Image Splicing Localization via Semi-Global Network and Fully Connected Conditional Random Fields

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01

INTRODUCTION OF IMAGE SPLICING LOCALIZATION

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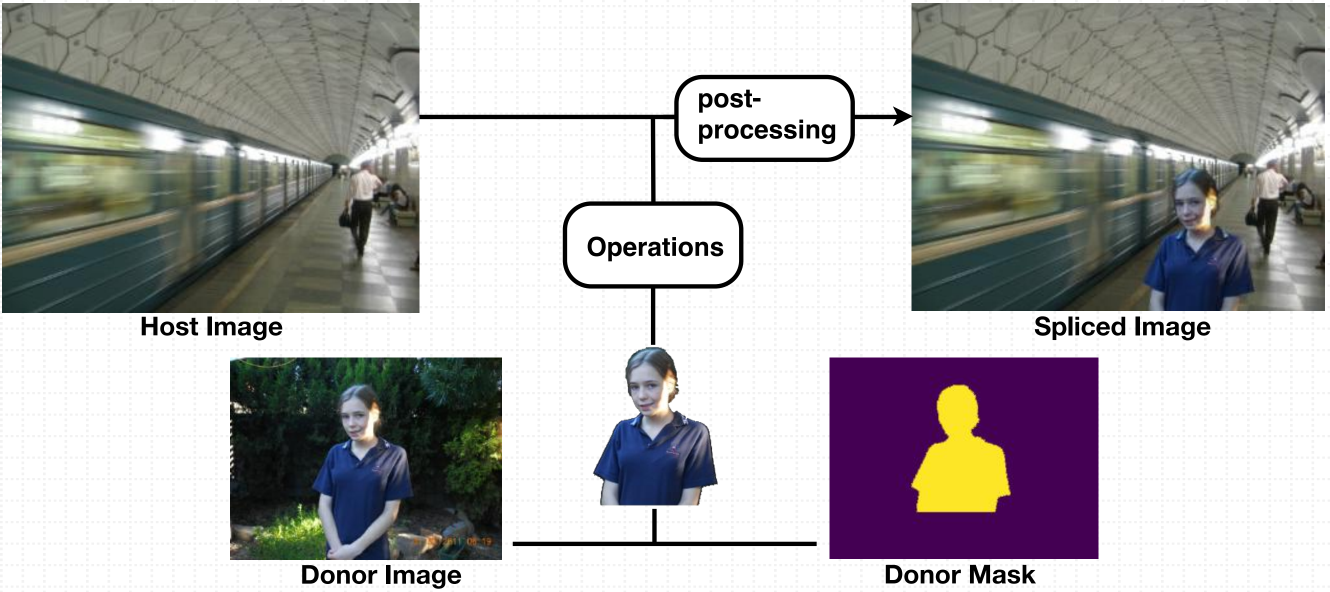


An example of Image Splicing

- **What is Image Splicing?**

  Spliced image is created from two authentic images. By masking the part of donor image, the selected region is pasted to the host image after some operations (translation and rescale the donor region). Sometimes, several post-processing techniques (such as Gaussian filter on the border of selected region) are used to the spliced region for the harmony of the selected region and host image.

- **Generate Fake News**

  Image splicing can be potentially used in generating false propaganda for political purposes.

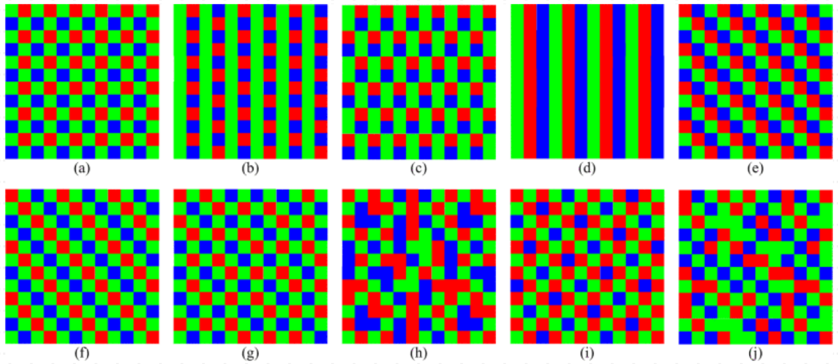
- **Image Splicing Localization**

  We want to identify the spliced region from the whole image

01 INTRODUCTION OF IMAGE SPLICING LOCALIZATION

- **Traditional Image Splicing Algorithms**

Traditional image splicing method only care about the features in local region because this is enough for splicing region detection/localization from specific features.



