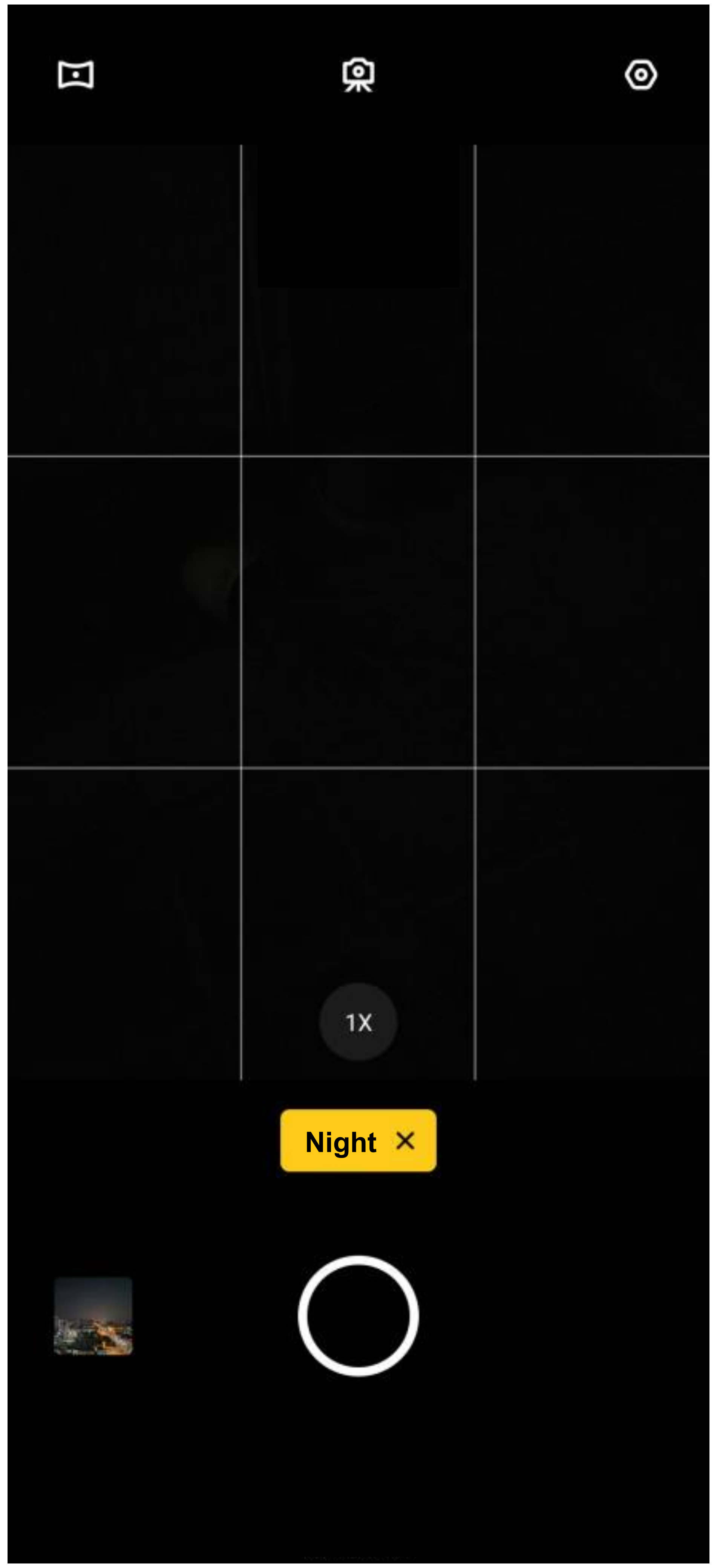
What’s hidden in the dark



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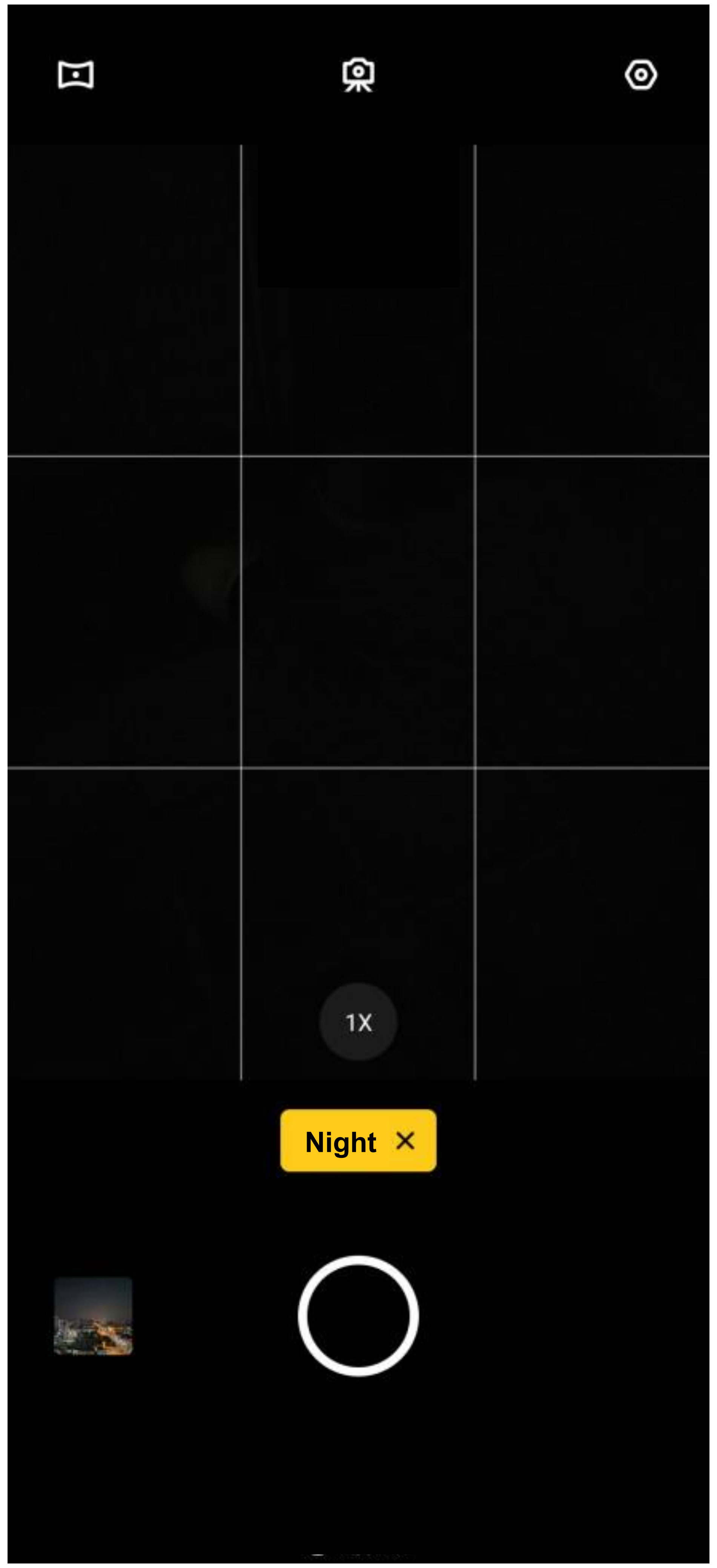

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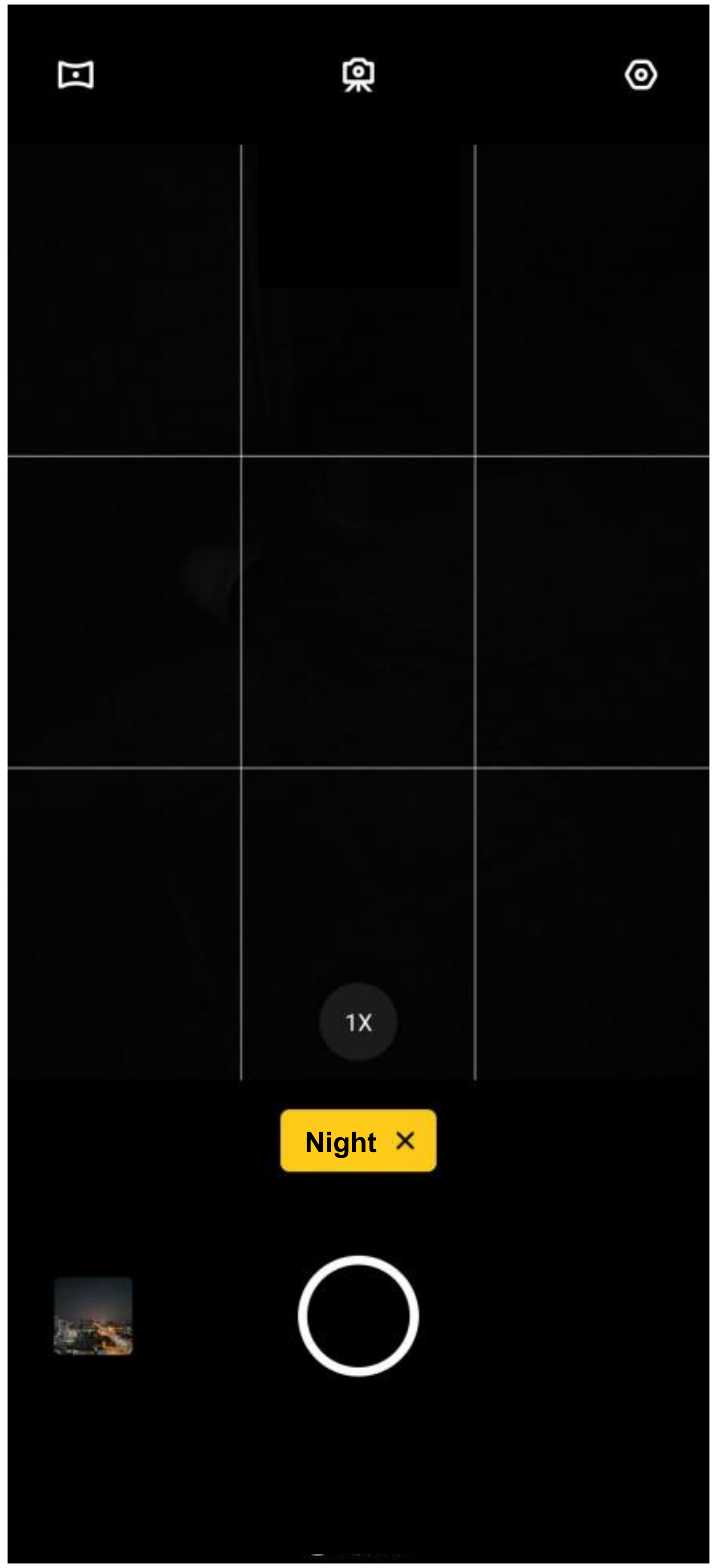

“Lux” is the standard unit of measure for illumination (i.e. brightness) of a surface at a given point.

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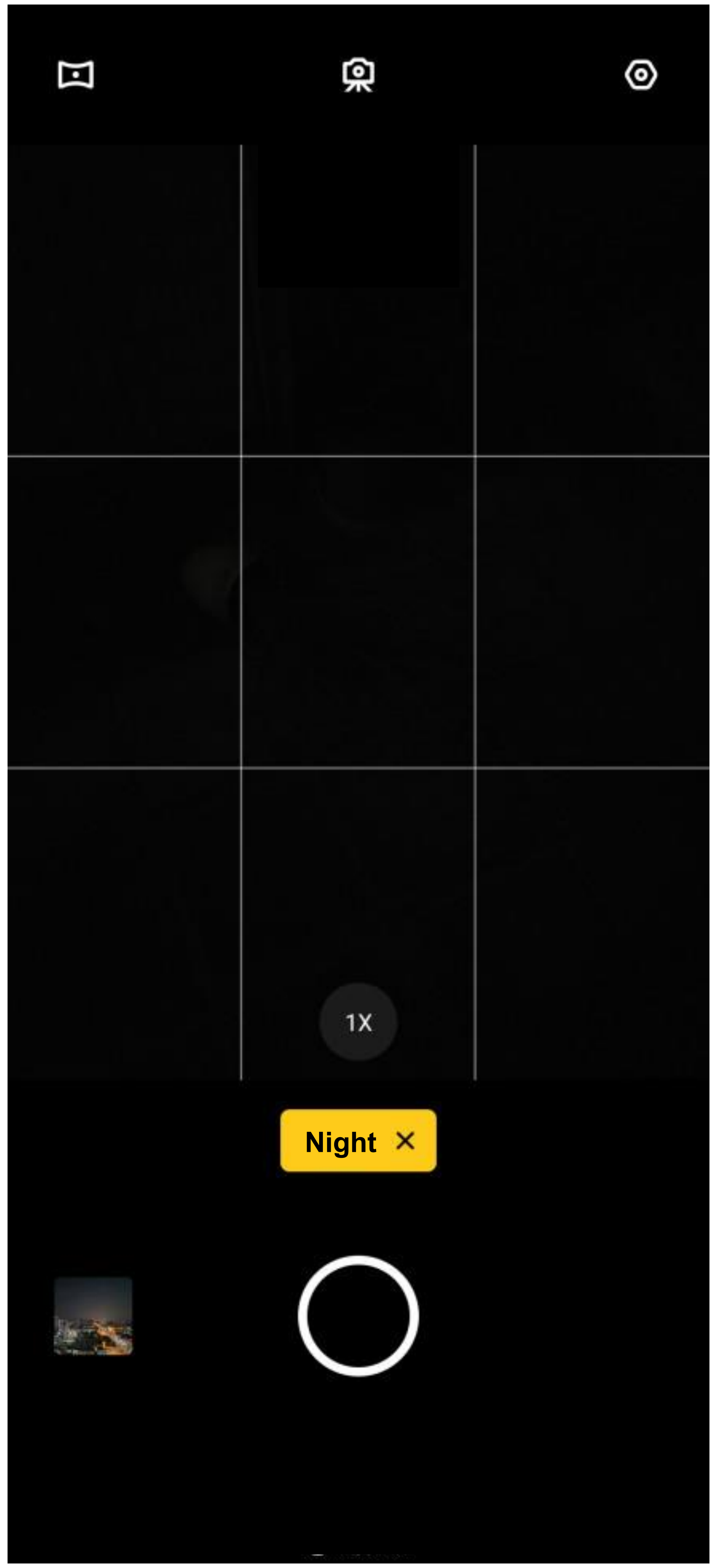
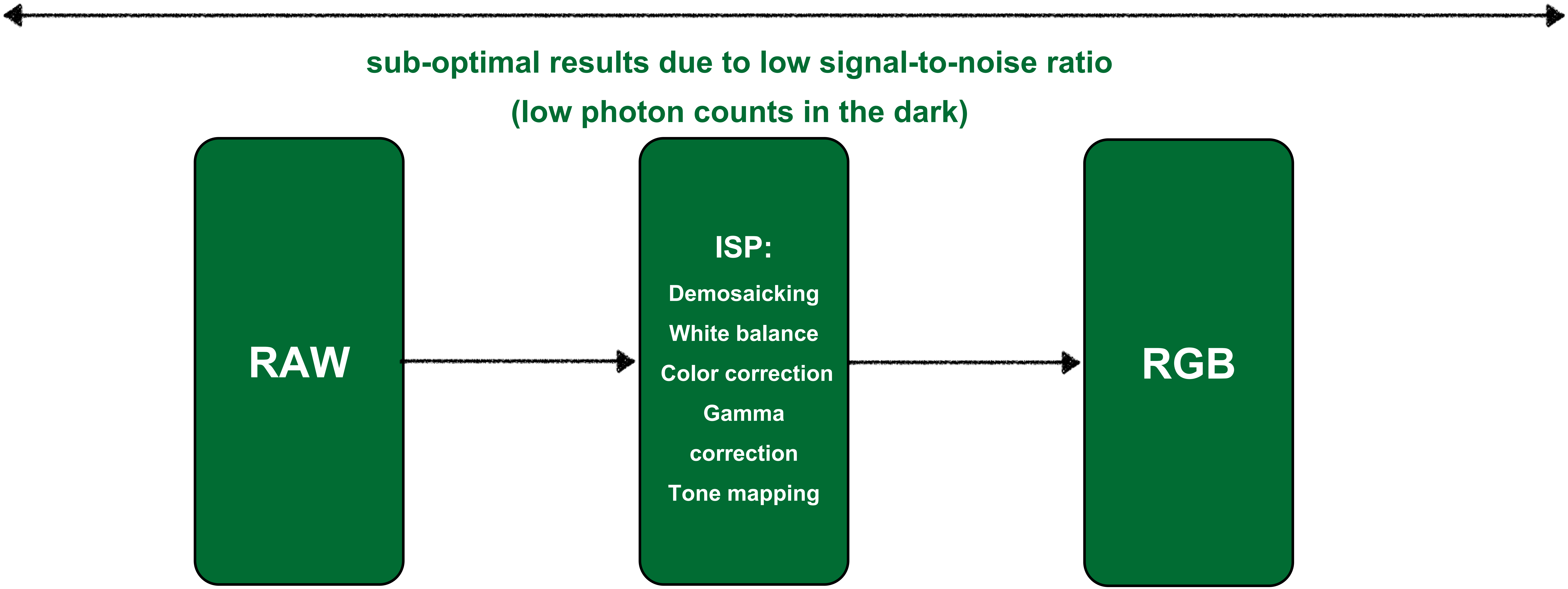


