ScrambleMix: A Privacy-Preserving Image Processing for Edge-Cloud Machine Learning

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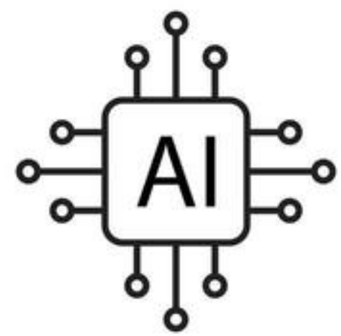
Edge Cloud Machine Learning

Use **Cloud AI model** for prediction

Edge side

Cloud side

Want to know tower name

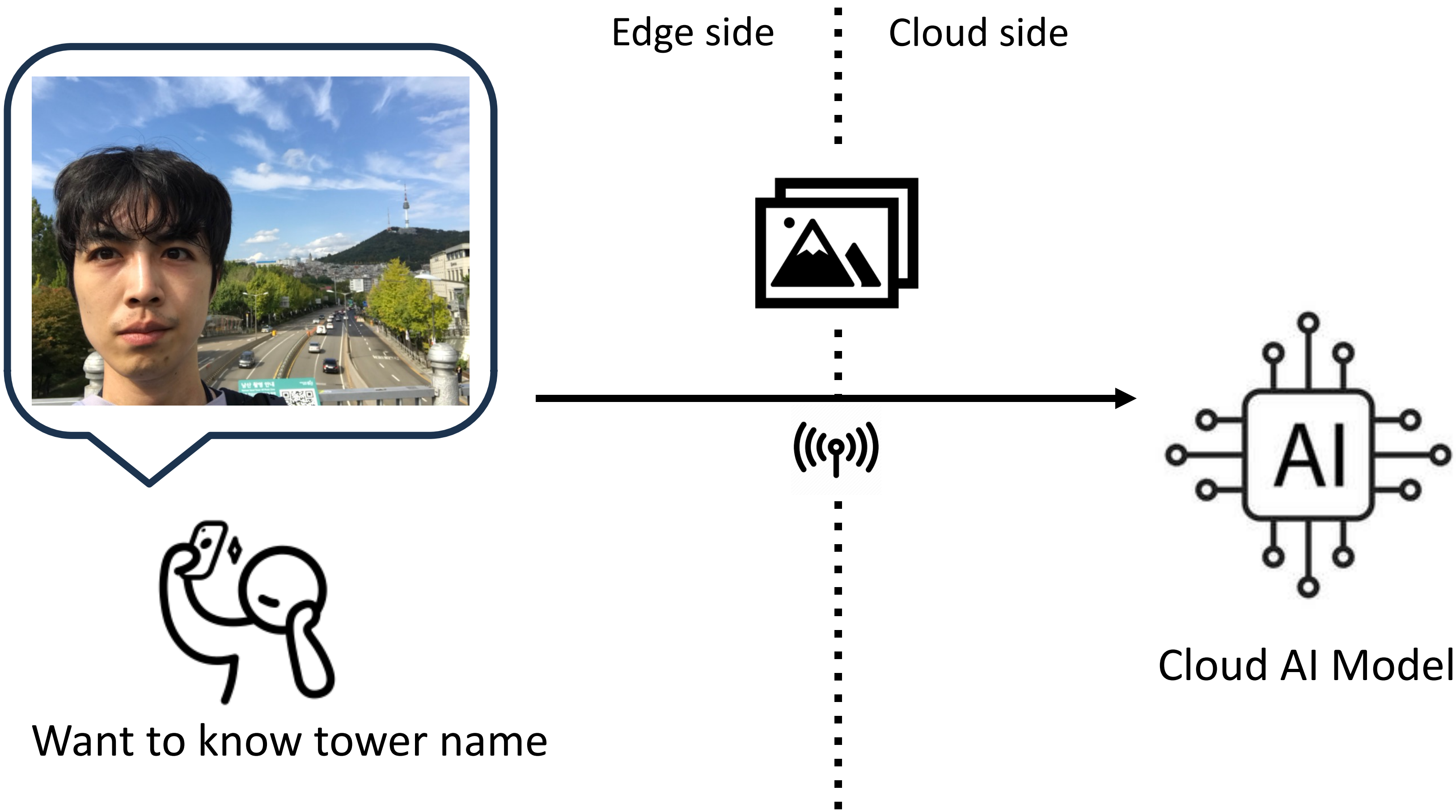


Cloud AI Model

Edge Cloud Machine Learning

Use Cloud AI model for prediction

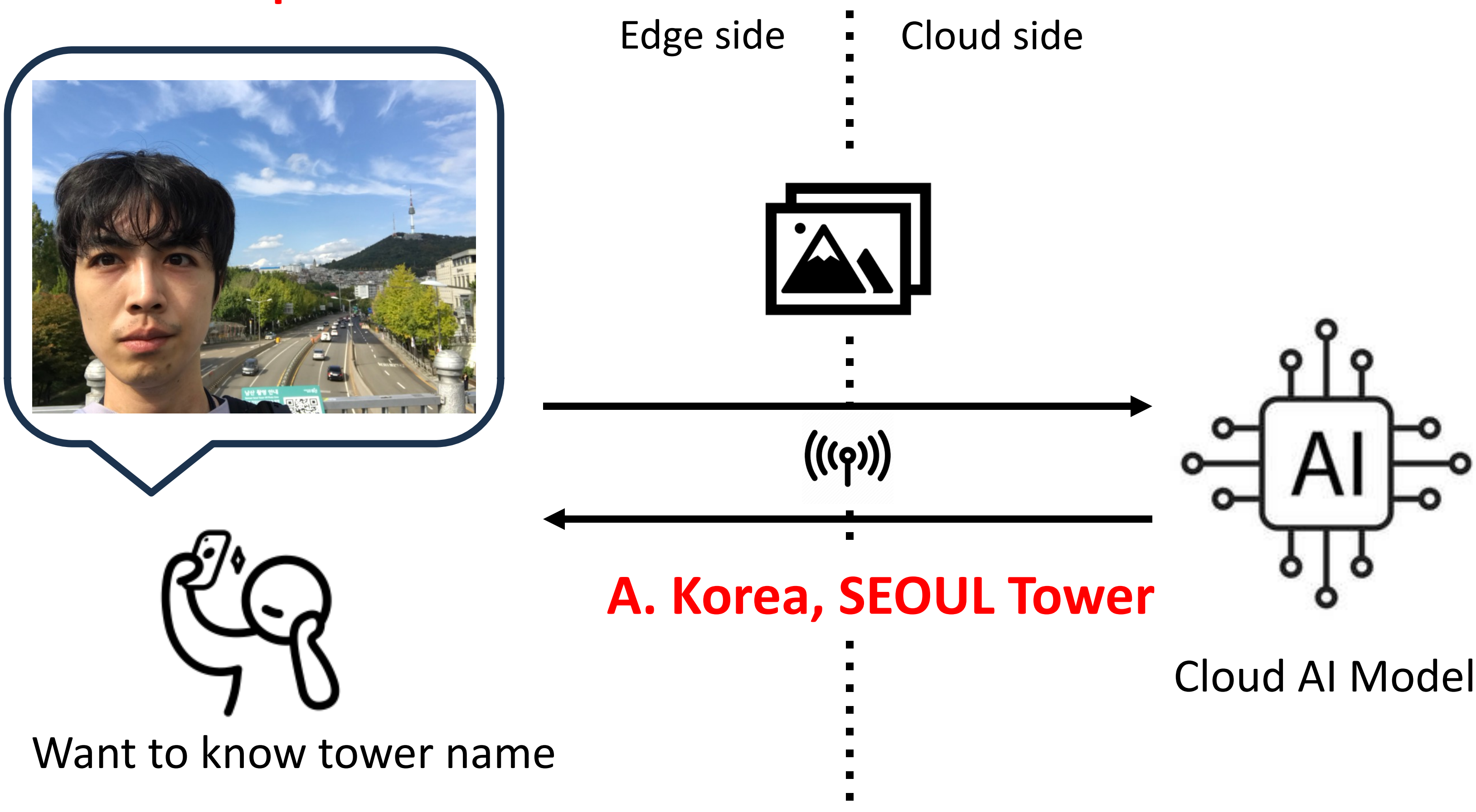