An example of different Color Filter Array

Noise patterns

Different images have different noise patterns as a result of a combination of different camera makes/models, the capture parameters of each image, and post-processing techniques.

Color Filter Array (CFA)

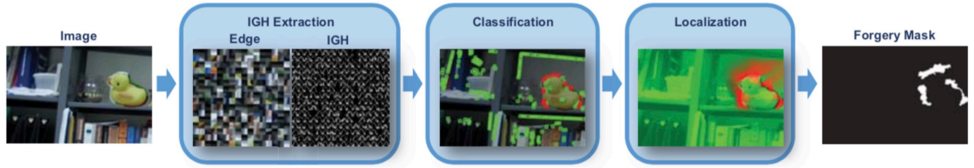
Most digital cameras acquire images using a single image sensor overlaid with a CFA that produces one value per pixel.

JPEG-related traces

The original image underwent consecutive JPEG compressions, while the spliced portion may have lost its initial JPEG compression characteristics due to smoothing or resampling of the spliced portion

01 INTRODUCTION OF IMAGE SPLICING LOCALIZATION

- **Deep Learning based method (Patches)**



Chen, Can, McCloskey, Scott, Yu, Jingyi: *Image Splicing Detection via Camera Response Function Analysis.* CVPR (2017) 1876–1885

- Extracting handcrafted feature firstly in image patches
- Feature classification by CNN
- Only can identify the edge between splicing region and non-splicing region
- Inspired by traditional Camera Internal feature based methods

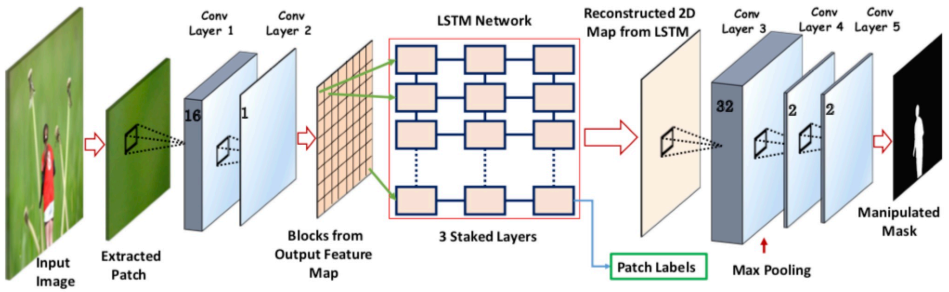


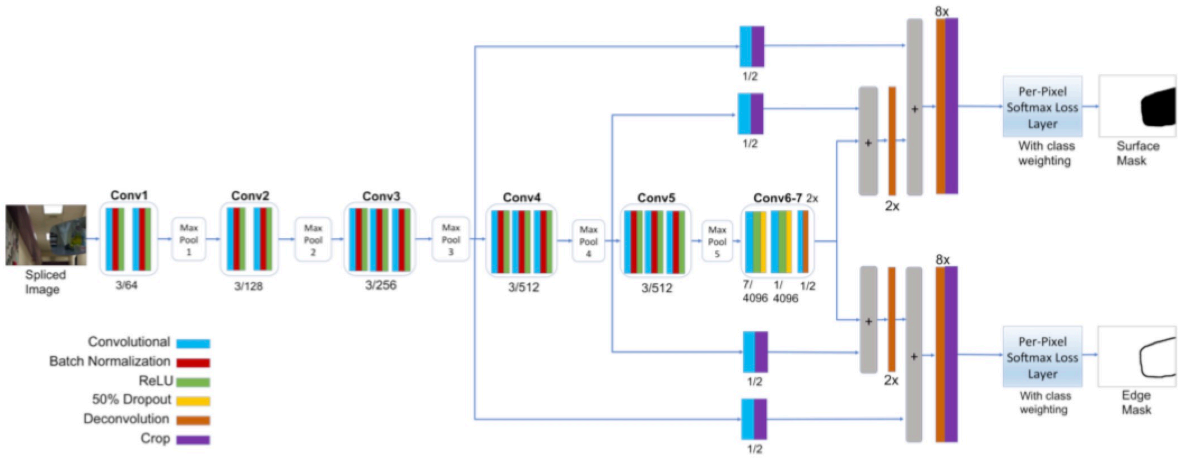
Figure 2. Overview of proposed framework for joint tasks- patch classification and manipulated region segmentation.