"Lux" is the standard unit of measure for illumination (i.e. brightness) of a surface at a given point.

	illuminance
direct sunlight	~100K lux
daylight (non-direct sunlight)	~10K lux
dark (e.g. moonlight)	< 1 lux

Traditional Camera Pipeline



sub-optimal results due to low signal-to-noise ratio

(low photon counts in the dark)

RAW

ISP:

Demosaicking

White balance

Color correction

Gamma correction

Tone mapping

RGB

Imaging in the dark

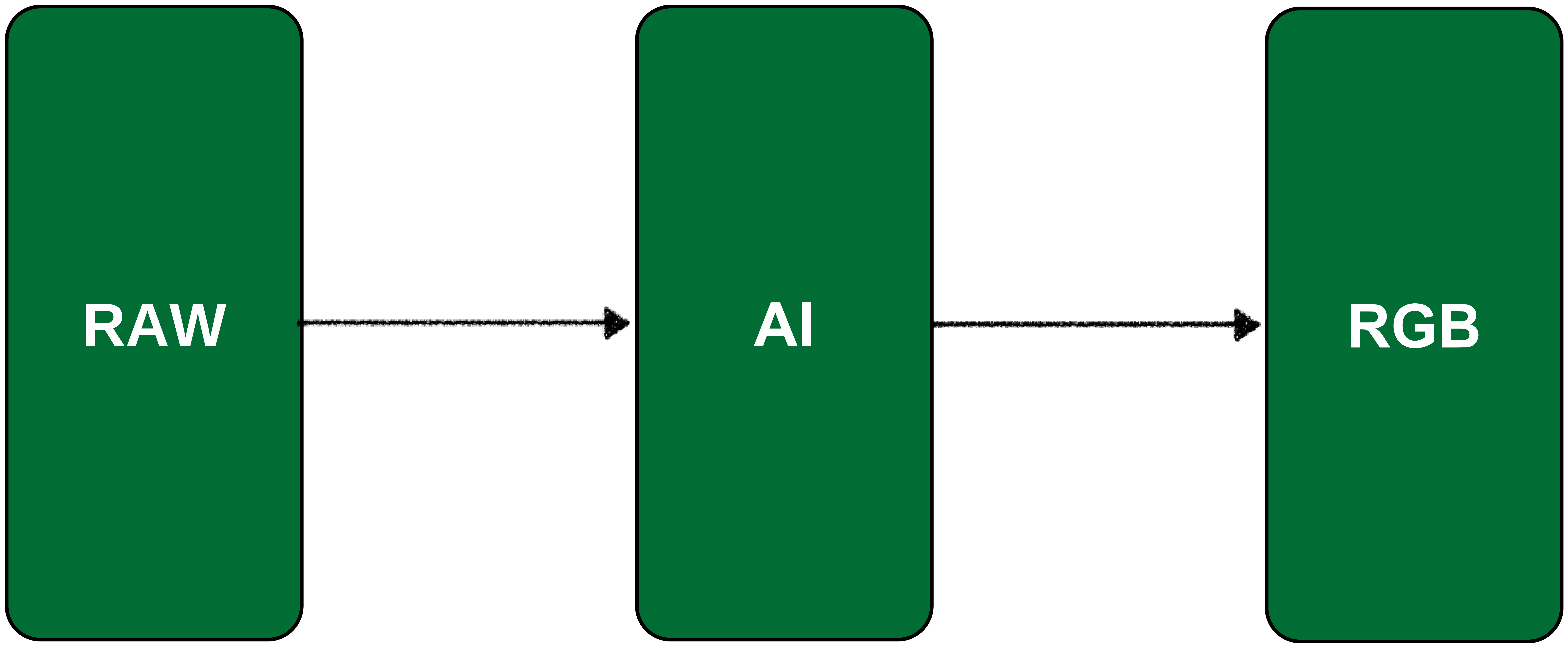
Raise ISO sensitivity to gain brightness?
noise amplification in the electronic signal

Increase exposure time?
blur due to hand shake or object motion

Use flash?