1. **sending the data**



Edge Cloud Machine Learning

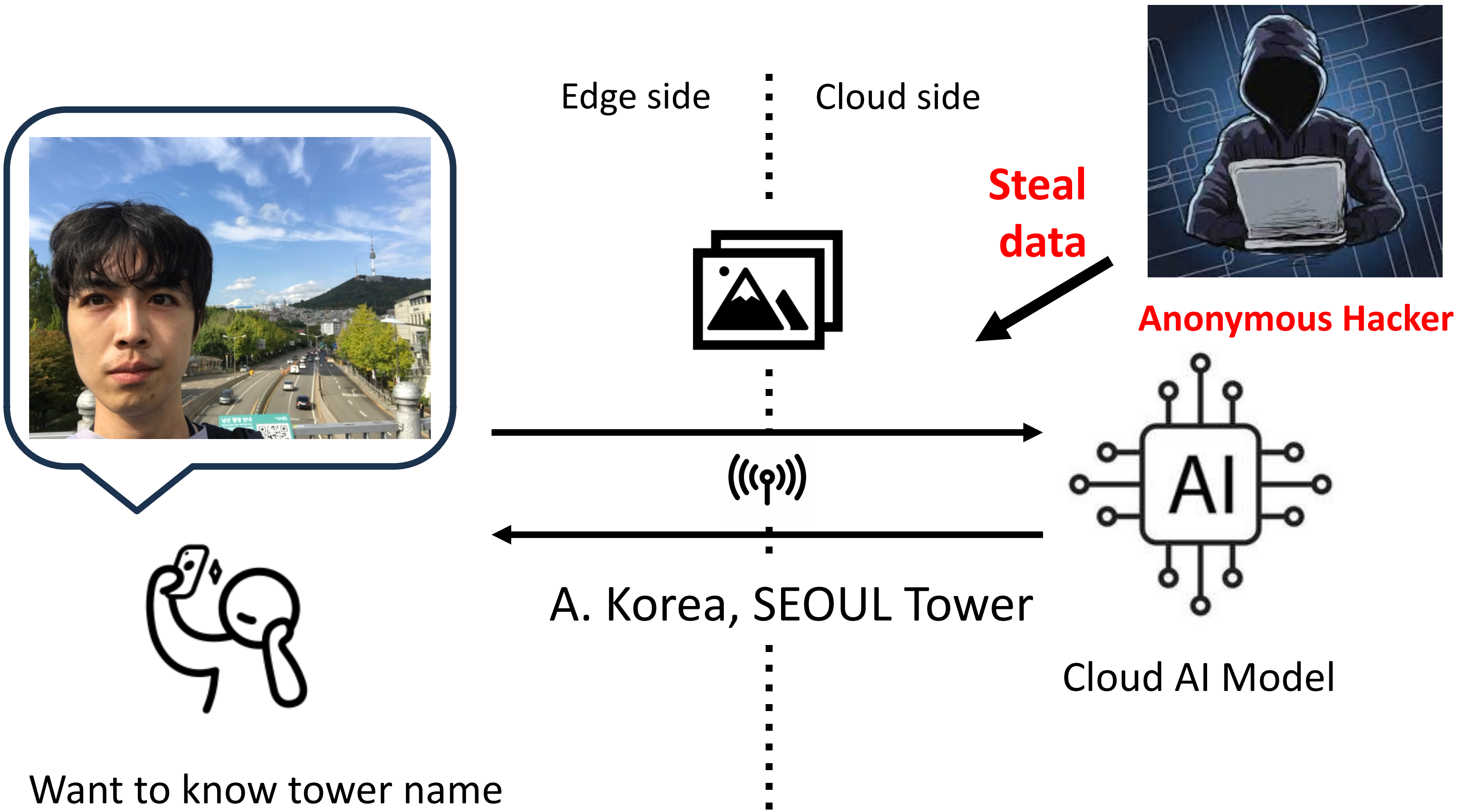
Use Cloud AI model for prediction

1. sending the data
2. **receive prediction results**



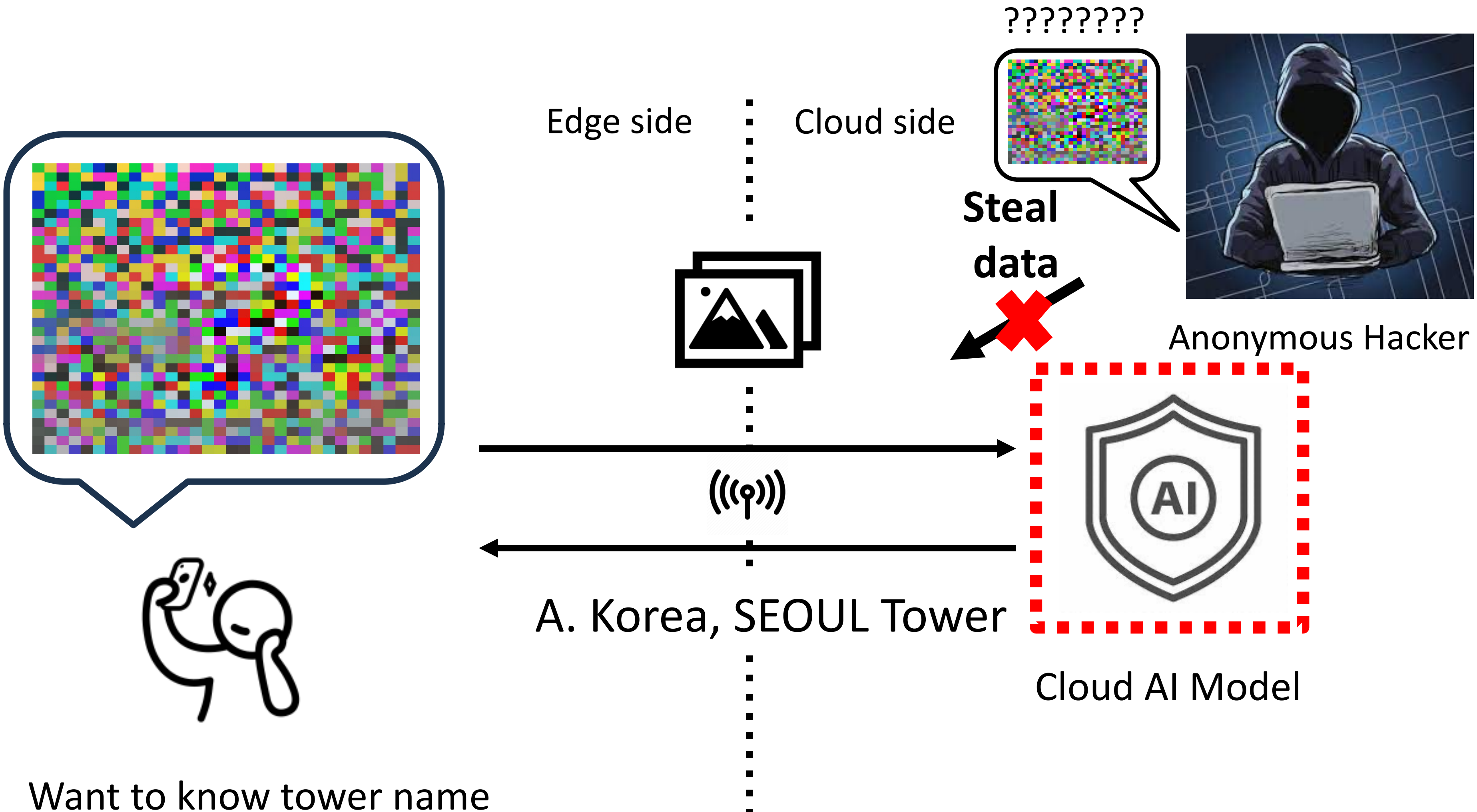
Edge Cloud Machine Learning

Personal data is dangerous to send public network



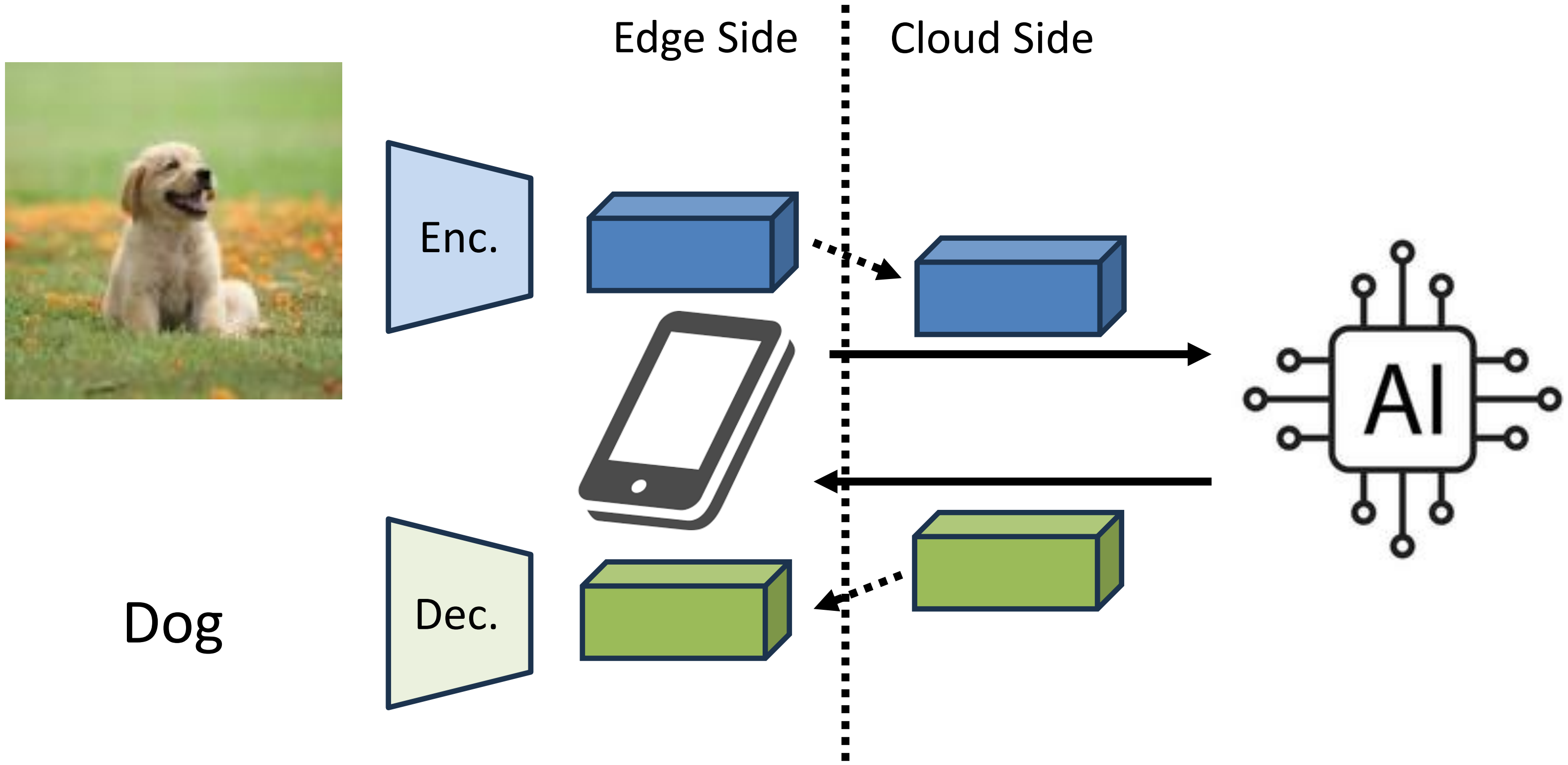
Edge Cloud Machine Learning

AI understandable Image Encryption is necessary



InstaHide [Haung et al]