Bappy, J.H., Roy-Chowdhury, A.K., Bunk, J., Nataraj, L., Manjunath, B.: **Exploiting spatial structure for localizing manipulated image regions.** ICCV,2017

- Classify and segment the local patches altogether by CNN
- LSTM based low level feature preservation

01 INTRODUCTION OF IMAGE SPLICING LOCALIZATION

- **Deep Learning based method (whole image)**



Salloum, Ronald, Y.R., Kuo, C.C.J.: Image splicing localization using a multi-task fully convolutional network (MFCN). arXiv preprint arXiv:1709.02016 (2017)

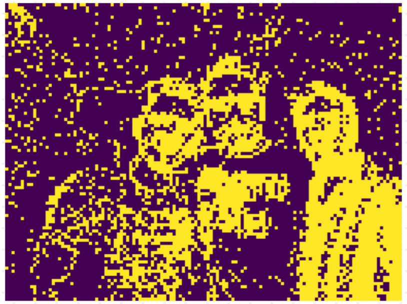
- Similar to Fully Convolutional Network
- Pre-trained VGG16 based feature extractor
- Not only the ground truth mask, but also the edge as the ground truth label.

01 INTRODUCTION OF IMAGE SPLICING LOCALIZATION

- **Drawbacks of Traditional (patch-based) Method**

  - Just identify the local patch is spliced region or not.
  - They use specific assumption for splicing detection.

Spliced Image



NOI
(Different local noise variance)

Ground Truth

Spliced region and non-spliced region not only have different local features (Noise Level, CFA…) but also different global features (Illumination, high level semantic features)

- **Drawbacks of whole image-based Method**
  - Low level Features might dismiss because of multi-level convolution
  - The splicing dataset is not big enough

01 INTRODUCTION OF IMAGE SPLICING LOCALIZATION

Local Neural Network → local Features

Global Neural Network → Global Features

Each pixel has been spliced or not?