reflections, glare, shadows

Let AI do the work

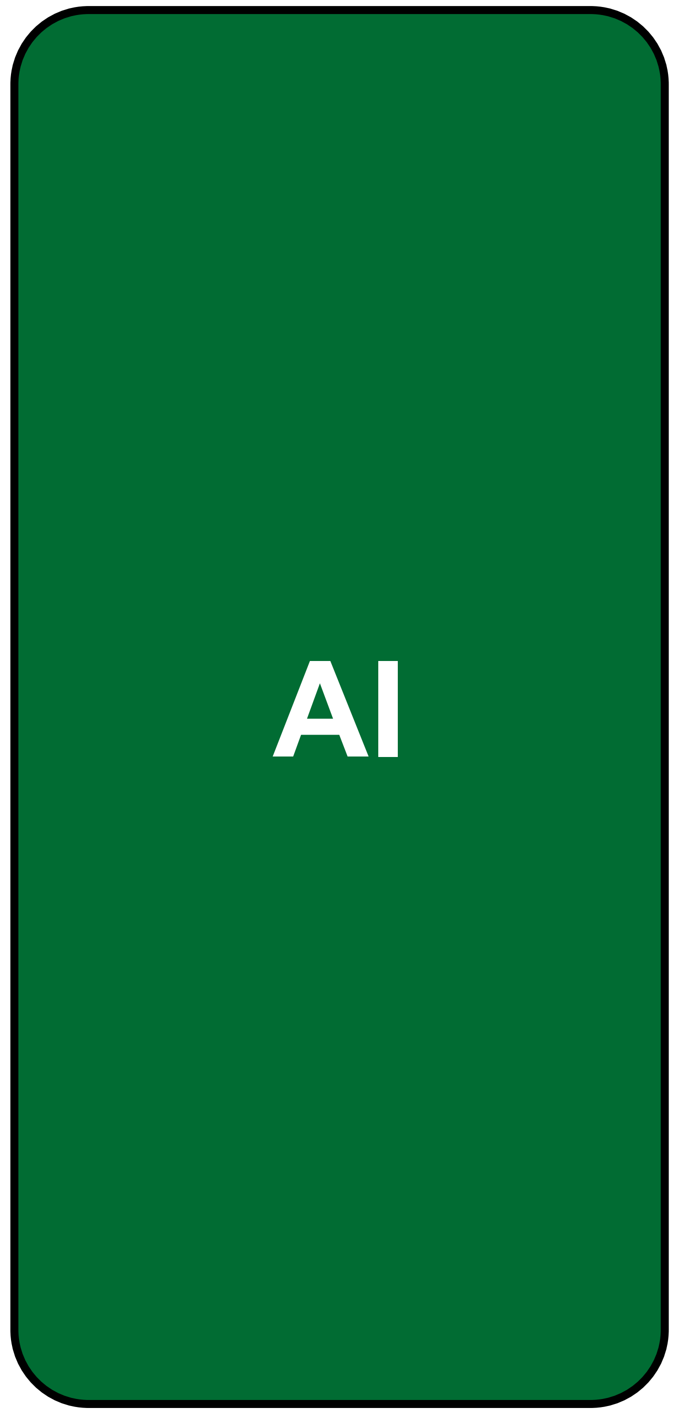


RAW

AI

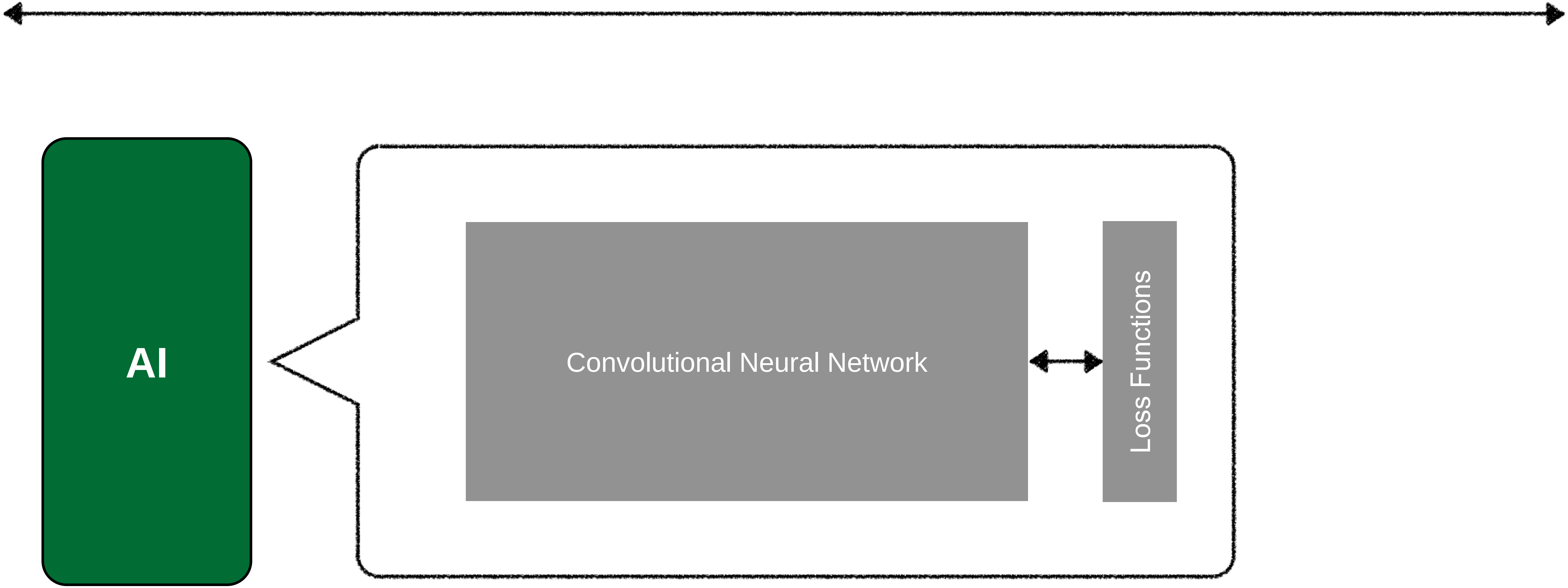
RGB

What's inside



AI

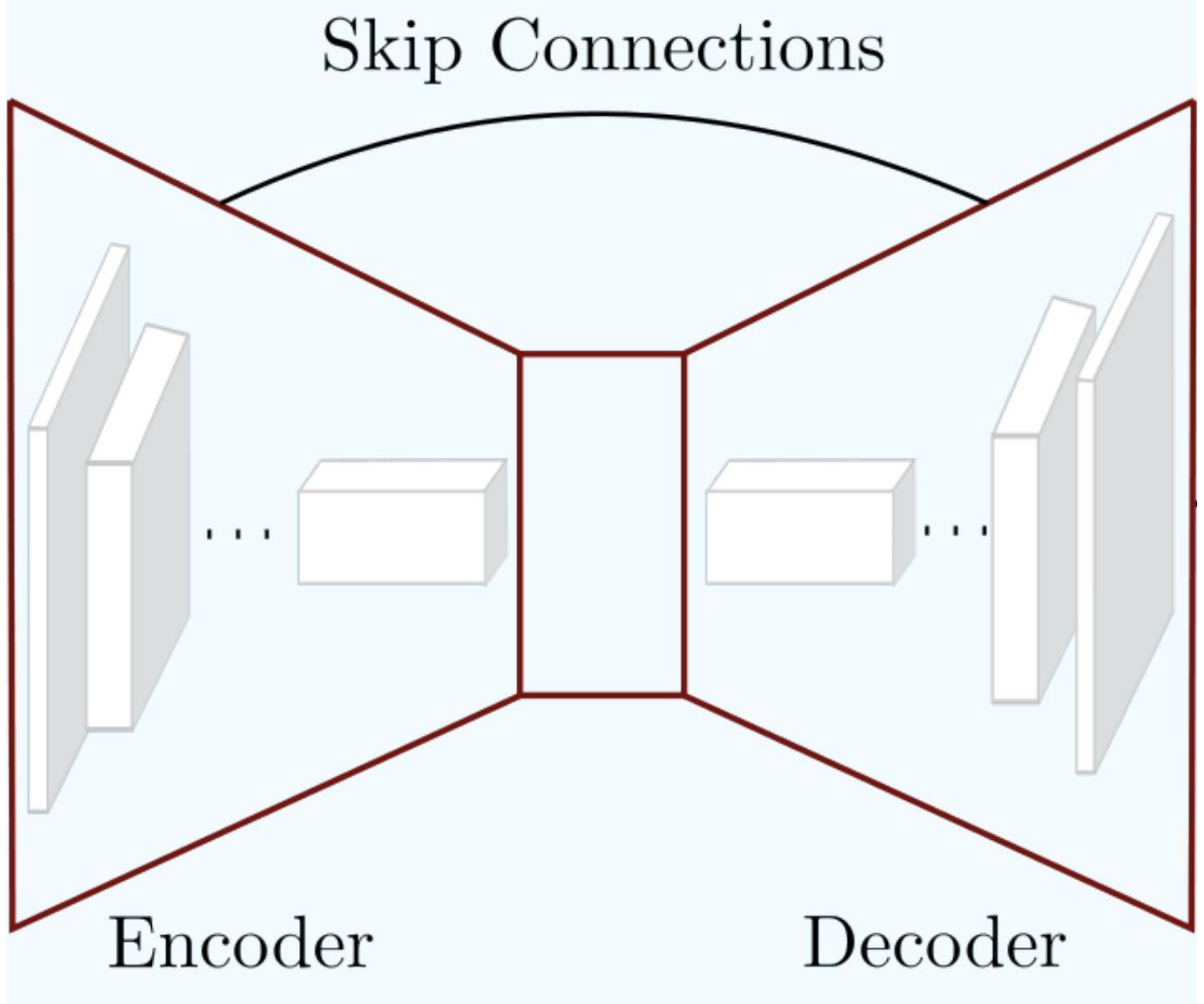
What’s inside

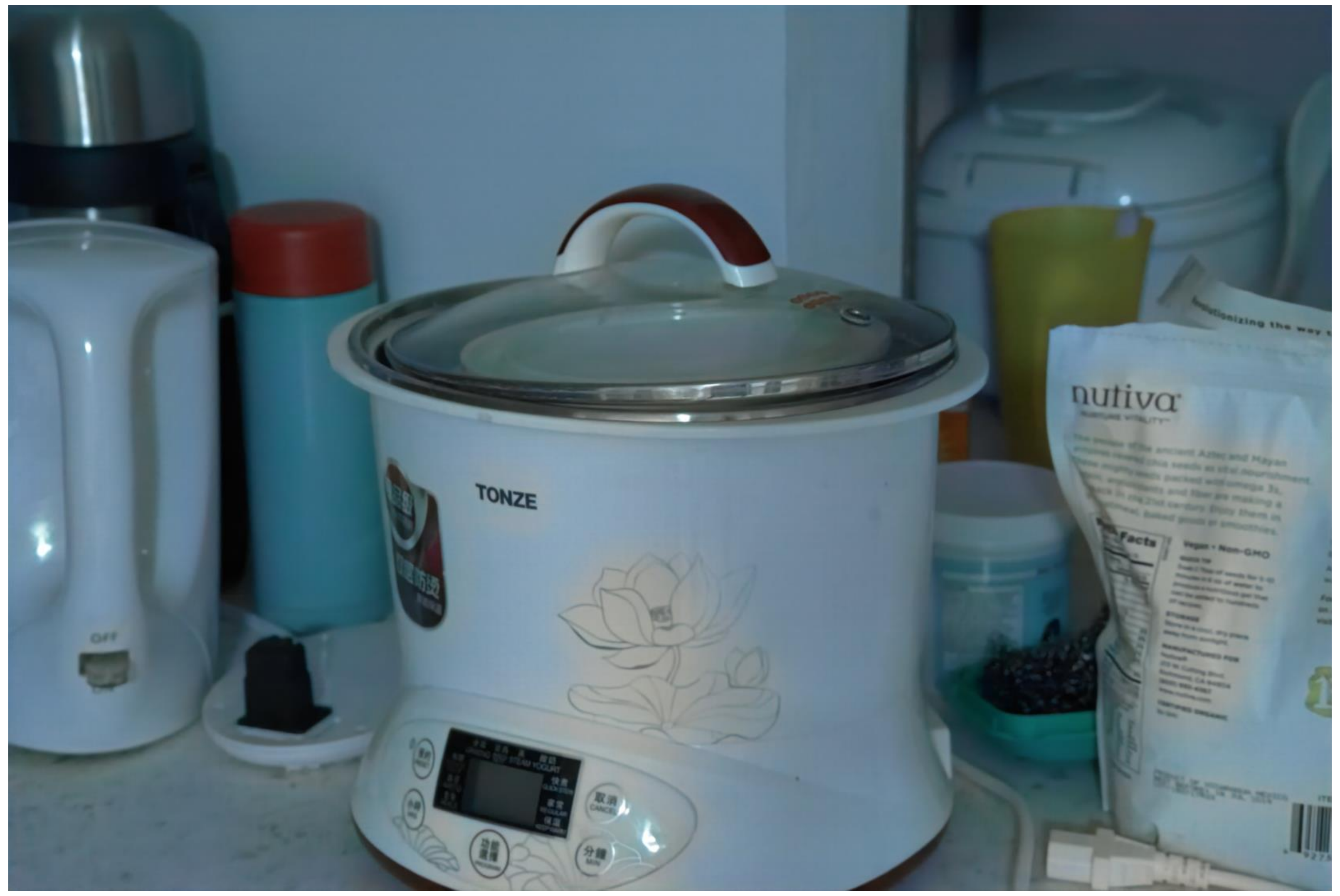


A Convolutional Neural Network

A U-net: an encoder-decoder network

Works great for image-to-image translation, but yields results with color inconsistency.





Chen et. al. & Zamir et. al.

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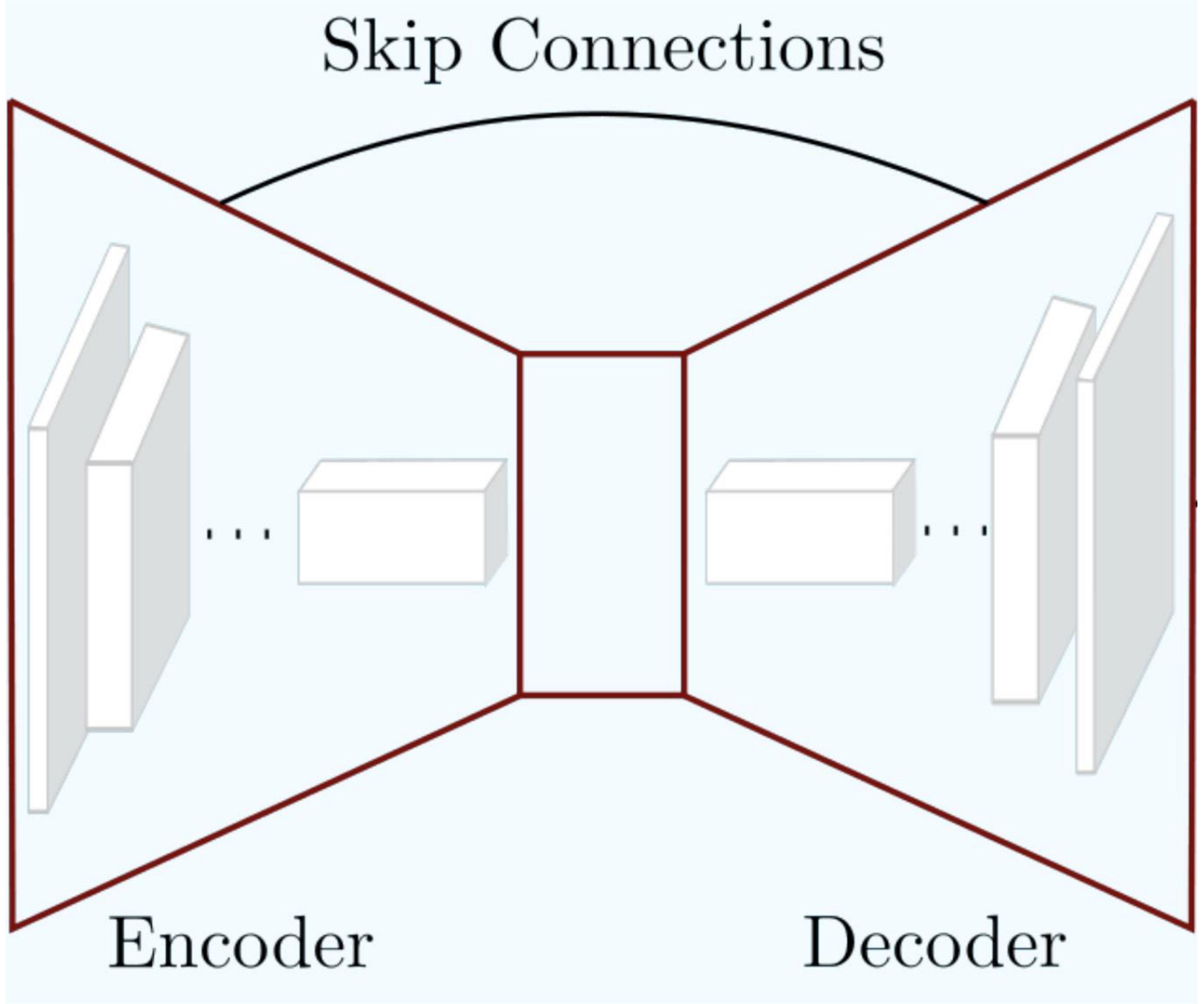

OPPO dark sight net

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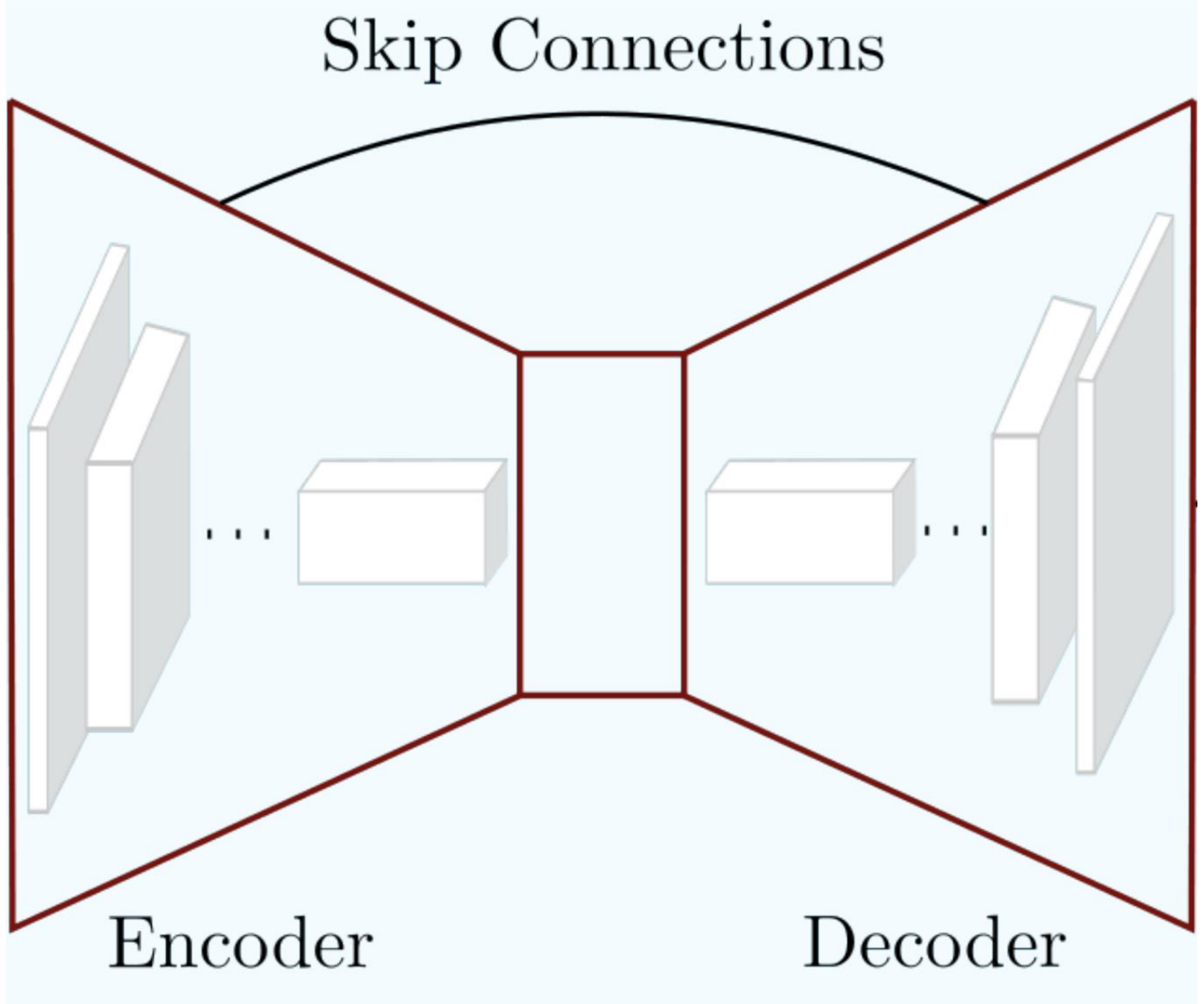