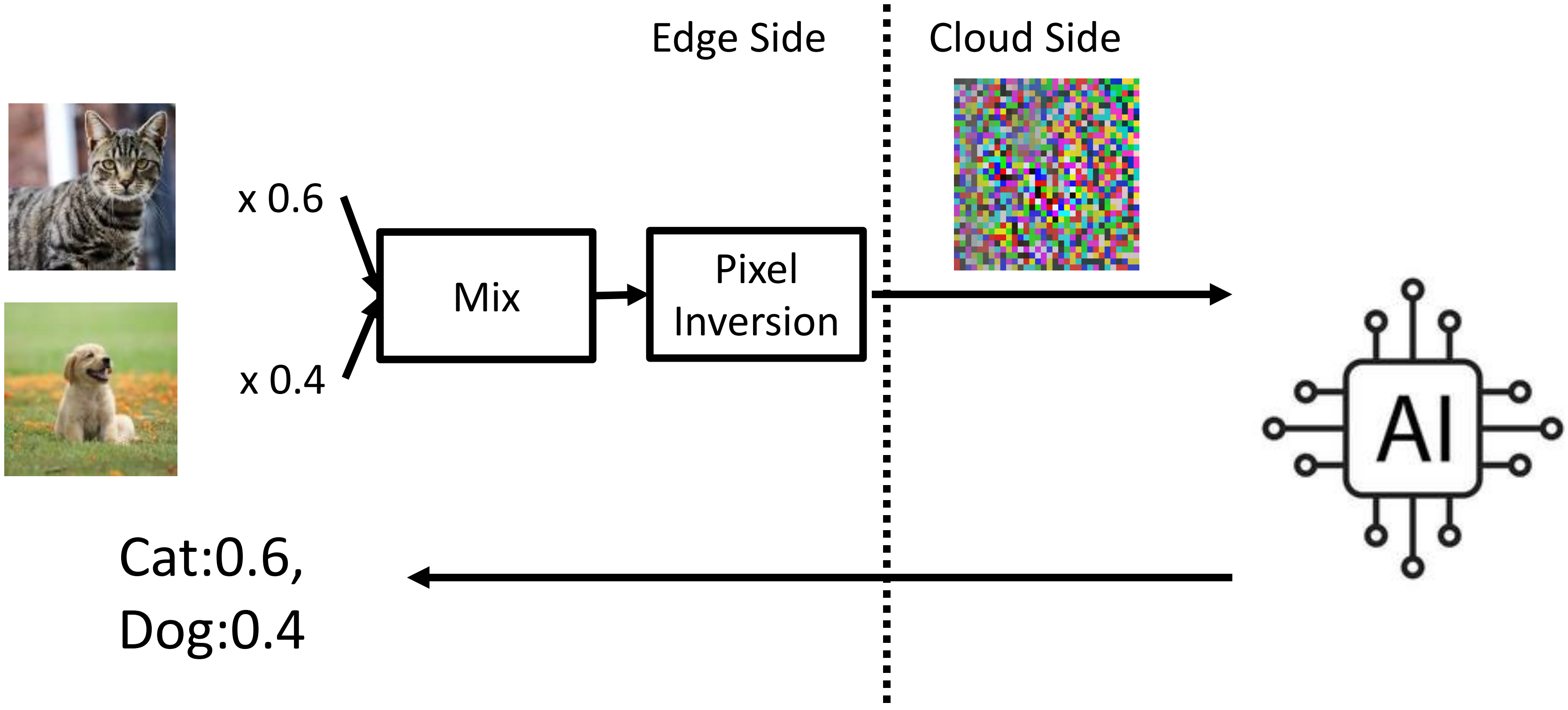
(1) Send encoded feature to the server
(2) Received feature and decode message.



Problem : Encoder/Decoder are necessary・feature limits accuracy.

DataMix [Liu et al]

(1) Mix Images and Encrypt images
(2) Received message.



Problem : Two images are necessary for prediction

Image Scrambling [Tanaka, Sirichoptedumrong et al]

1. Train AI model with Scrambled images

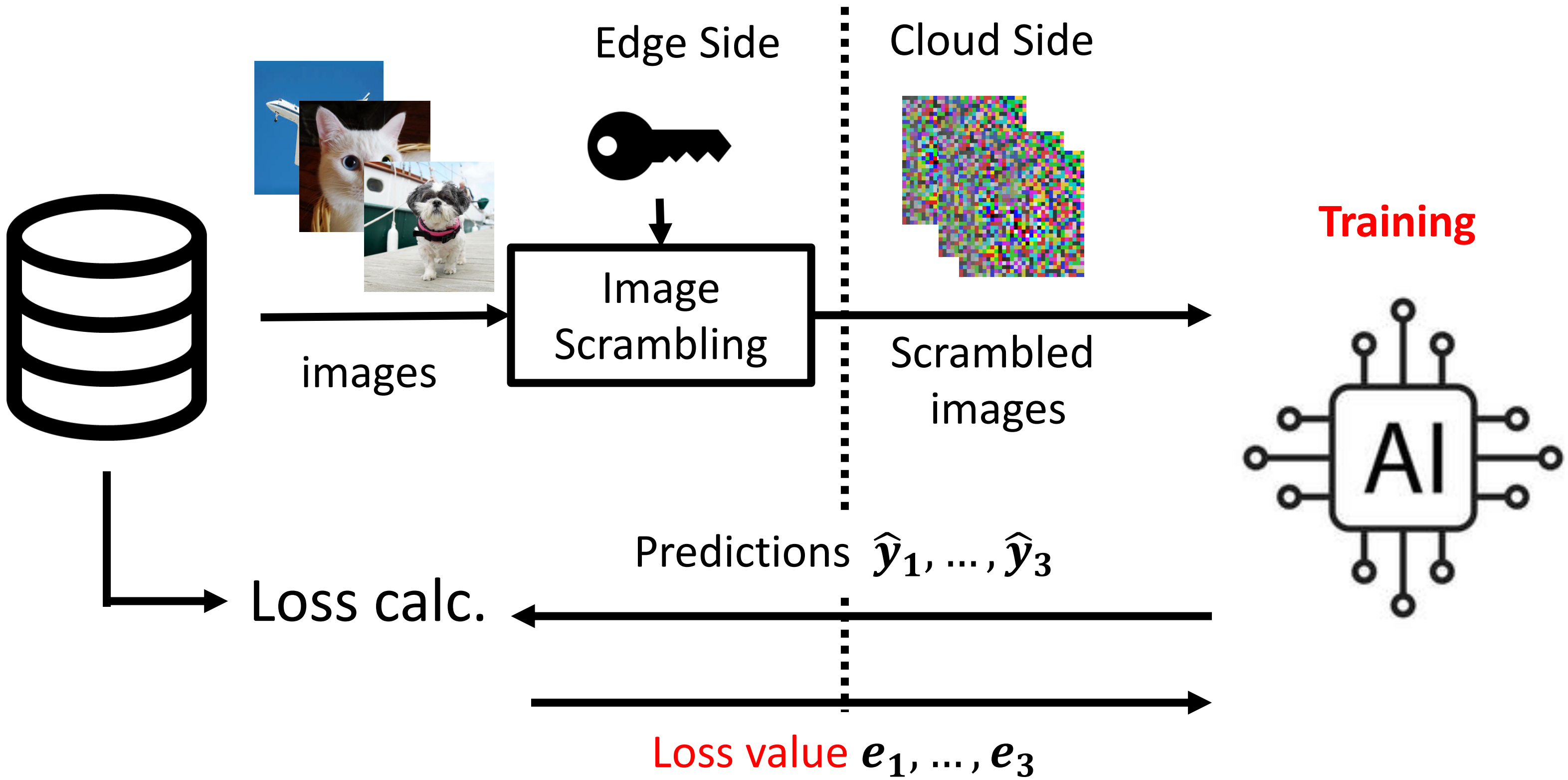


Image Scrambling [Tanaka, Sirichoptedumrong et al]