02

PROPOSED METHODS

02 PROPOSED METHODS

Local Network

LSTM-based classification and segmentation

Loss Function

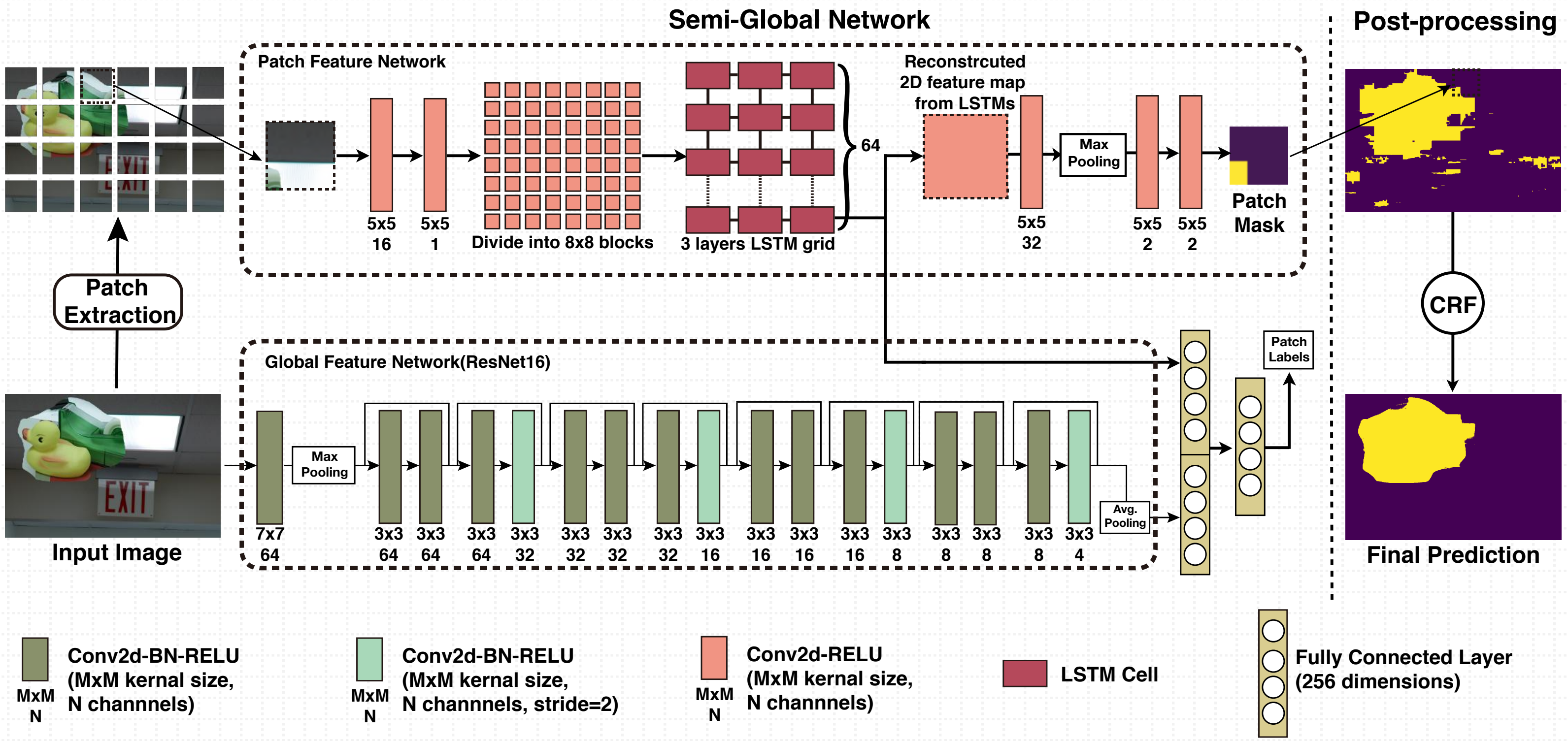
Smooth Term for final prediction

Post-Processing

Fully Connected CRFs as Post-Processing

Global Network

ResNet-18 as global feature extraction

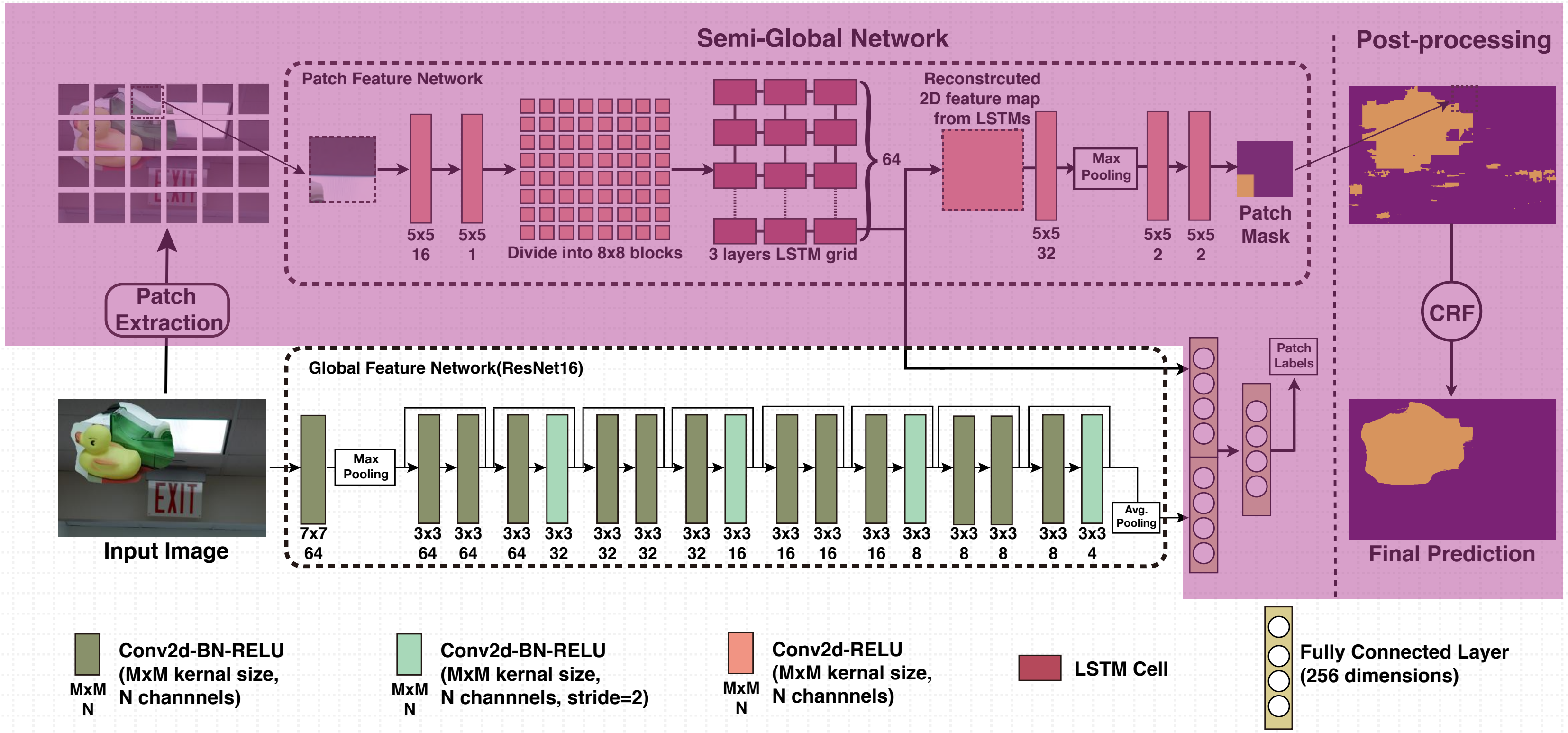


02 PROPOSED METHODS

Global Network

ResNet-18 as global feature extraction

We use a pre-trained model on ImageNet dataset for image classification tasks as our global feature extractor. We freeze all the weights in the neural network because ImageNet dataset is much bigger than our database. These features from image classification benefits the training of our task.



02 PROPOSED METHODS

Local Network

LSTM-based classification and segmentation

Local Neural Network

Which pixels belong to spliced region? (segmentation of patch)

The whole patch is spliced or not? (classification of patch)