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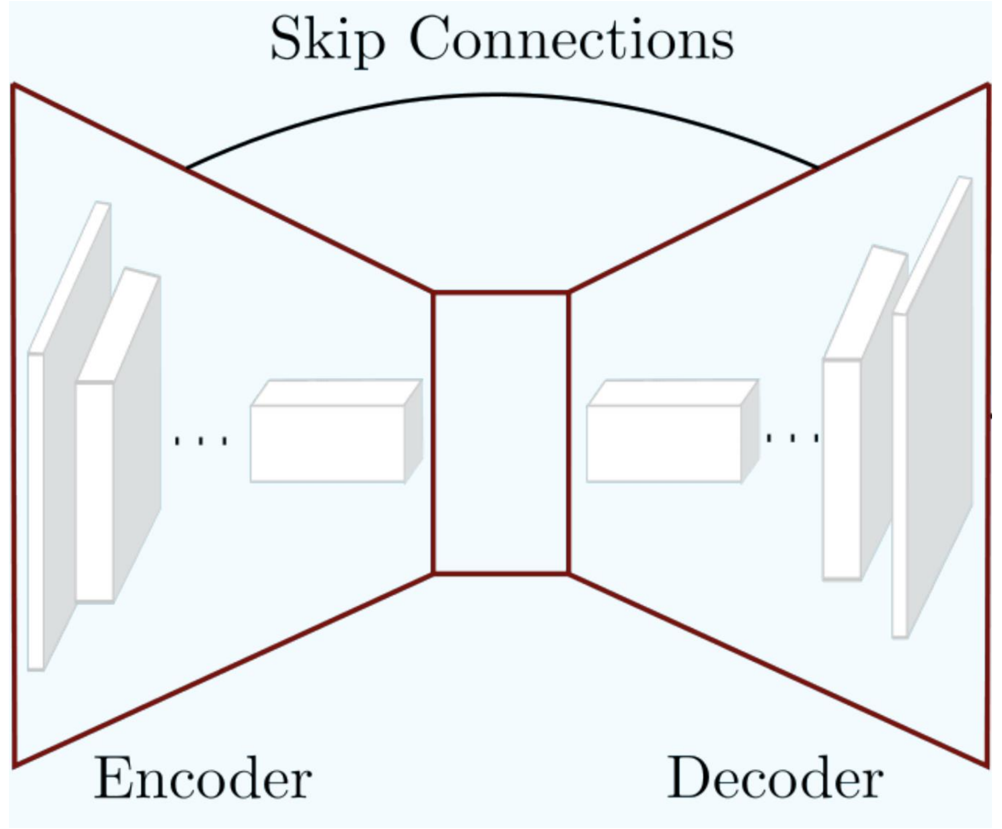

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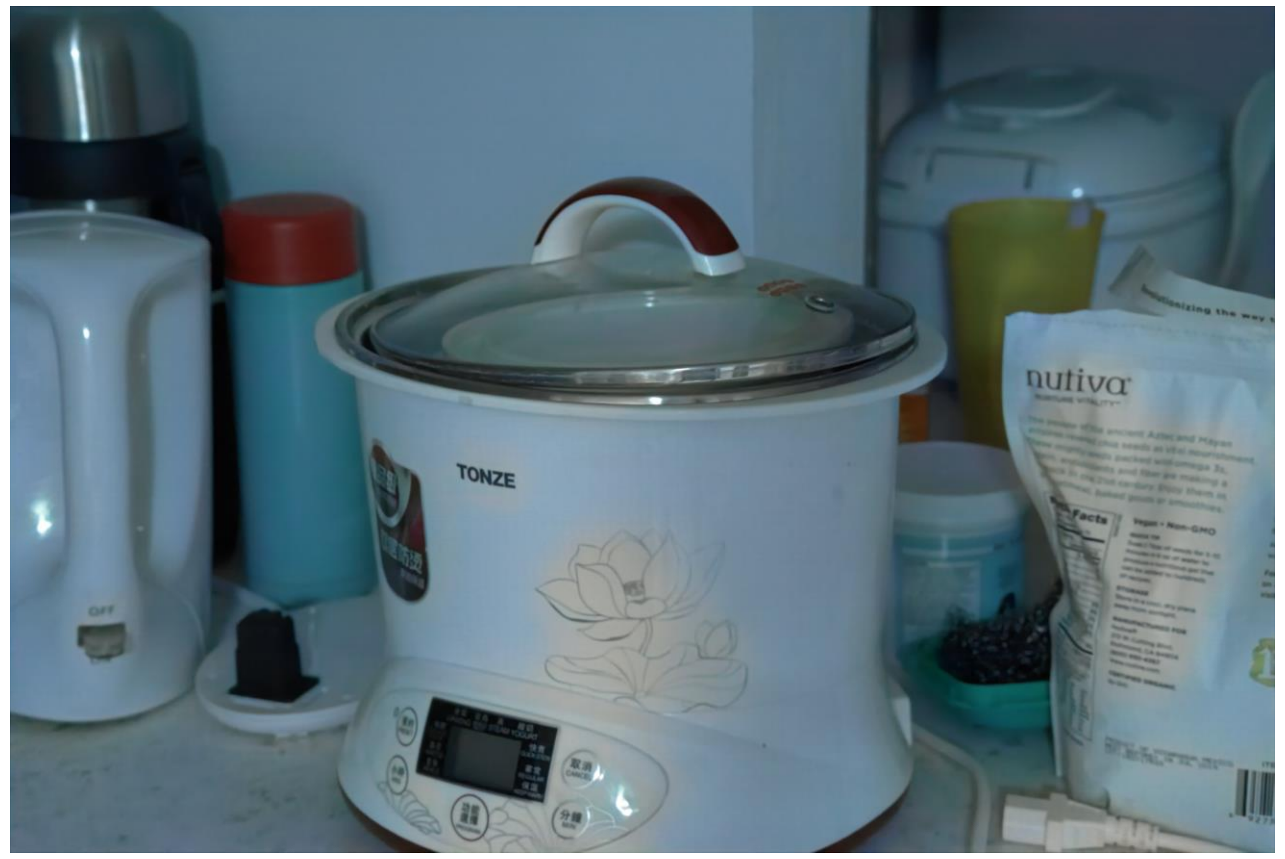

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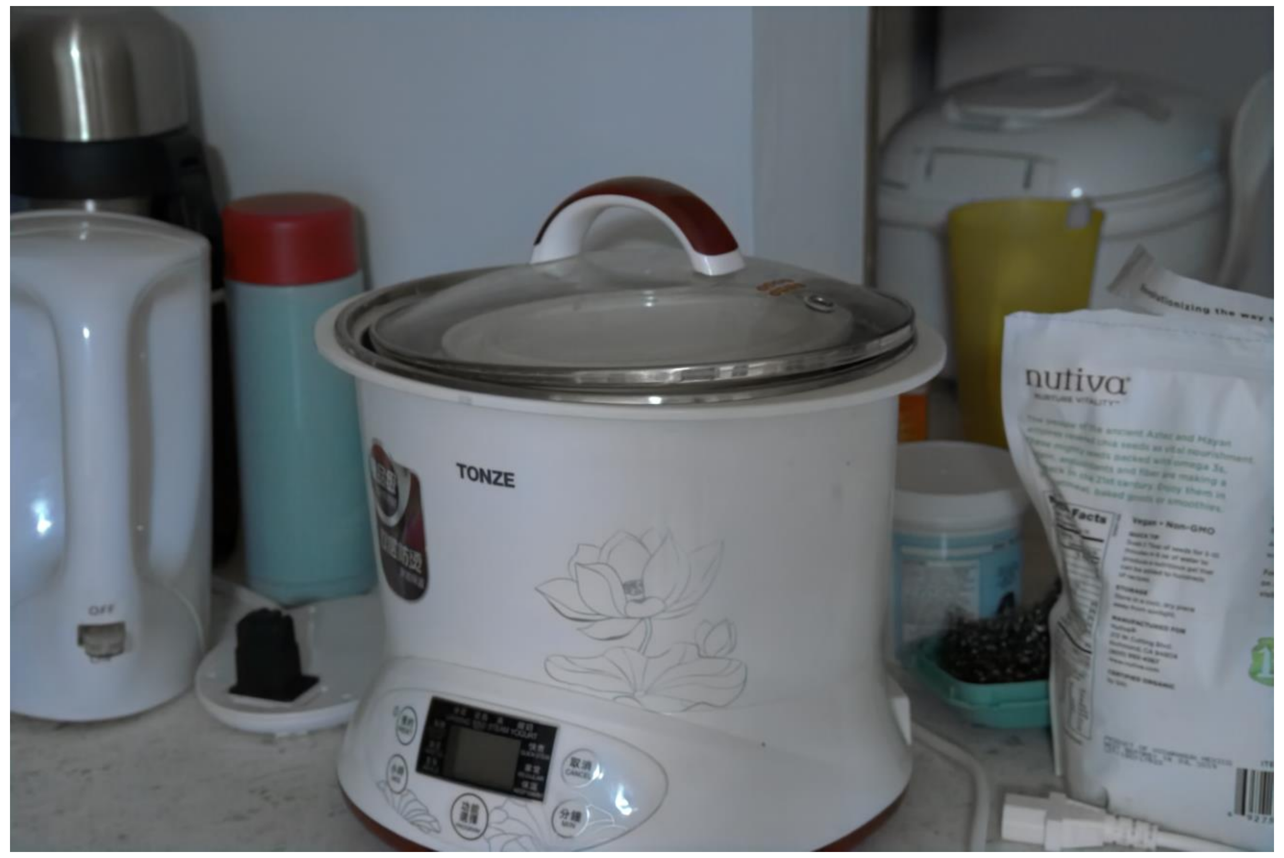


Loss Functions

Some Choices of Loss Functions

$$\mathcal{L}_1 = \frac{1}{N}\sum_{p=1}^{N}\left|\hat{y}_p - y_p\right|$$

$$MSE = \frac{1}{N}\sum_{p=1}^{N}(\hat{y}_p - y_p)^2$$

$$\mathcal{L}_{SSIM} = 1 - \frac{1}{N}\sum_{p=1}^{N} SSIM(\hat{y}_p, y_p)$$

$$\mathcal{L}_{MS-SSIM} = 1 - \frac{1}{N}\sum_{p=1}^{N} MS-SSIM(\hat{y}_p, y_p)$$

$$\mathcal{L}_{perceptual} = \frac{1}{N}\sum_{p=1}^{N}\left(\phi(\hat{y}_p) - \phi(y_p)\right)^2$$

Loss Functions

$$PSNR = 20 \cdot \log_{10}\left(\frac{MaxPixelValue}{\sqrt{MSE}}\right)$$

Simple to calculate

Has clear physical meanings

Does not correlate very well with human's perceived visual quality

Loss Functions

Structural Similarity (SSIM)

Natural images are highly structured: pixels exhibit strong dependencies on each other

Sensitivity of human visual system (HVS) is related to:

luminance (mean) , contrast (variance), structure (covariance)

$$SSIM(\hat{y}_p, y_p) = luminance \cdot contrast \cdot structure = l(\hat{y}_p, y_p) \cdot c(\hat{y}_p, y_p) \cdot s(\hat{y}_p, y_p)$$

$$= \frac{2\mu_{\hat{y}_p}\mu_{y_p} + C_1}{\mu_{\hat{y}_p}^2 + \mu_{y_p}^2 + C_1} \cdot \frac{2\sigma_{\hat{y}_p}\sigma_{y_p} + C_2}{\sigma_{\hat{y}_p}^2 + \sigma_{y_p}^2 + C_2} \cdot \frac{\sigma_{\hat{y}_p y_p} + C_3}{\sigma_{\hat{y}_p}\sigma_{y_p} + C_3}$$

$$= \frac{2\mu_{\hat{y}_p}\mu_{y_p} + C_1}{\mu_{\hat{y}_p}^2 + \mu_{y_p}^2 + C_1} \cdot \frac{2\sigma_{\hat{y}_p y_p} + C_2}{\sigma_{\hat{y}_p}^2 + \sigma_{y_p}^2 + C_2} = l(\hat{y}_p, y_p) \cdot cs(\hat{y}_p, y_p)$$

$$C_1 = (K_1 \cdot MaxPixelValue)^2 C_2 = (K_2 \cdot MaxPixelValue)^2 C_3 = C_2/2$$

Loss Functions

Multi-Scale Structural Similarity (MS-SSIM)

$$SSIM(\hat{y}, y) = \frac{2\mu_{\hat{y}}\mu_y + C_1}{\mu_{\hat{y}}^2 + \mu_y^2 + C_1} \cdot \frac{2\sigma_{\hat{y}y} + C_2}{\sigma_{\hat{y}}^2 + \sigma_y^2 + C_2} = l(\hat{y}, y) \cdot cs(\hat{y}, y)$$

$$C_1 = (K_1 \cdot MaxPixelValue)^2 C_2 = (K_2 \cdot MaxPixelValue)^2$$

$$MS{-}SSIM(\hat{y}_p, y_p) = \left[l_M(\hat{y}_p, y_p)\right]^{\gamma_M} \cdot \Pi_{k=1}^{M}\left[cs_k(\hat{y}_p, y_p)\right]^{\eta_k}$$

MS-SSIM extends SSIM by computing variance and covariance components at M scales

k^{th}**scale image = sub-sampling original image by factor of 2 in both spatial dimensions for (k-1) times**

More flexible than single-scale SSIM: incorporated variations of image resolution and viewing conditions

Loss Functions

Perceptual Loss

$$\mathcal{L}_{perceptual} = \frac{1}{N}\sum_{p=1}^{N}\left(\phi(\hat{y_p}) - \phi(y_p)\right)^2$$

Measures the difference between deep feature representations of the output and ground-truth images, each extracted from a pre-trained neural network on ImageNet.

Enhances semantic similarity at deep feature representation level and serves as a perceptual metric.