2. Deployed AI model and use for inference

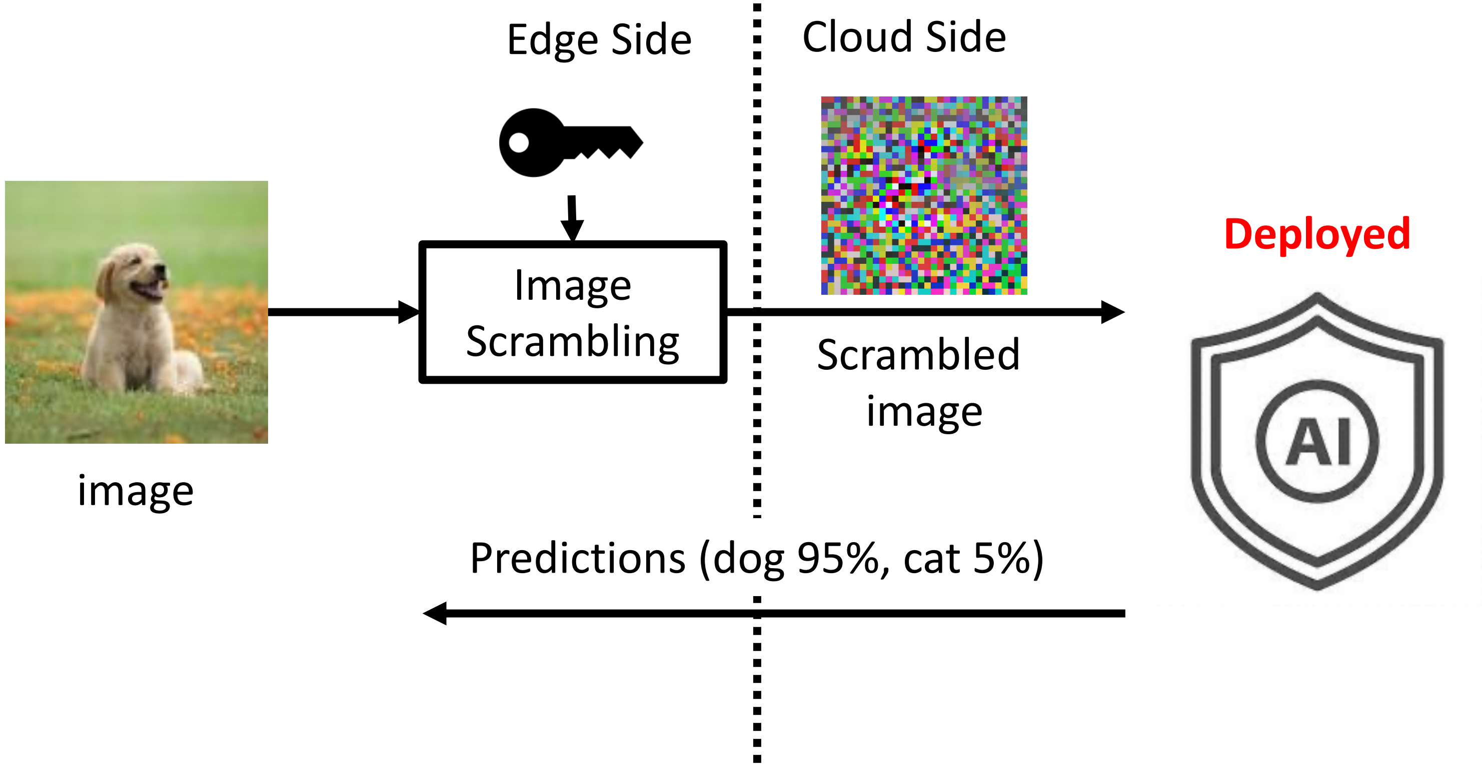
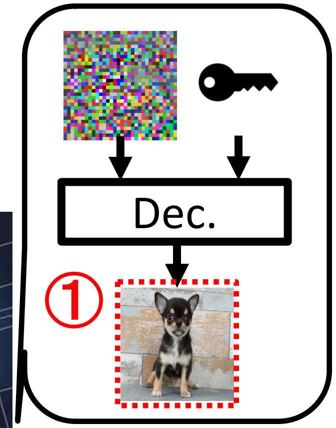


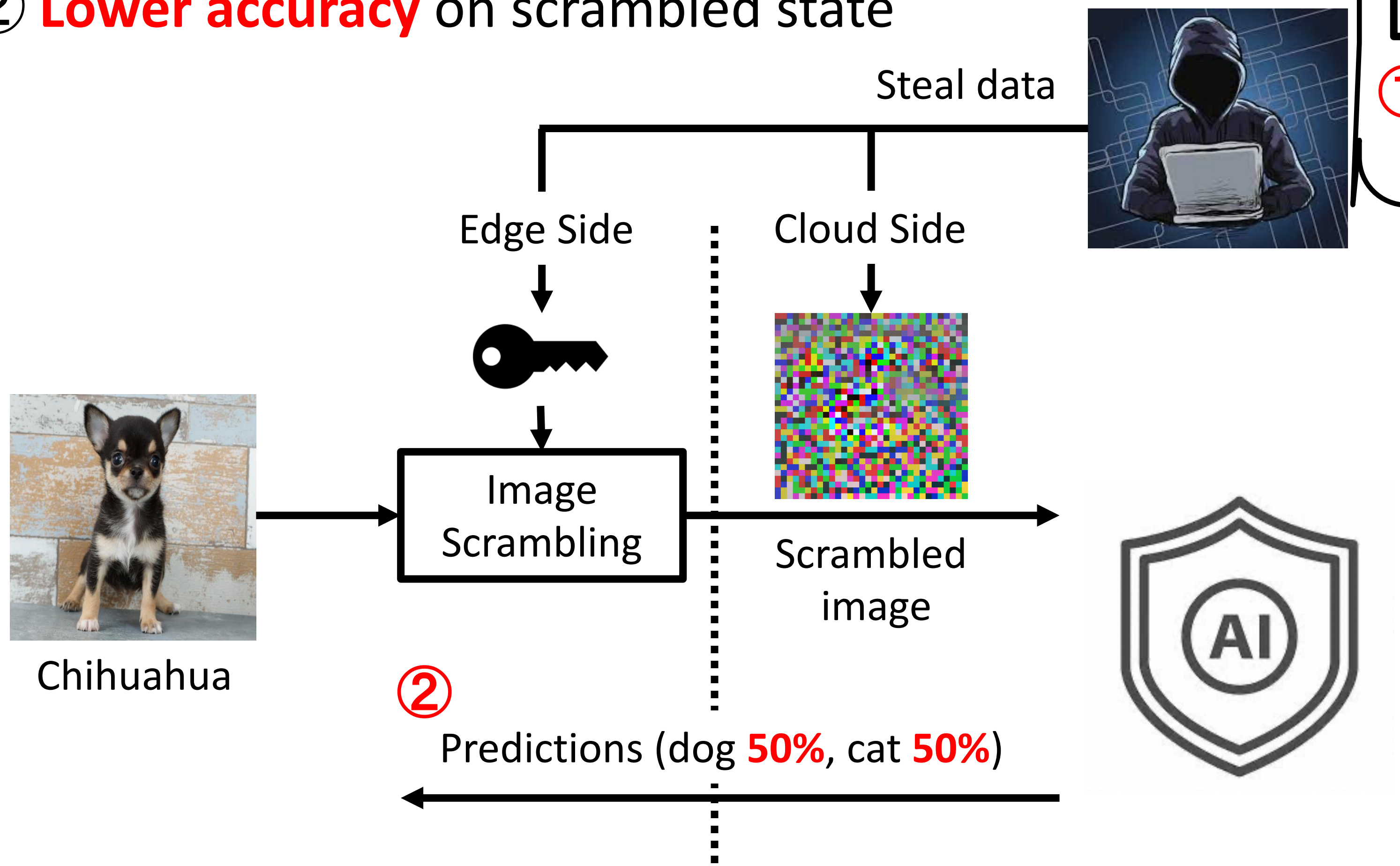
Image Scrambling [Tanaka, Sirichoptedumrong et al]