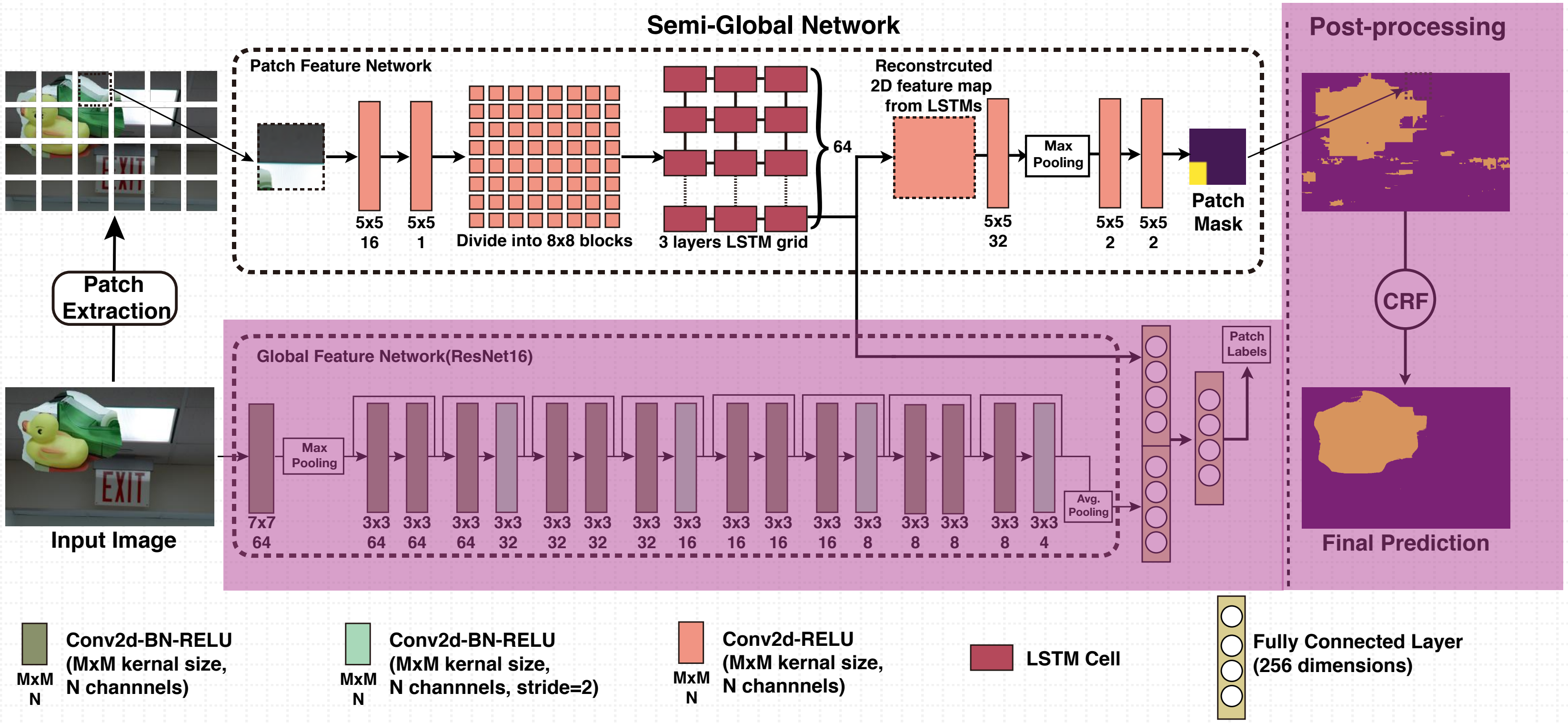
Our local model tries to learn the features from local patch to classify or segment the local patches from image.

02 PROPOSED METHODS

Local Network

LSTM-based classification and segmentation

1. All the convolution layers are the same resolution for the features between the pixels are important.
2. LSTM is used to control the features of nearby pixels.
3. Both Segmentation and Classification are necessary for better results.