Zhang et. al. arXiv:1801.03924, CVPR 2018

Loss Functions

Chen et. al. (arXiv:1805.01934):

$\mathcal{L}_1 (also \quad tried \quad \mathcal{L}_2 \quad and \quad \mathcal{L}_{SSIM} \quad separately)$

Zamir et. al. (arXiv:1904.05939):

$\alpha(\beta\mathcal{L}_1 + (1-\beta)\mathcal{L}_{MS-SSIM}) + (1-\alpha)\mathcal{L}_{perceptual} \quad \alpha = 0.9 \quad \beta = 0.99$

OPPO: $\mathcal{L}_1$ $\mathcal{L}_{MS-SSIM}$ $????$

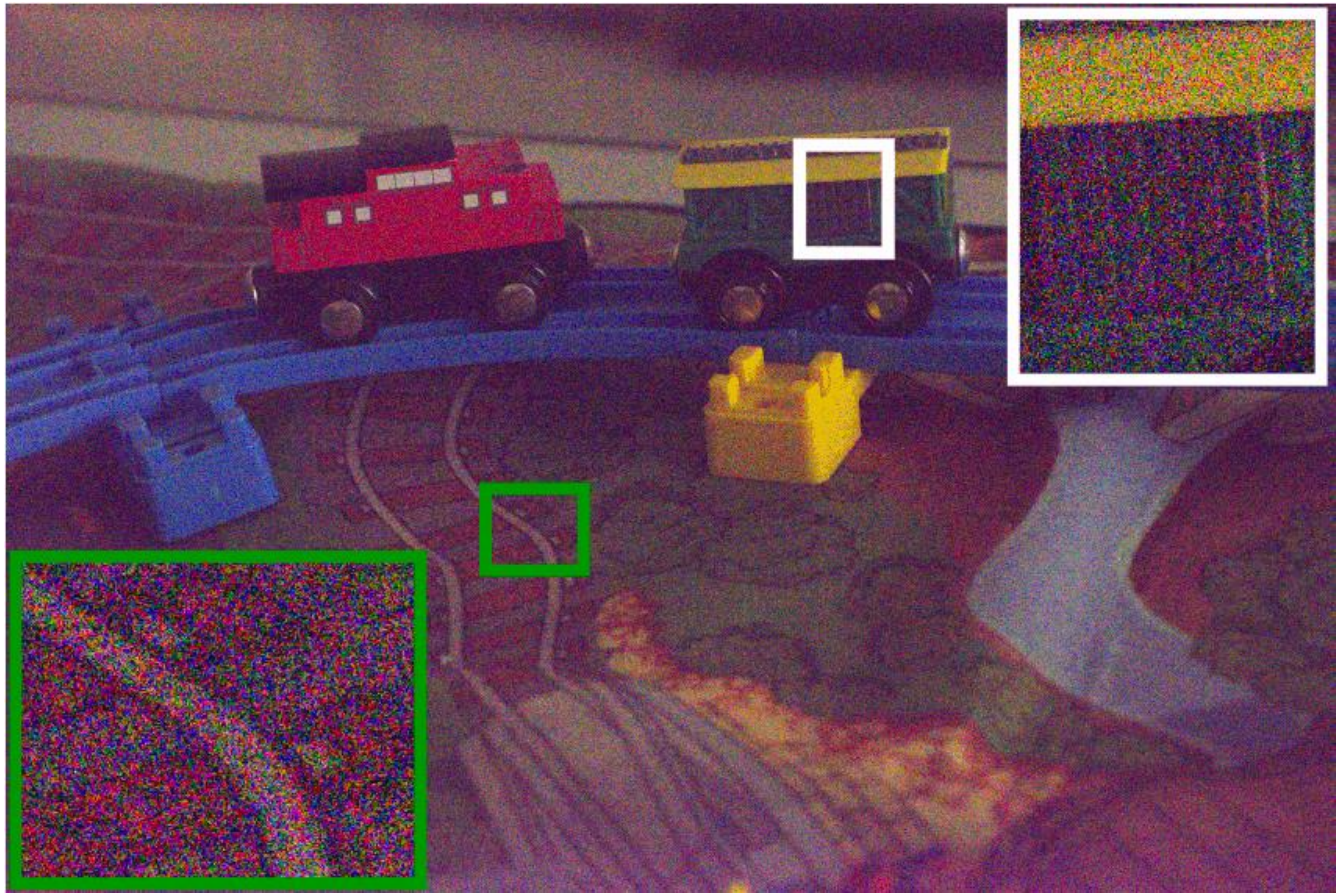
Quantitative Results

$$PSNR = 10 \cdot \log_{10}\left(\frac{MaxPixelValue^2}{MSE}\right) \qquad MeanSquaredError(MSE) = \frac{1}{N}\sum_{p=1}^{N}\left(\hat{y}_p - y_p\right)^2$$

	Sony 7SII camera Bayer sensor 4240 x 2832		Fujifilm X-T2 camera APS-C X-Trans sensor 6000 x 4000	
	PSNR	SSIM	PSNR	SSIM
Chen et. al. (arXiv:1805.01934)	**28.88**	**0.787**	**26.61**	**0.68**
Zamir et. al. (arXiv:1904.05939)	**29.43**	**-**	**27.63**	**-**
OPPO	**29.72**	**0.795**	**28.15**	**0.722**

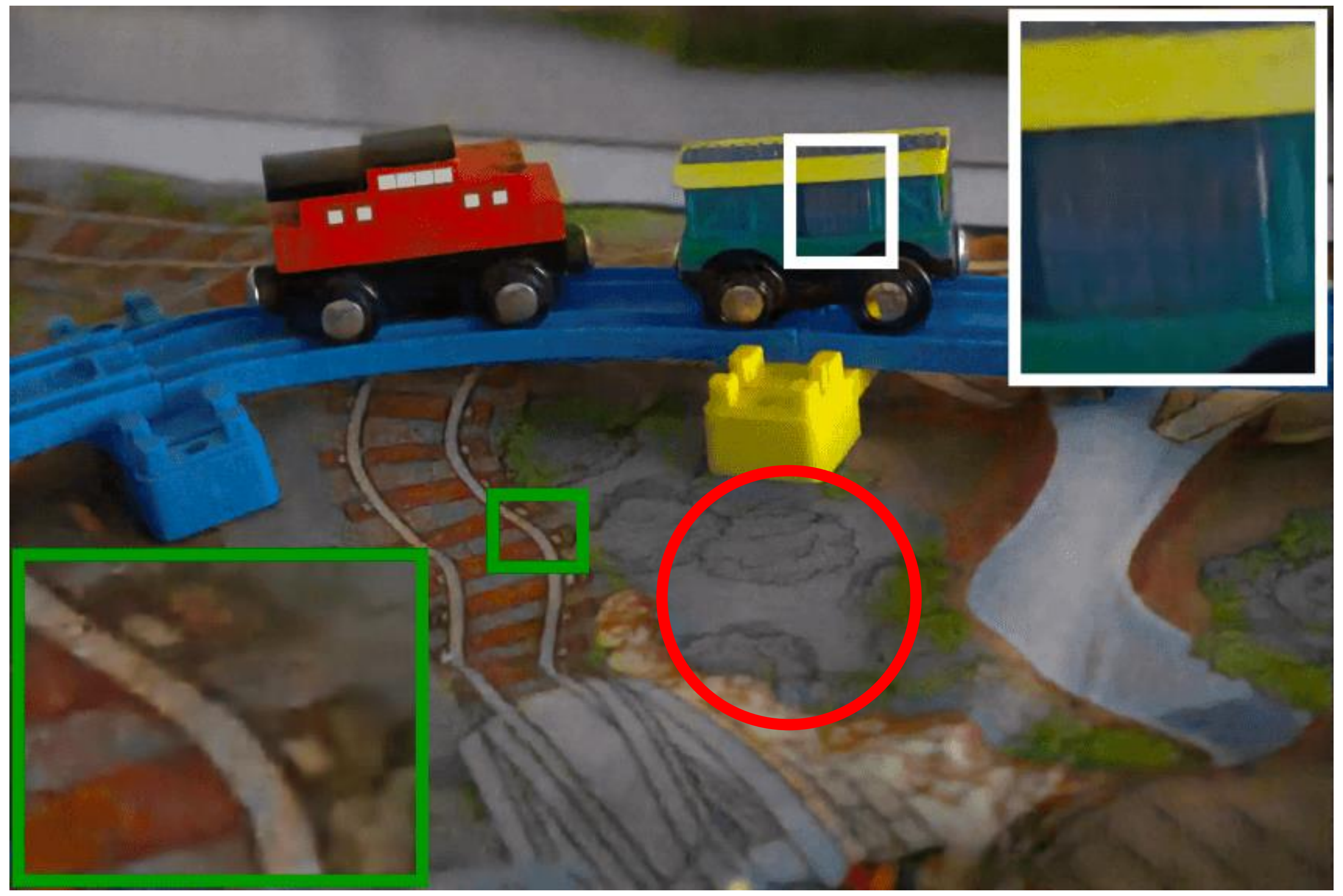
Qualitative Results

Fujifilm X-T2 camera (APS-C X-Trans sensor, 6000 x 4000)
ISO = 6400
exposure time = 100ms



Qualitative Results

Chen et. al.



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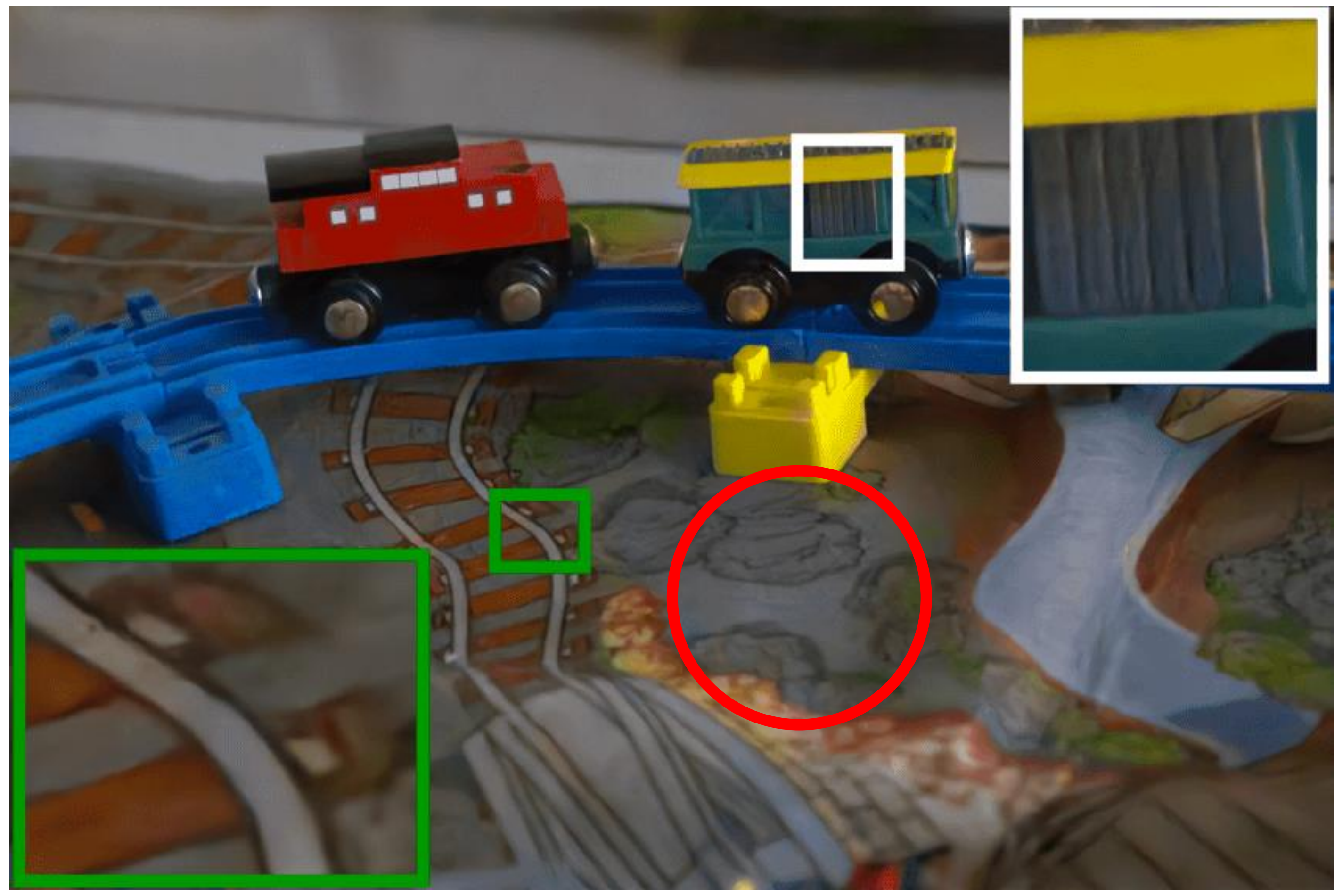