Limitation

① Scrambled image is **unsecure**

② **Lower accuracy** on scrambled state



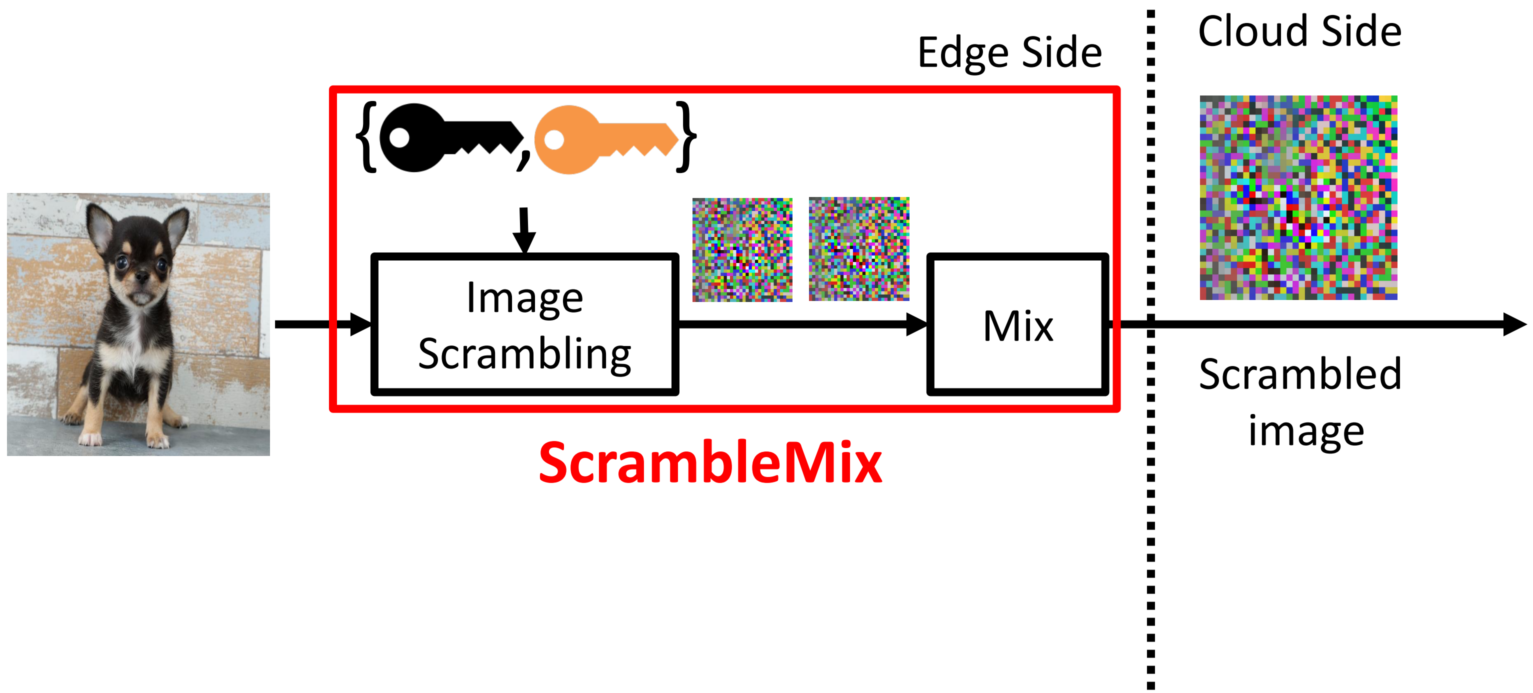


ScrambleMix (Proposed)

Differences from Image scrambling

① Two keys for scrambling

② Mix two scrambled images

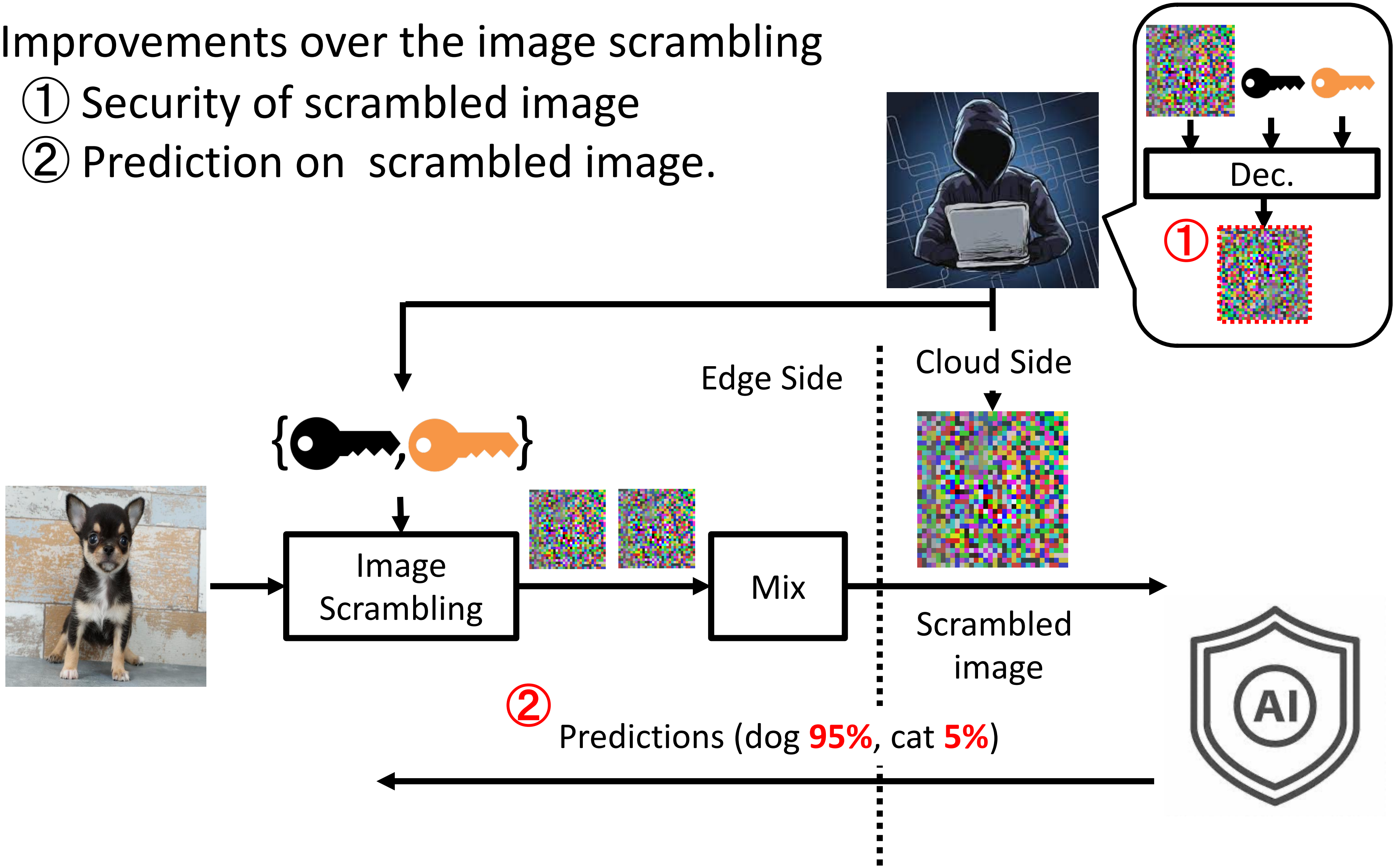


ScrambleMix (Proposed)

Improvements over the image scrambling

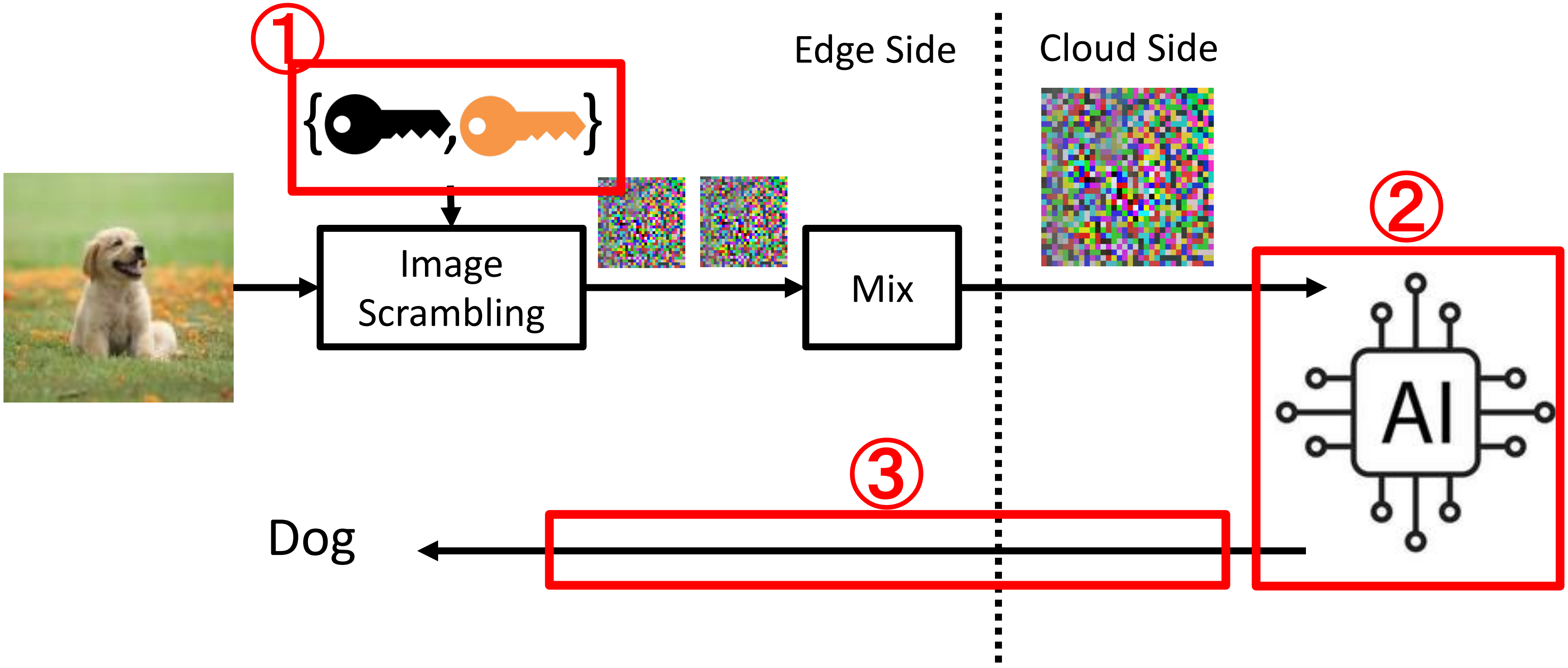
① Security of scrambled image

② Prediction on scrambled image.