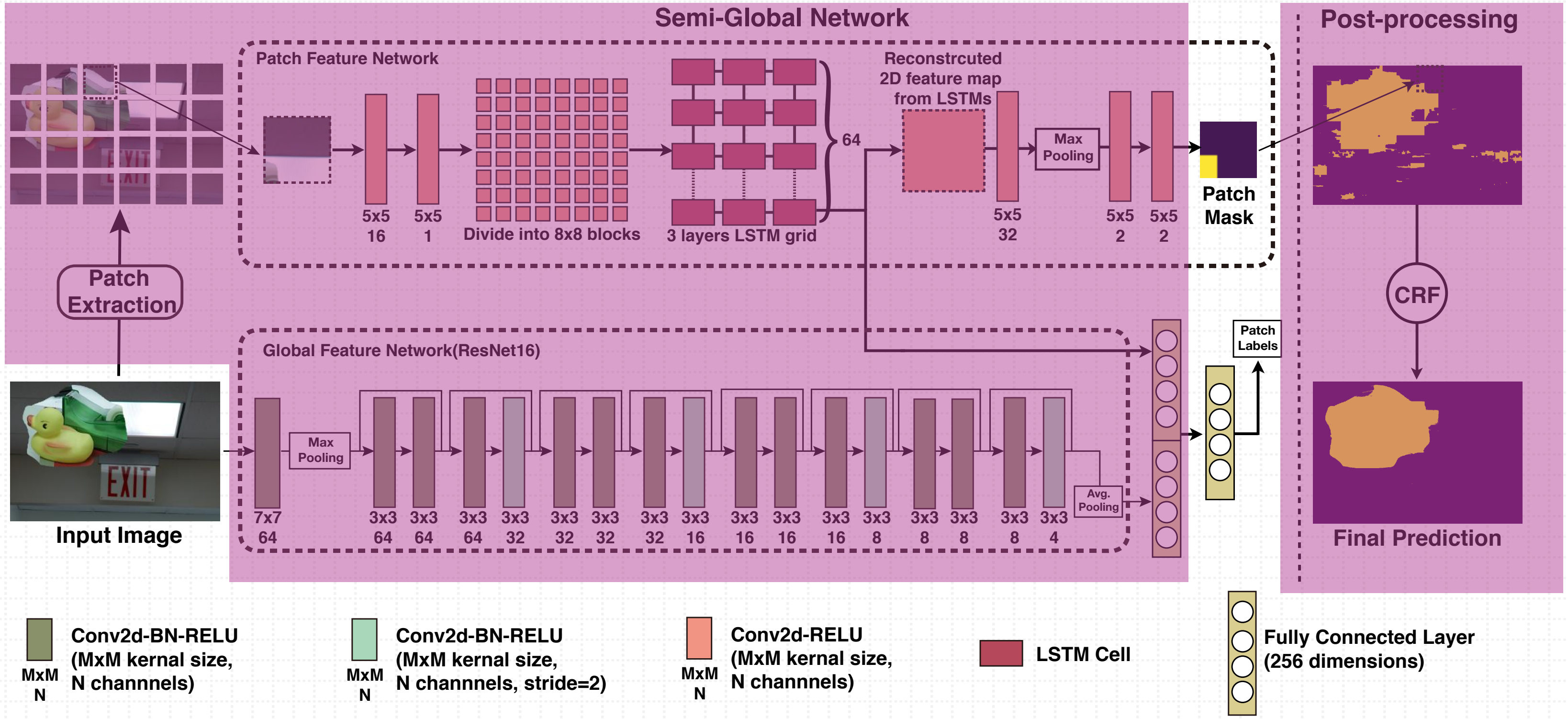
02 PROPOSED METHODS

Loss Function

Smooth Term for final prediction

Our Loss Function(Φ) is based on the results of patch mask segmentation ($\Phi_{classification}$) and patch label classification ($\Phi_{segmentation}$) . For further united the results of these two criterion. We add a new smooth term for task harmonious.(Φ_{smooth}), we add two hyper-parameter (β, λ) to control the relationship between losses.

$$\Phi = \Phi_{classification} + \beta\Phi_{segmentation} + \lambda\Phi_{smooth}$$



02 PROPOSED METHODS

Loss Function

Smooth Term for final prediction

$$\Phi_{classification}(L, L_{gt}) = \frac{1}{N}\sum_{i \in I_p} W_n(1 - L_{gt})log(1 - L_i) + W_s L_{gt} log(L_i)$$

$$\Phi_{segmentation}(M, M_{gt}) = \frac{1}{N}\sum_{i \in I_p}\sum_{j \in M_i} W_n(1 - M_{gt})log(1 - M) + W_s M_{gt} log(M_i)$$