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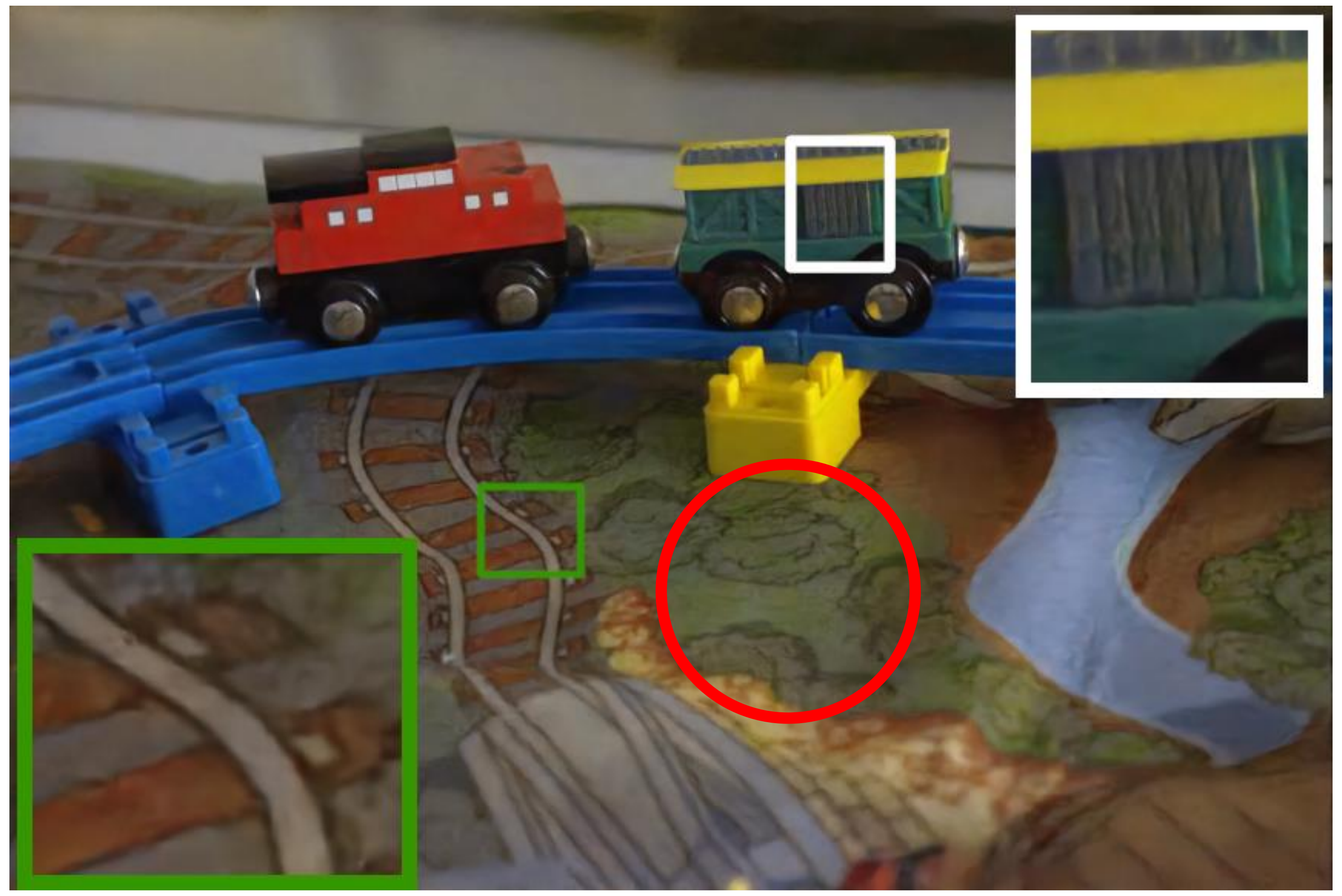
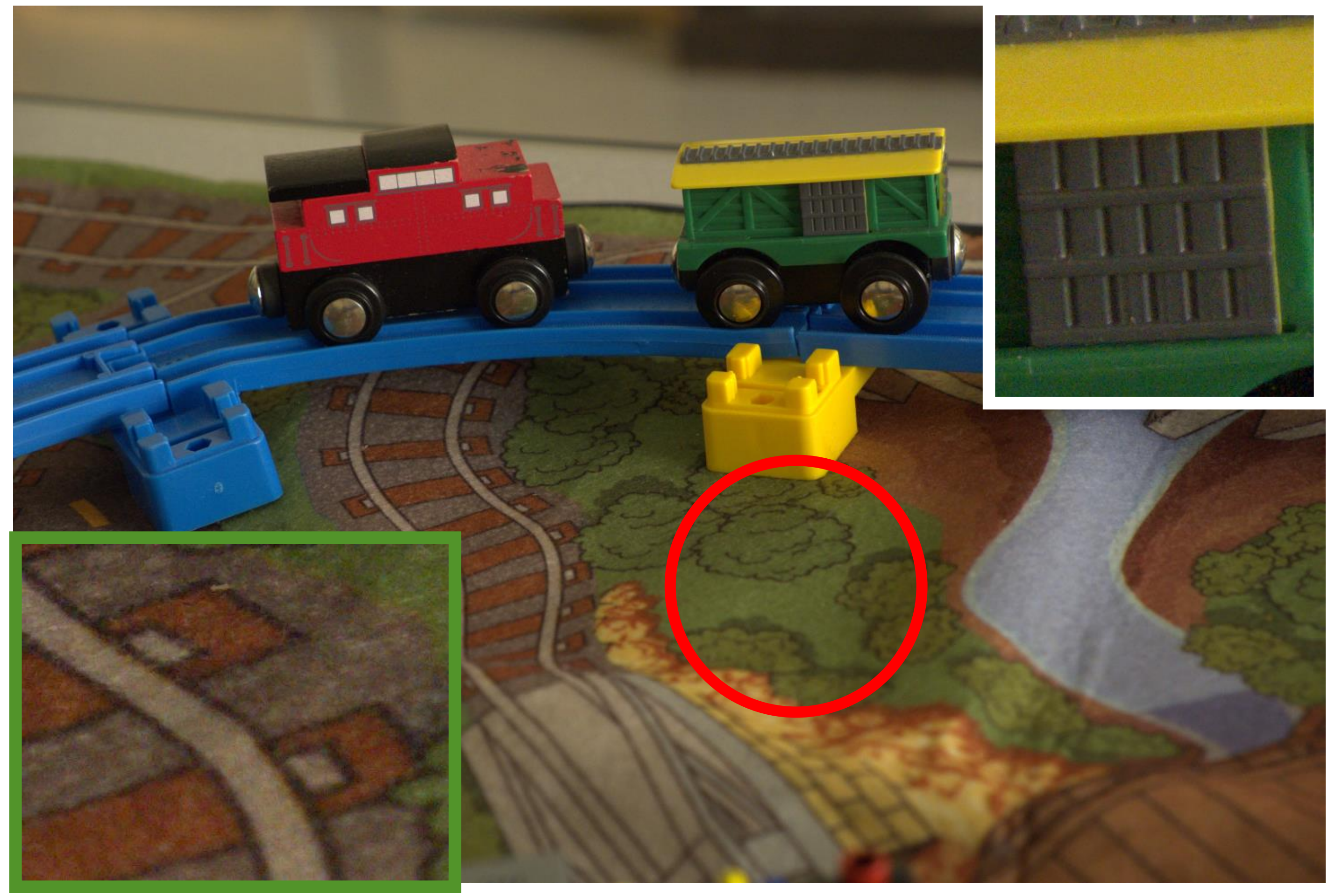
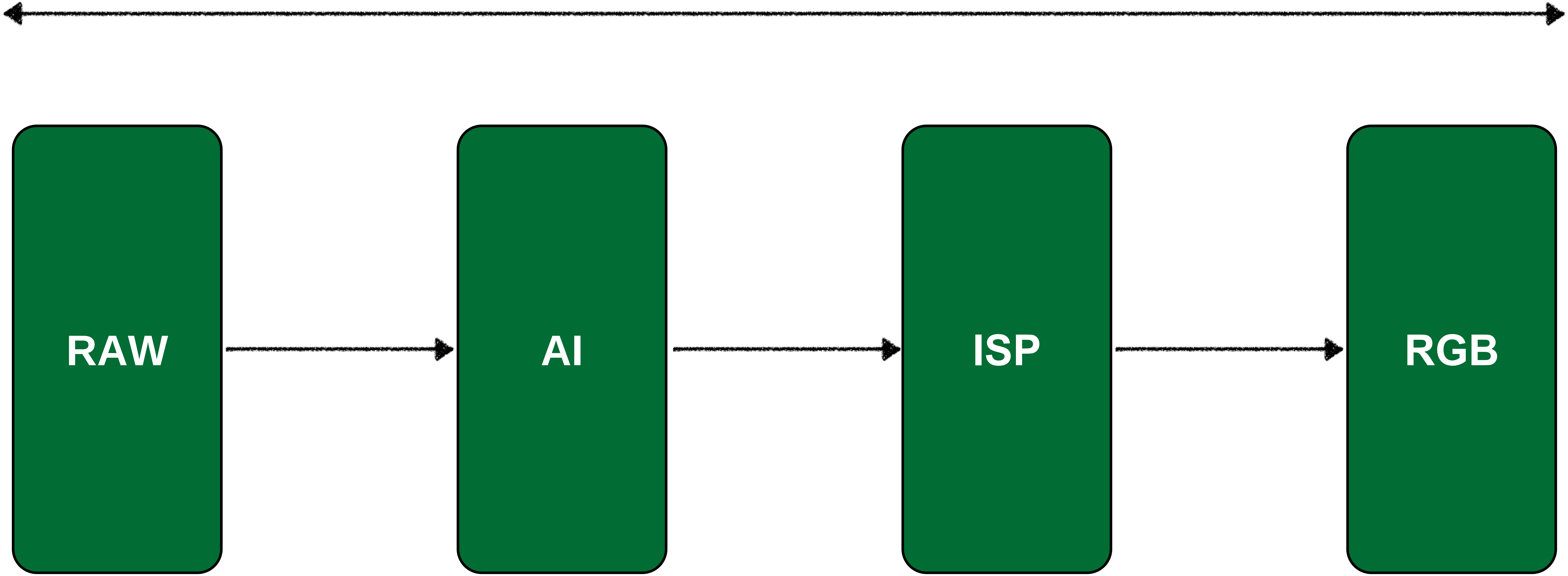