Overview of ScrambleMix

1. (Key Selection : Select visually secure keys [Madono, EI21])
2. **Training**
3. **Inference**

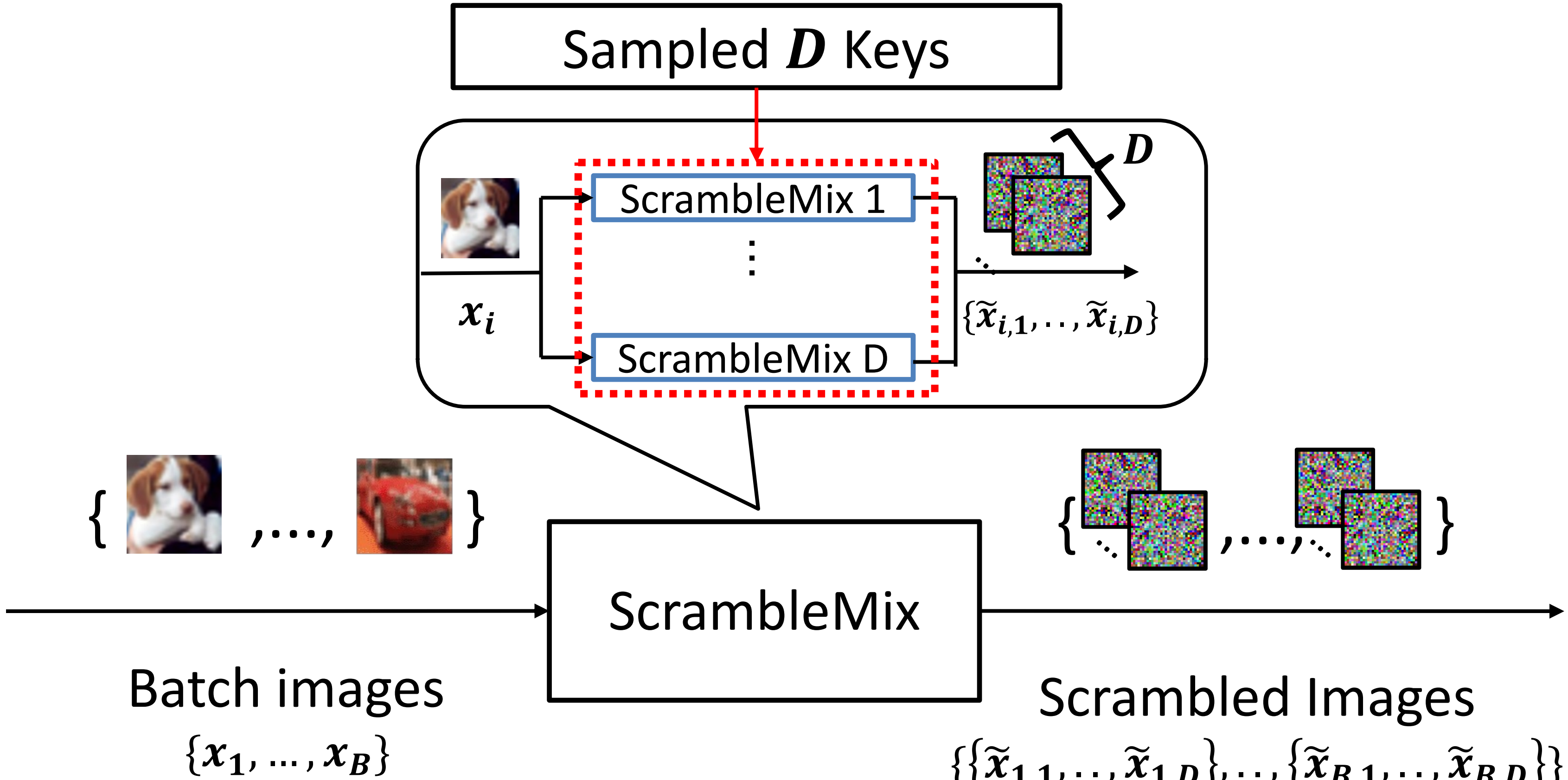


Training

1. ScrambleMix on each image

Training

1. Image Scrambling on each image
 - Each image is augmented $\boldsymbol{D}$ scrambled images.



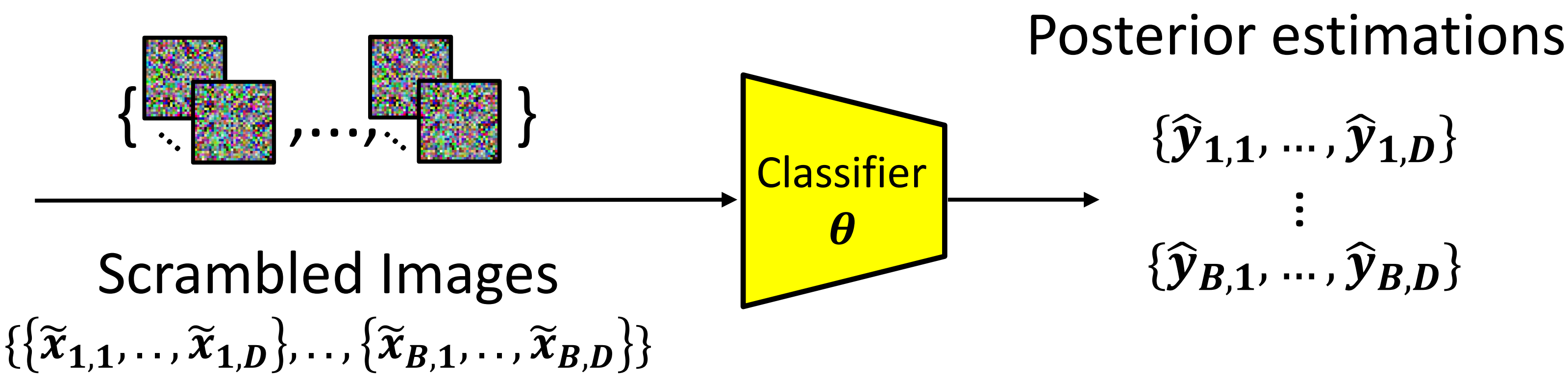
Training

2. Compute the loss for optimization

+ L_{CE} : Cross-entropy Loss

+ L_{ST} : Self-teaching Loss (proposed)

$$L = L_{CE} + \lambda L_{ST}$$

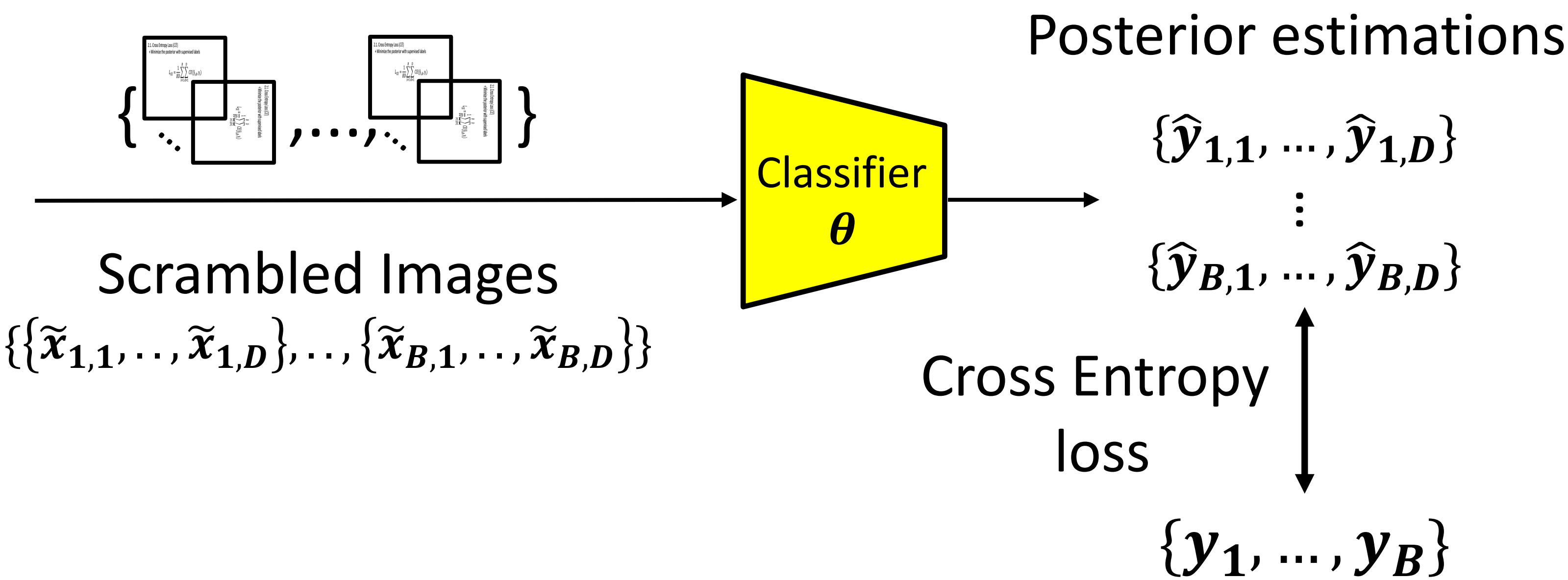


Training

2.1. Cross Entropy Loss (CE)

+ Minimize the posterior with supervised labels

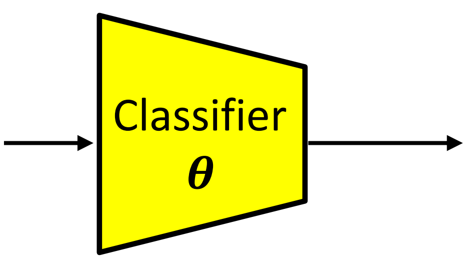
$$L_{CE} = \frac{1}{BD} \sum_{i=1}^{B} \sum_{d=1}^{D} CE(\hat{y}_{i,d}, y_i)$$



