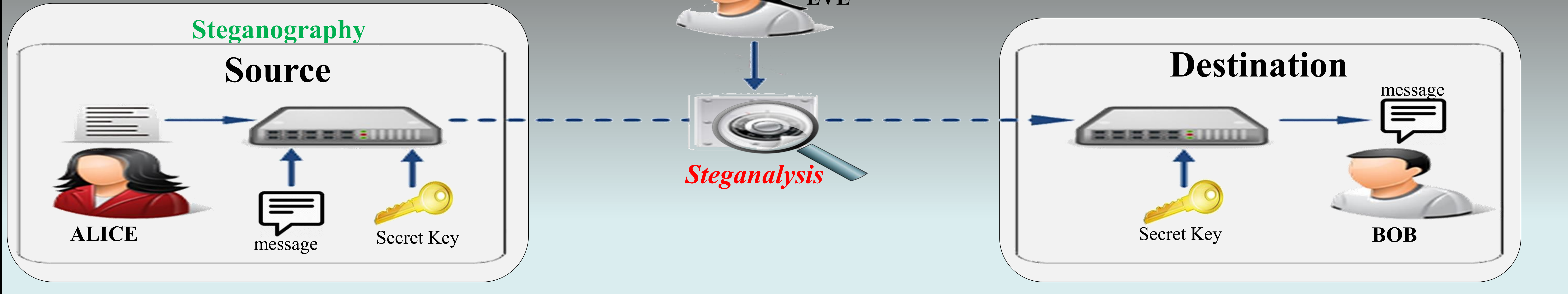


Yedrouj-Net: An efficient CNN for spatial steganalysis

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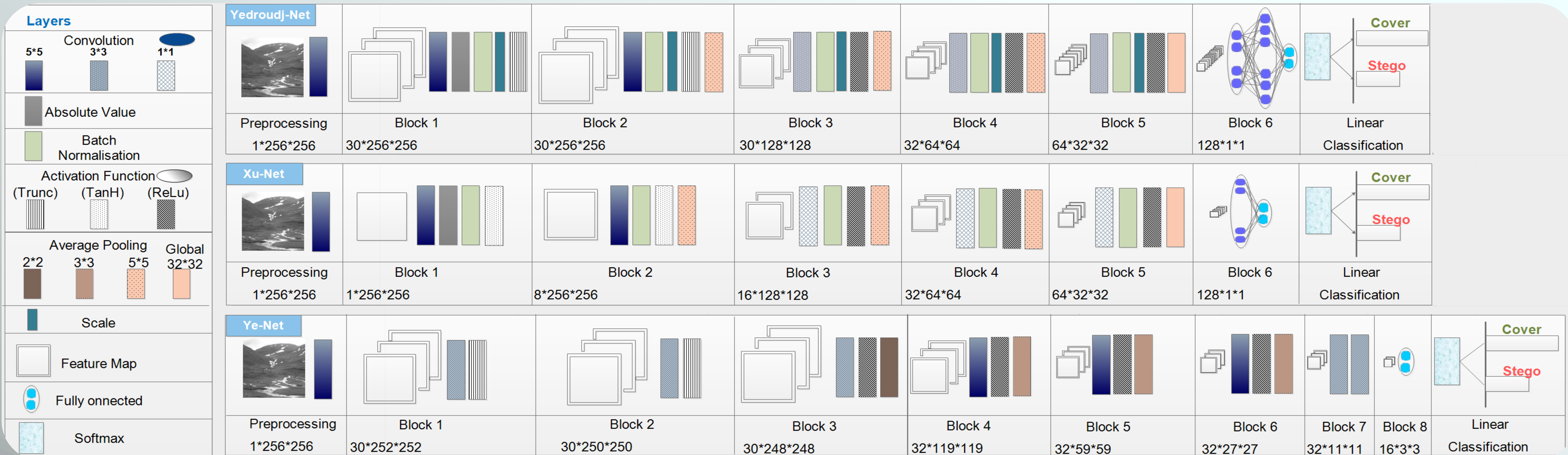
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What is Steganalysis / Steganography?



Proposed architecture

Yedroudj-Net comparison with two other steganalysis approaches based on deep learning (fair comparison).



Yedroudj-Net:

1. It has the advantage of using 30 SRM kernels which increases the diversity.
2. A shallow network compared to the Ye-Net equipped with a “value clipper” (hard tanh) activation function.
3. Thanks to batch normalization, Yedroudj-Net converges faster and is more robust with respect to hyperparameters.

Results

1. Clairvoyant protocol:

- Resize the 10000 images of BOSSBase to 256*256.
- Use the two algorithms WOW and S-UNIWARD to generate the stegos.
- Select 1000 pairs from the training set for validation.
- Use the 5000 images of the test set to evaluate the obtained model.

Comparison of Yedroudj-Net and three state-of-the-art steganalysis methods in terms of steganalysis probability of error.

	BOSS 256×256			
	WOW [6]		S-UNIWARD [5]	
	0.2 bpp	0.4 bpp	0.2 bpp	0.4 bpp
SRM+EC [1], [2]	36.5 %	25.5 %	36.6 %	24.7 %
Yedroudj-Net	27.8 %	14.1 %	36.7 %	22.8 %
Xu-Net [3]	32.4 %	20.7 %	39.1 %	27.2 %
Ye-Net [4]	33.1 %	23.2 %	40.0 %	31.2 %

2. Base augmentation protocol:

- Add 10 000 pairs of cover/stego of BOWS2Base to the training set (Clairvoyant protocol).
- Rotate and flip the 14000 images of the training set.
- Use the 5000 images of the test set to evaluate the obtained model.

Comparison of Yedroudj-Net's and two state-of-the-art steganalysis's probability of error against a steganographic algorithm WOW at a payload of 0.2 bit per pixel (bpp).

	WOW 0.2 bpp		
	BOSS	BOSS+BOWS2	BOSS+BOWS2+VA
Yedroudj-Net	27.8 %	23.7 %	20.8 %
Ye-Net	33.1 %	26.1 %	22.2 %
Xu-Net	32.4 %	30.3 %	30.5 %

Conclusions

- An efficient approach based on deep learning (CNN) for steganalysis.
- Our method outperforms the state-of-the-art and others CNN-based models with and without taking extra measures (train set augmentation).
- Future work:
 1. Increase the size of the training set.
 2. Try other tricks such as transfer learning.
 3. Try an ensemble of Yedroudj-Nets.

Related Work[7]

- For an efficient database augmentation 2 options:
- Produce new images using the same cameras and development than the original base.
 - Eve has an access to the original RAW images to use them for producing new images with similar developments.

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