Ground truth



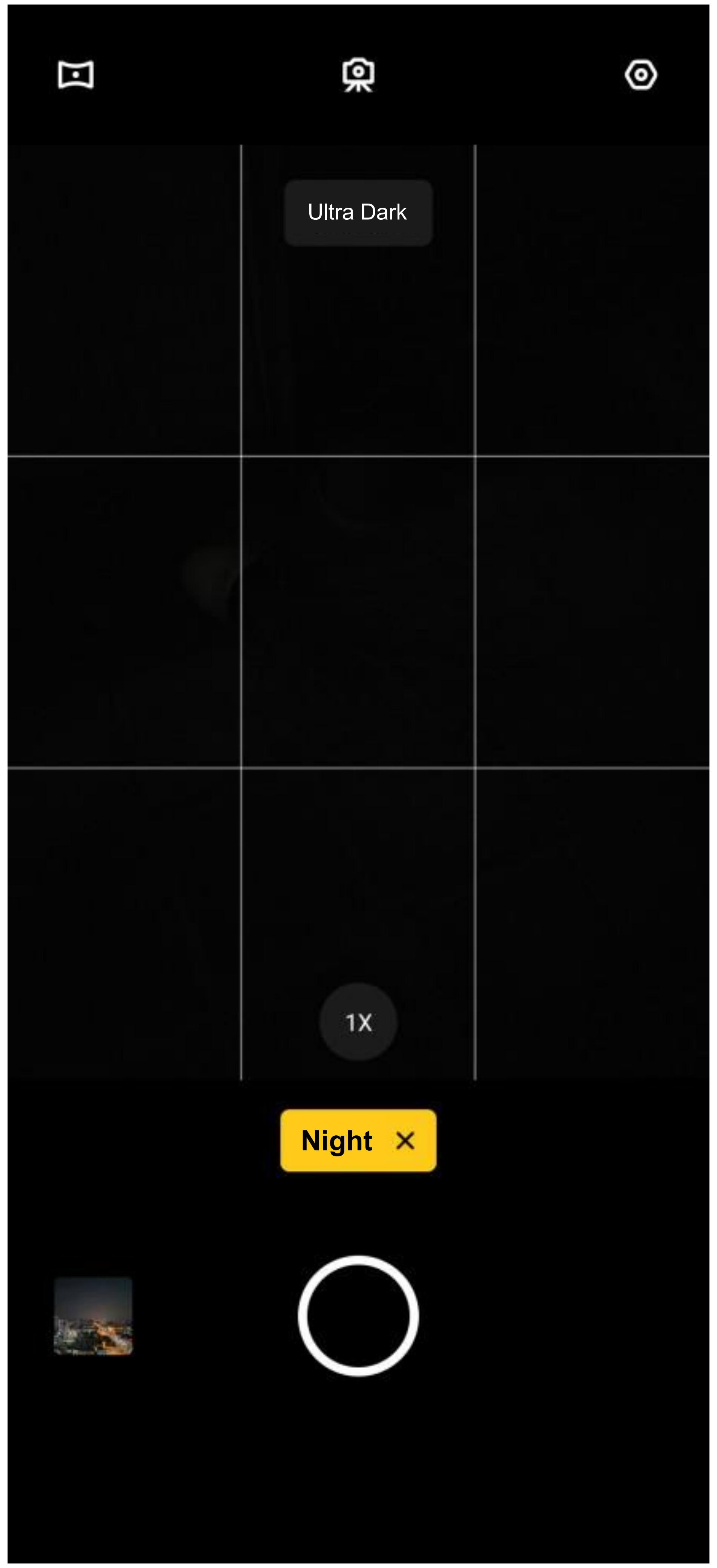
Deliver to Cell Phones



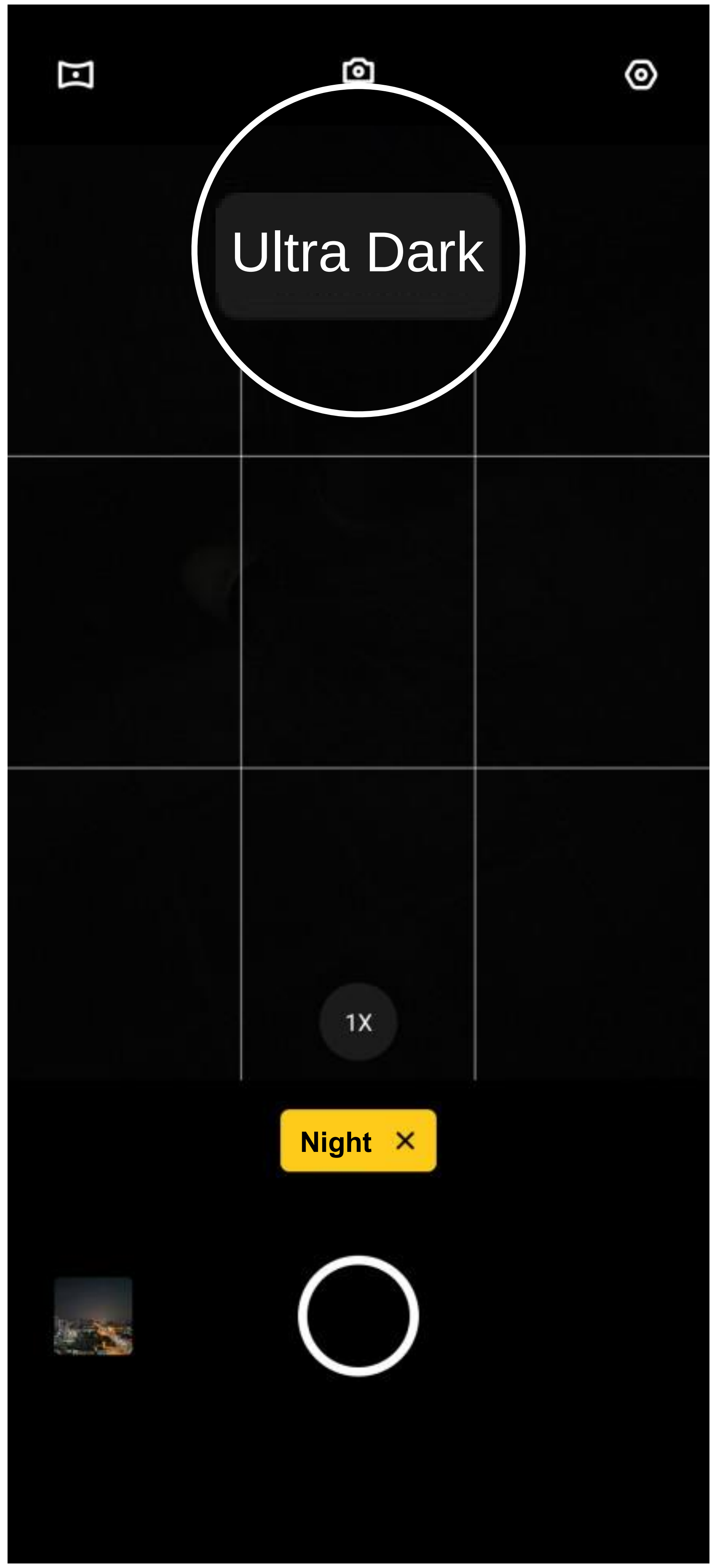
RAW → AI → ISP → RGB

Deliver to Cell Phones

Light up the darkness



Light up the darkness



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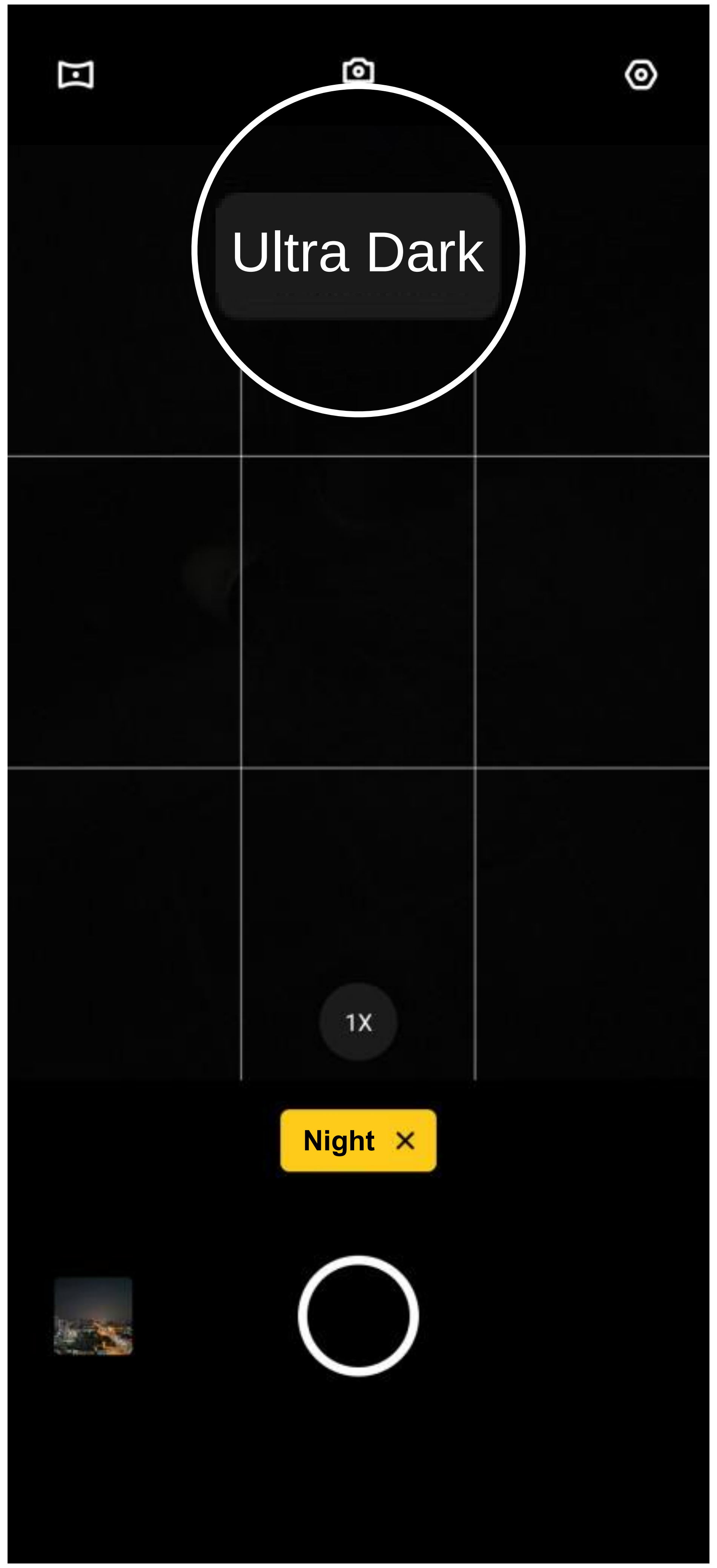
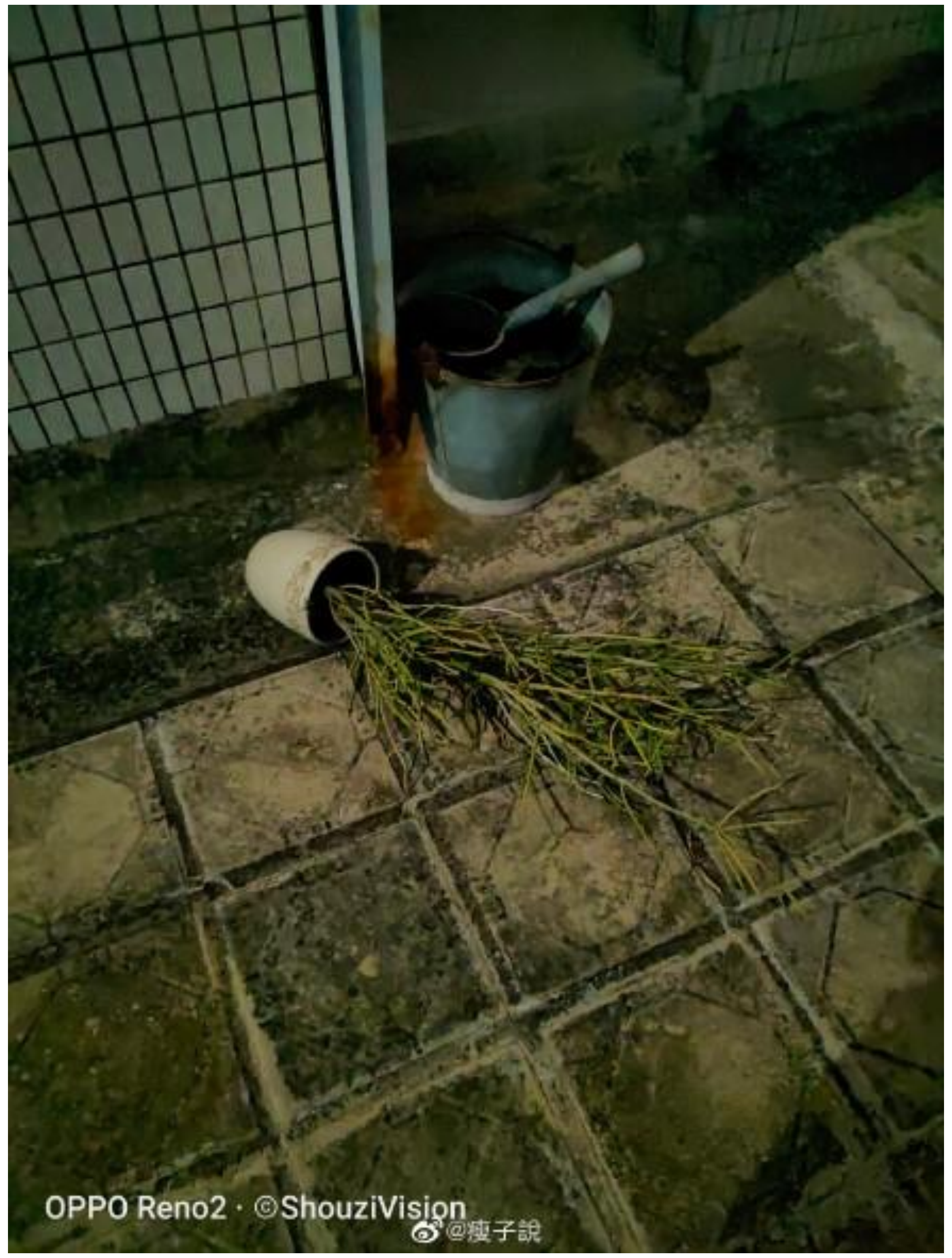
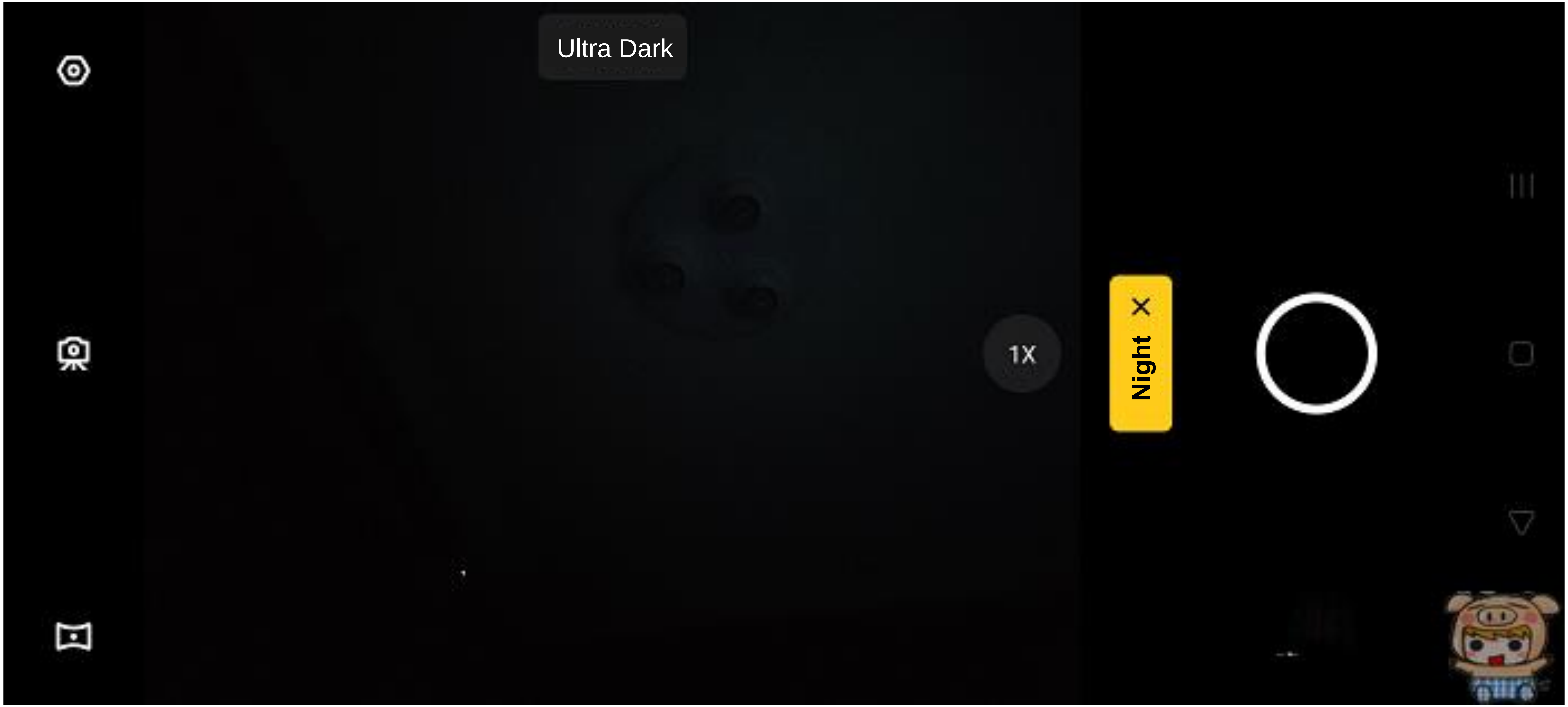




More demonstrations



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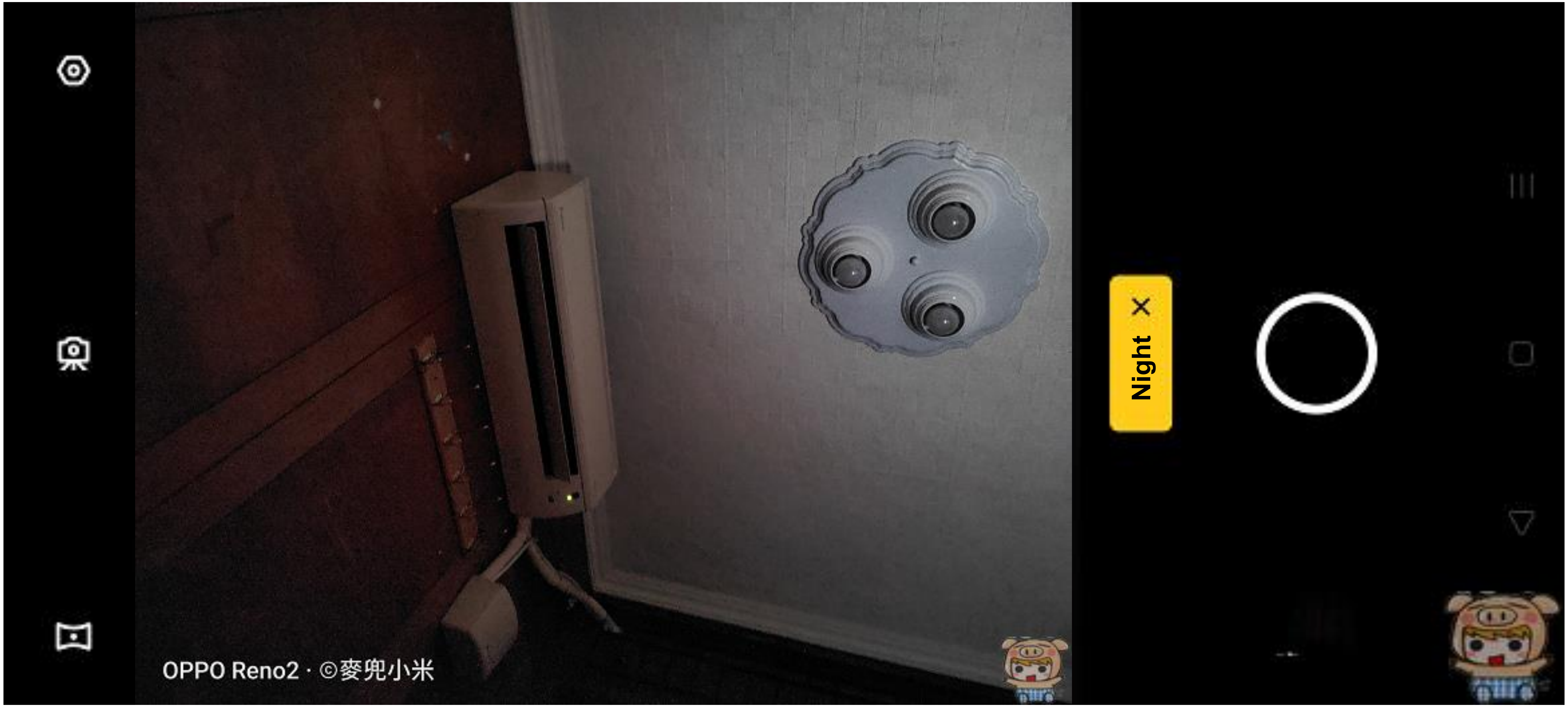