Training

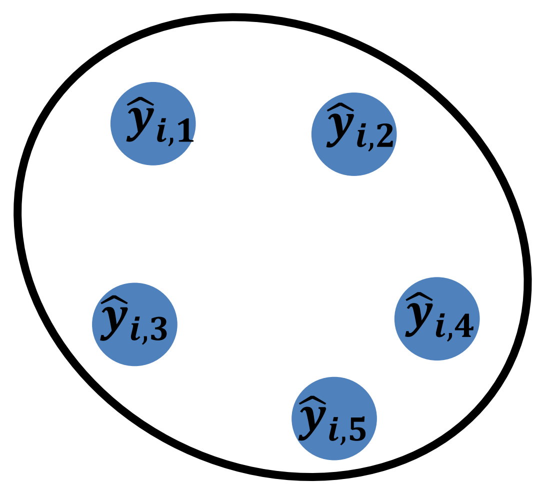
2.2. Self-Teaching Loss (ST)
 + posterior changes due to different keys

2D visualization



$\{\hat{\boldsymbol{y}}_{\boldsymbol{i},\mathbf{1}}, \dots, \hat{\boldsymbol{y}}_{\boldsymbol{i},\boldsymbol{D}}\}$

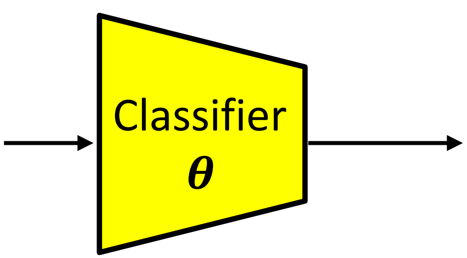
Posterior estimations



Training

2.2. Self-Teaching Loss (ST)

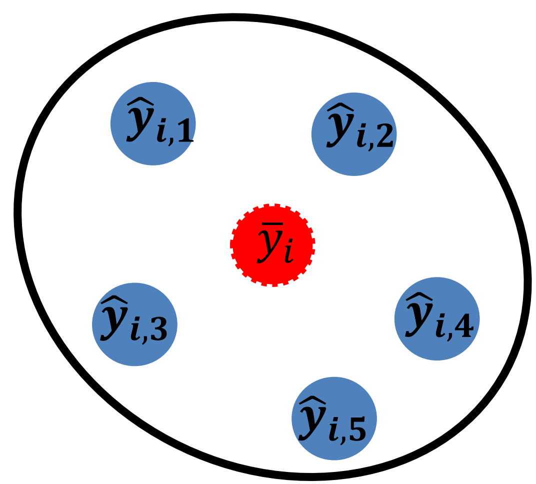
+ Same original image should have same posterior



$\{\hat{\boldsymbol{y}}_{\boldsymbol{i},\mathbf{1}}, \dots, \hat{\boldsymbol{y}}_{\boldsymbol{i},\boldsymbol{D}}\}$

Posterior estimations

2D visualization

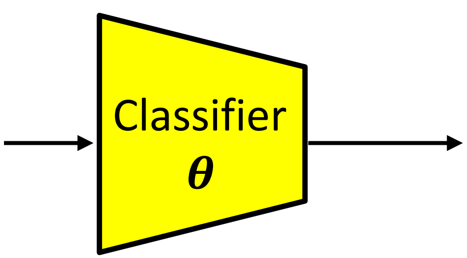


Training

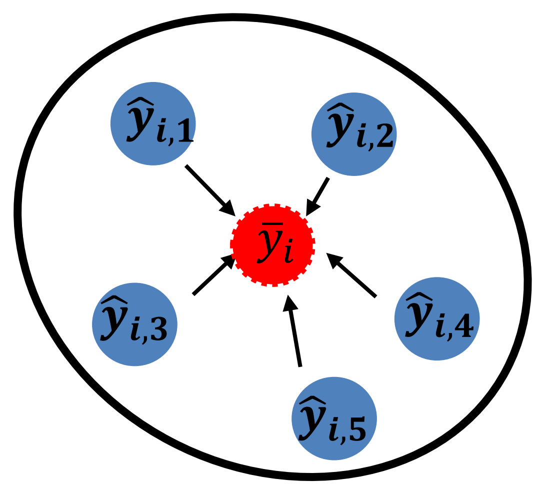
2.2. Self-Teaching Loss (ST)

+ Approach : Minimize each posterior and average posterior

2D visualization



$\{\hat{\boldsymbol{y}}_{i,1}, \dots, \hat{\boldsymbol{y}}_{i,D}\}$



Posterior estimations

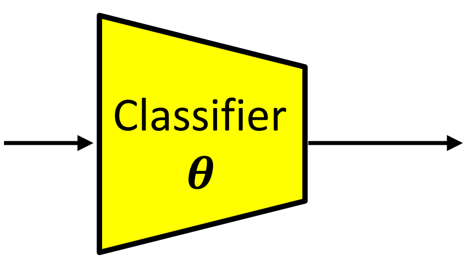
Training

2.2. Self-Teaching Loss (ST)

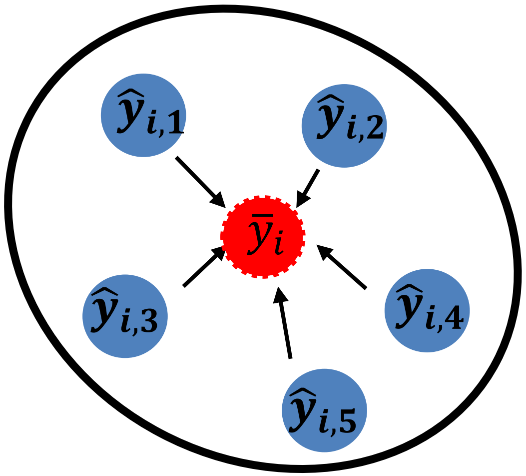
+ Average posterior: $\bar{y}_i$

$$\bar{y}_i = \mathrm{StopGrad}\left[\frac{1}{D}\sum_{d=1}^{D}\widehat{\boldsymbol{y}}_{\boldsymbol{i,d}}\right]$$

2D visualization



$\{\widehat{\boldsymbol{y}}_{\boldsymbol{i},\mathbf{1}}, \dots, \widehat{\boldsymbol{y}}_{\boldsymbol{i},\boldsymbol{D}}\}$



Posterior estimations

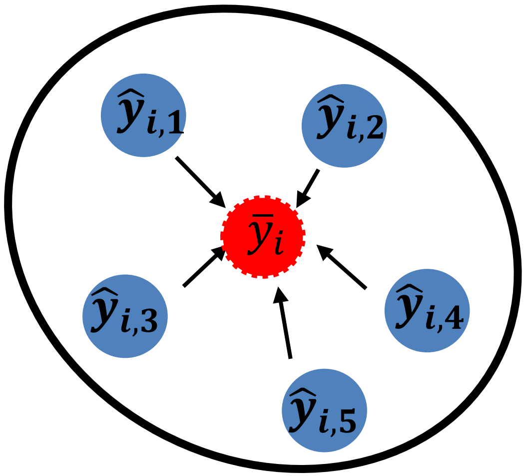
Training

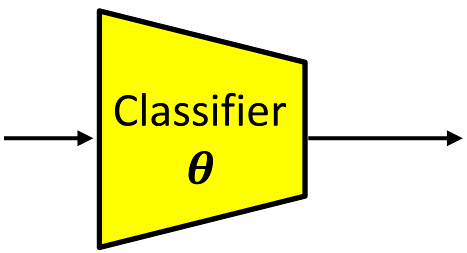
2.2. Self-Teaching Loss (ST)

+ Minimize the posterior with supervised labels

$$L_{ST} = \frac{1}{BD} \sum_{i=1}^{B} \sum_{d=1}^{D} KL(\hat{y}_{i,d} || \bar{y}_i)$$