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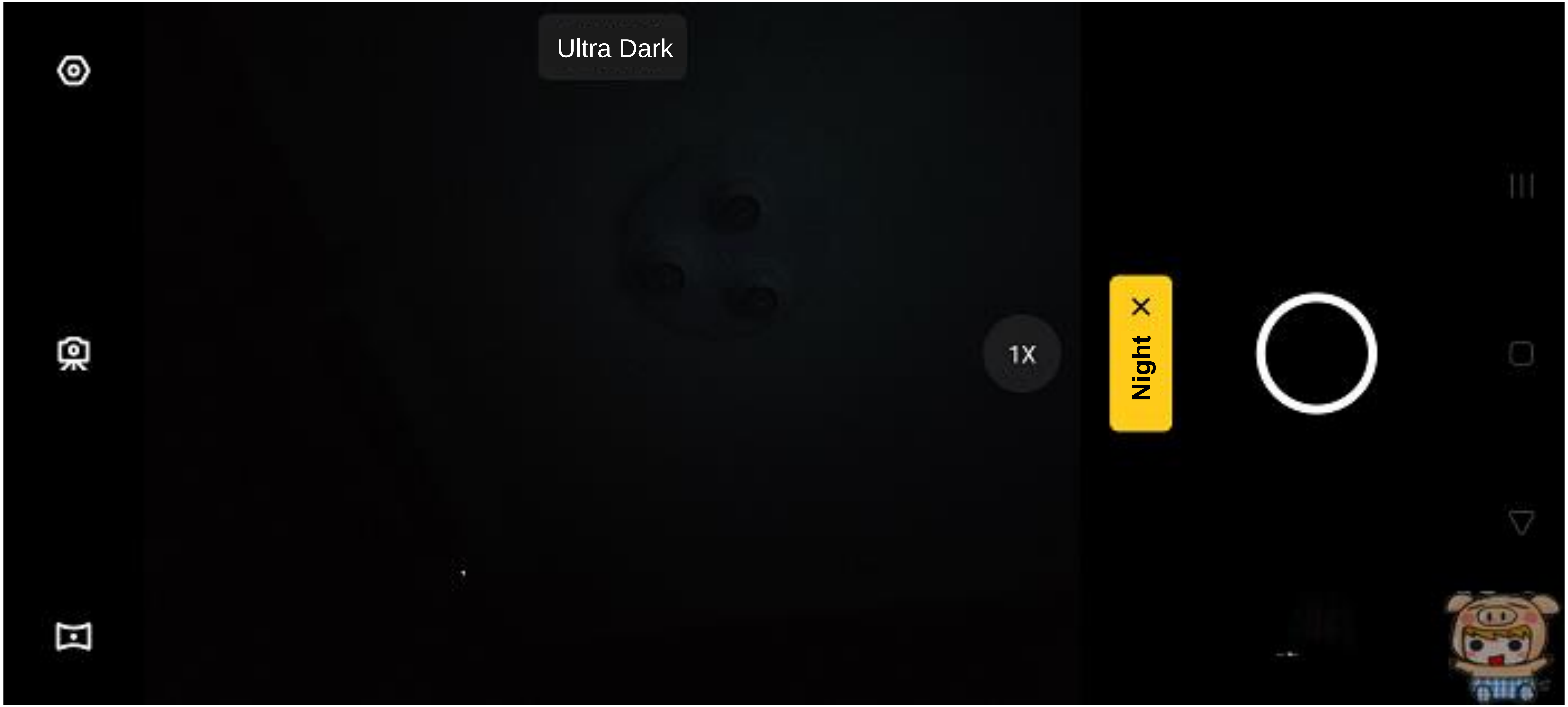

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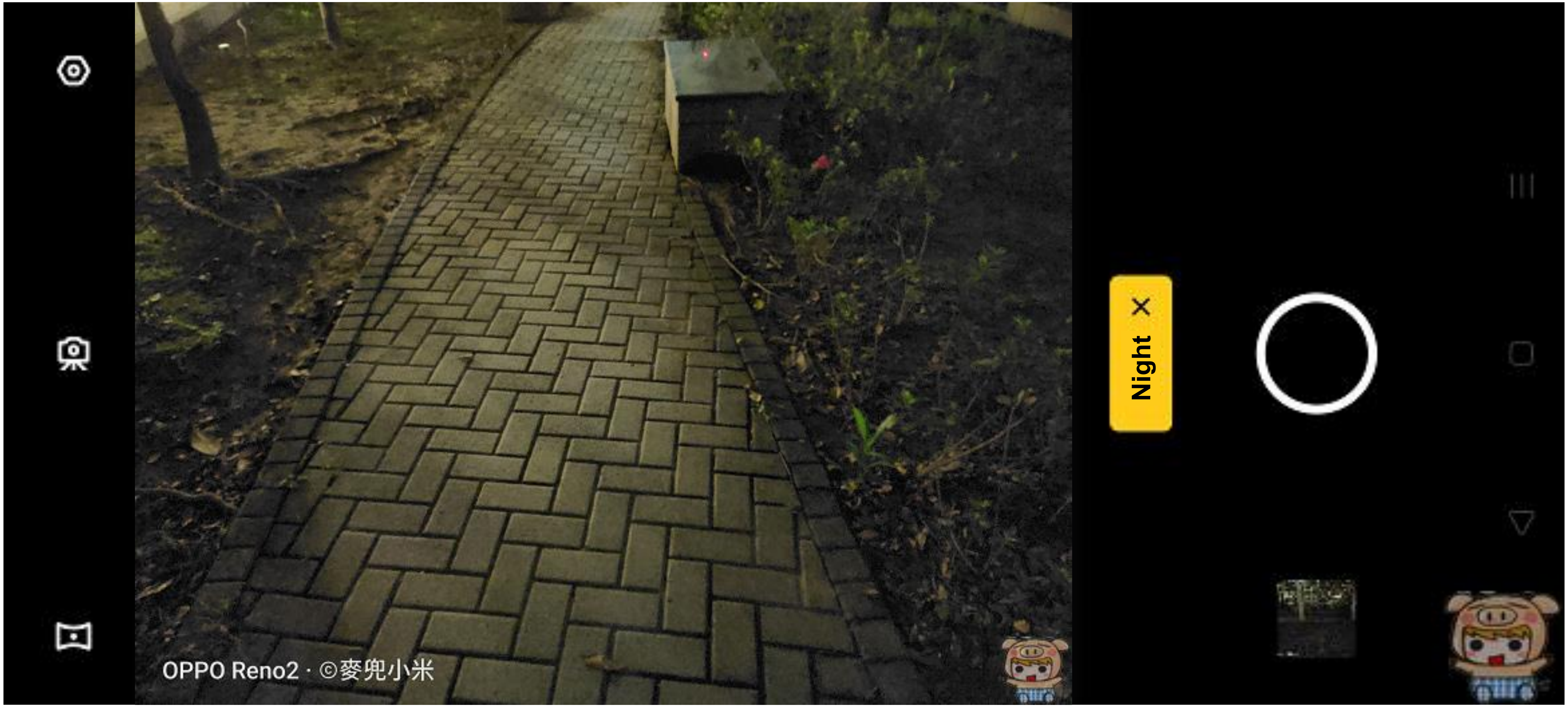

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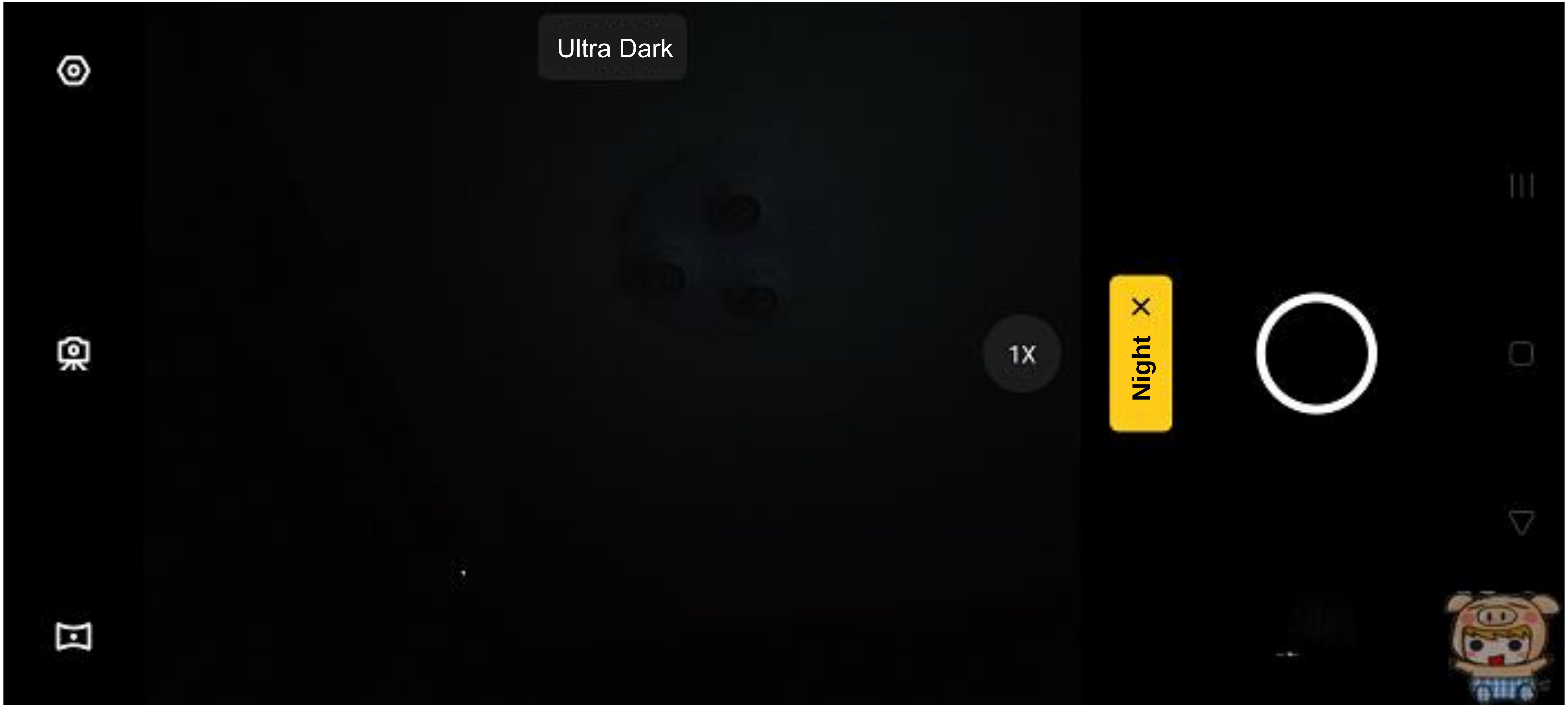

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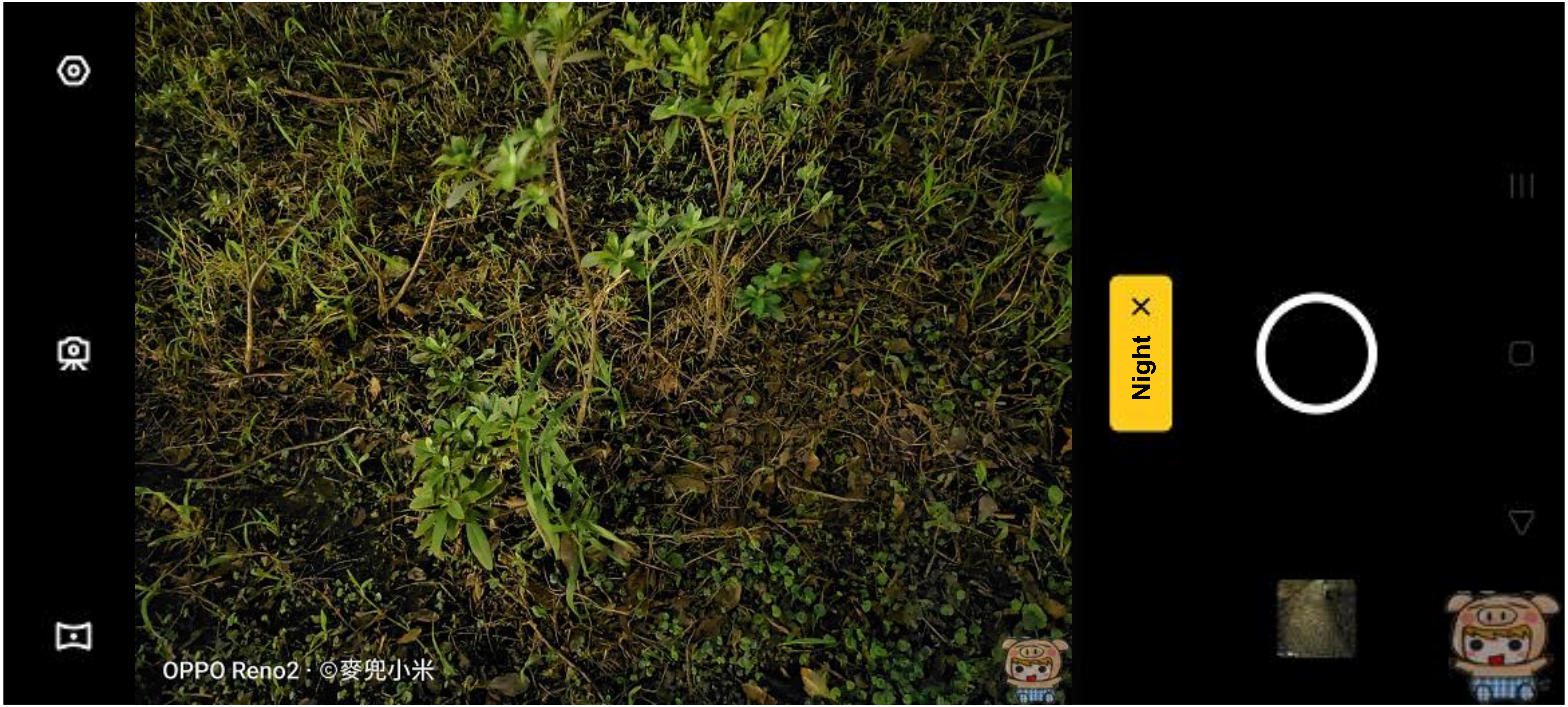

Move to videos

Hard to produce paired data for videos

The algorithm should run in real time

The processed frames should be temporally consistent

Move to videos

Hard to produce paired data for videos

Adopted the model based on single images

The algorithm should run in real time

The processed frames should be temporally consistent

Move to videos

Hard to produce paired data for videos
Adopted the model based on single images

The algorithm should run in real time
The model should be extensively compressed

The processed frames should be temporally consistent

Move to videos

Hard to produce paired data for videos
Adopted the model based on single images

The algorithm should run in real time
The model should be extensively compressed

The processed frames should be temporally consistent
A temporal filtering approach should be employed

Thank you!