2D visualization





$\{\hat{y}_{i,1}, \dots ; \hat{y}_{i,D}\}$

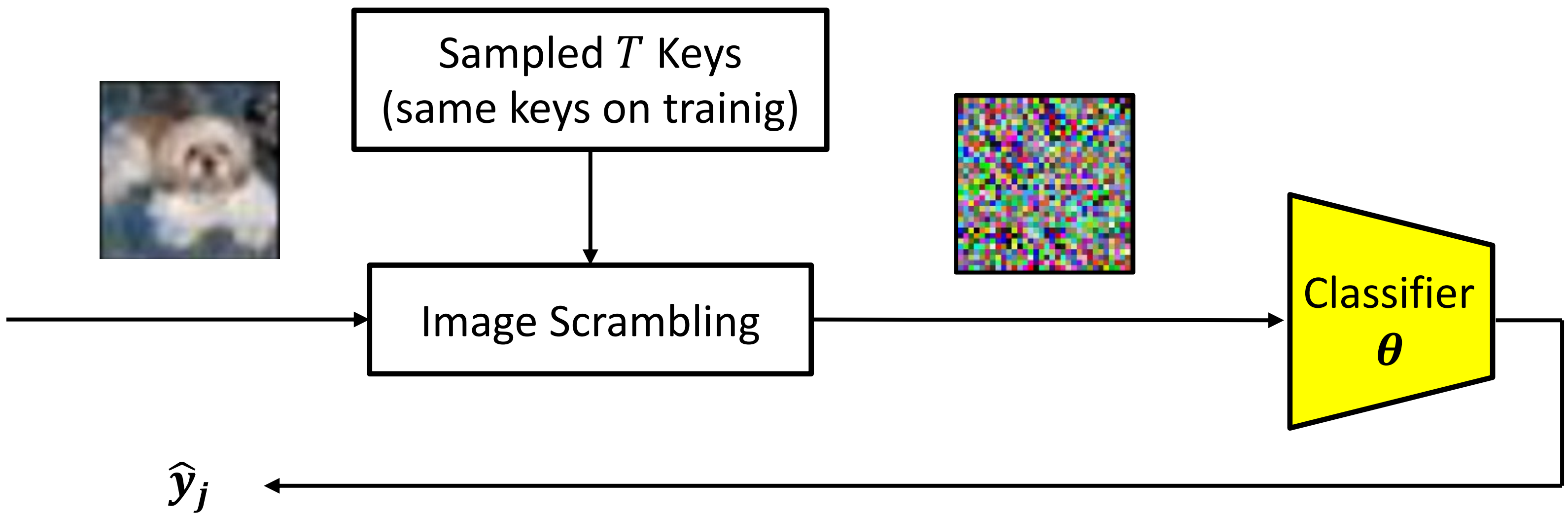
Posterior estimations

Inference

Posterior Estimation using sampled keys

- T Keys : Aimed at TTA (Test Time Augmentation)

$$\hat{y}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_{j,t}$$



Experiment

Baseline

+ InstaHide [Haung 2020]
+ DataMix [Liu 2020]
+ Image Scrambling
  - Learnable Encryption [Tanaka 2018]
  - Random Pixel-wise Encryption [Sirichoptedumrong 2019]

Proposed

+ ScrambleMix

Evaluation

1. Classification task: on Cifar10/100, SVHN
2. Security score : on InstaHide attack[Carlini 2020]

Results (T=1, w/o Test-Time Augmentation)

WideResNet40x10

Accuracy scores	**CIFAR10**	**CIFAR100**	**SVHN**
DataMix	66.89	38.31	19.60
InstaHide	53.58	39.06	52.47
LE	91.34	70.62	96.50
Random PE	92.23	70.82	96.83
ScrambleMix (Proposed)	**93.08**	**71.71**	**96.96**

Shakedrop

Accuracy scores	**CIFAR10**	**CIFAR100**	**SVHN**
DataMix	80.10	50.97	93.42
InstaHide	52.93	39.95	52.87
LE	94.02	77.59	97.26
Random PE	93.51	77.10	97.26
ScrambleMix (Proposed)	**95.02**	**79.39**	**97.47**

Results (T>=1, with Test-Time Augmentation)

Our approach : better on several scores

+ Even if T is small, our approach can get a comparable result

WideResNet40x10

Accuracy scores	CIFAR10	CIFAR100	SVHN
InstaHide, T=10	**94.92**	**78.32**	94.97
ScrambleMix, T=4	93.12	71.87	**97.01**

Shakedrop

Accuracy scores	CIFAR10	CIFAR100	SVHN
InstaHide, T=10	92.91	74.06	93.38
ScrambleMix, T=4	**95.31**	**79.41**	**97.54**

Results (Security Evaluation)

Attacked Results by InstaHide Attack [Carlini 2020]

+ Evaluate by inception score: high inception score means unsecure state

+ Our approach keeps low score (→ keep security)

	InstaHide	**ScrambleMix**
Non-attacked Scrambled Image	1.394 	1.012 
Attacked Scramble Image	2.777 	**1.177** 

+1.383

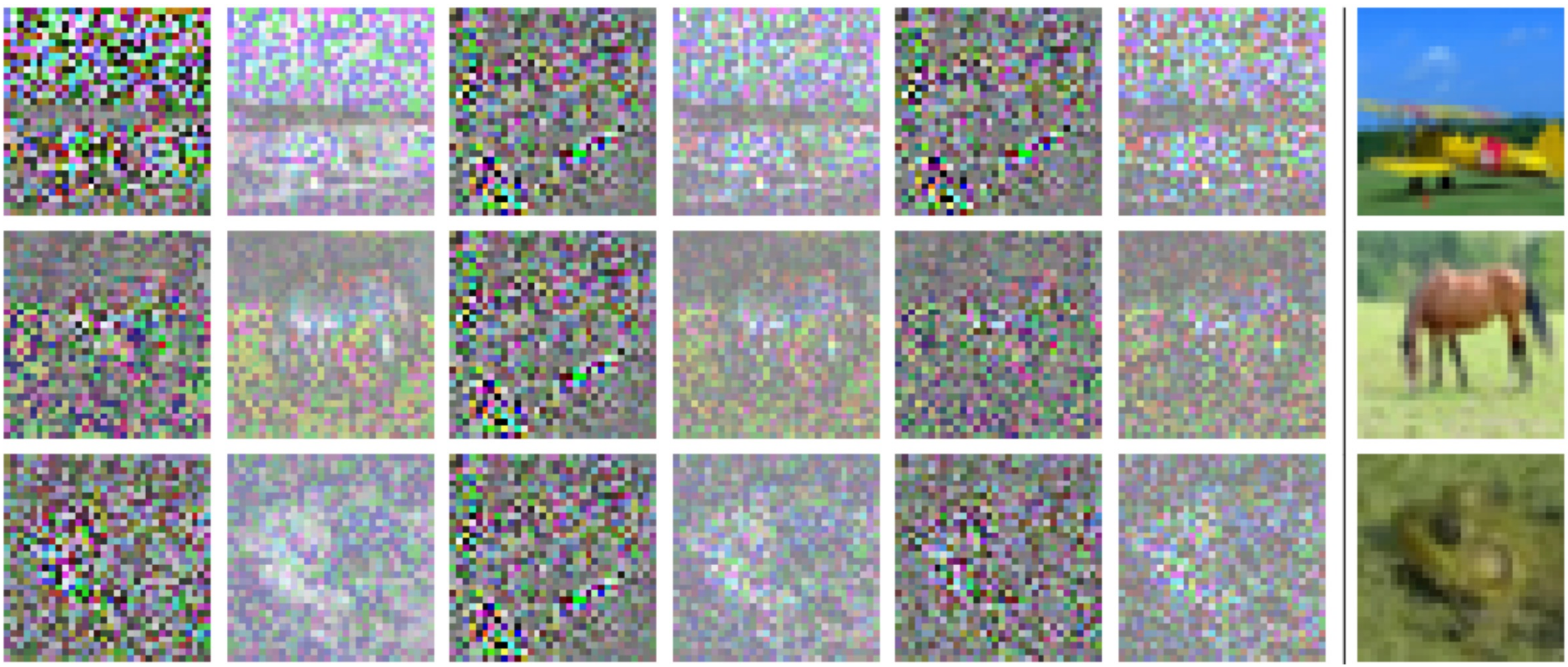
+0.165

Results (Security Evaluation)

Attacked Results by InstaHide Attack

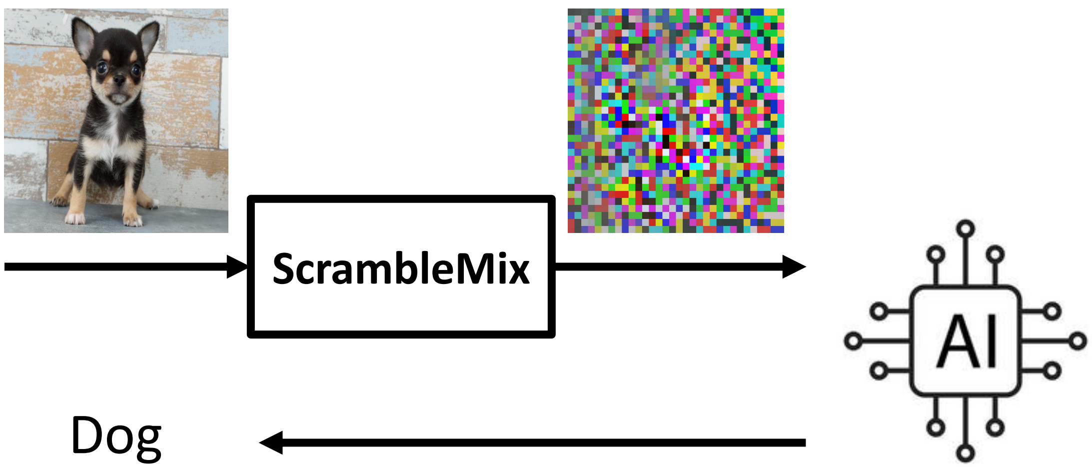
m=0.1 m=0.3 m=0.5

Scramble Mix | Attacked | Scramble Mix | Attacked | Scramble Mix | Attacked | Original



Summary

ScrambleMix : new scrambling method for **edge-cloud machine larning**
- improve **classification accuracy** over almost settings
- improve **security** over the strong attack method



Overview of ScrambleMix

GitHub / slide