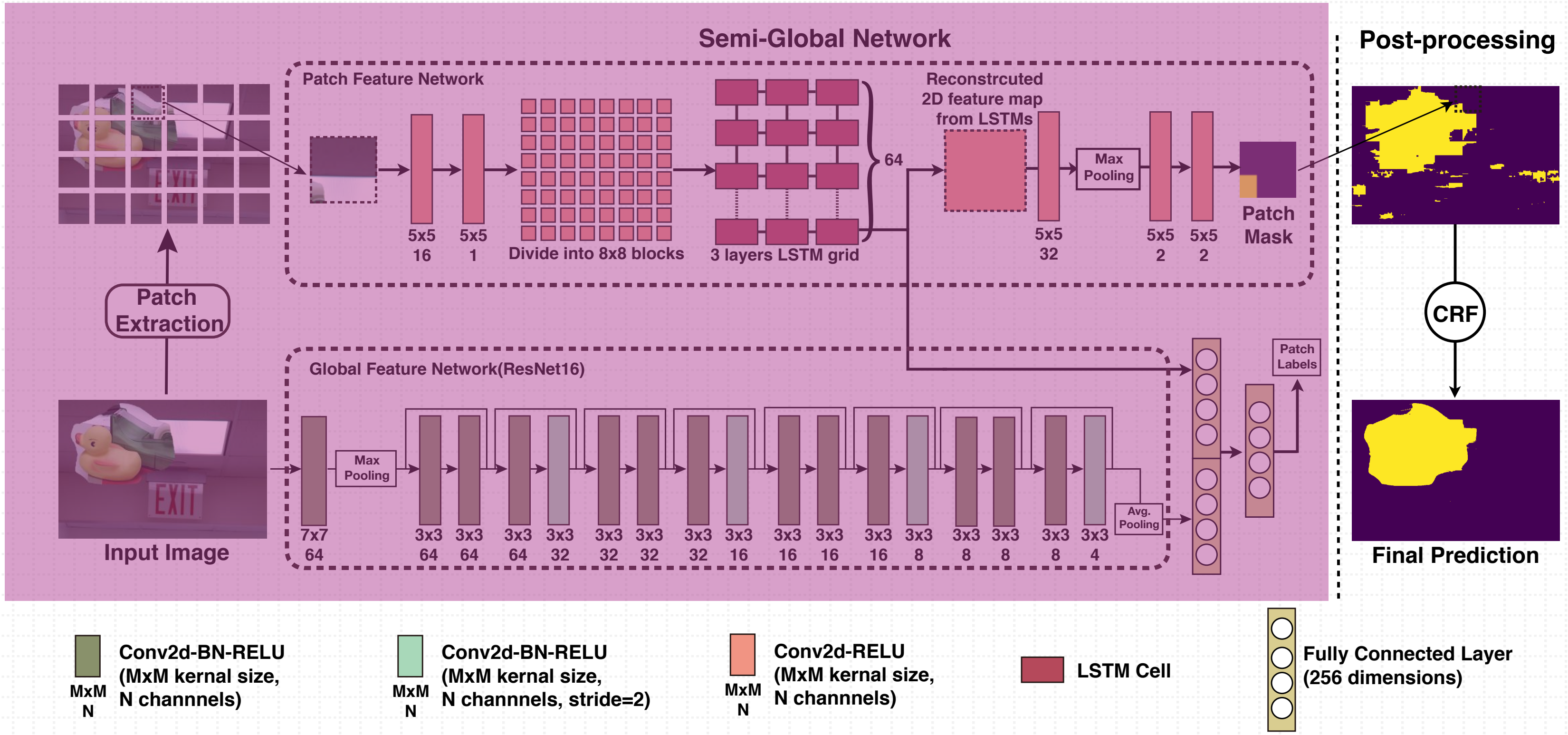
Weighted Cross Entropy Loss

$$\Phi_{smooth}(M, L) = |\frac{\sum_{i \in I_p} M_i}{numel(M_i)} - L|$$

02 PROPOSED METHODS

Post-Processing

We use Fully Connected CRFs as Post-Processing of the rebuild image.



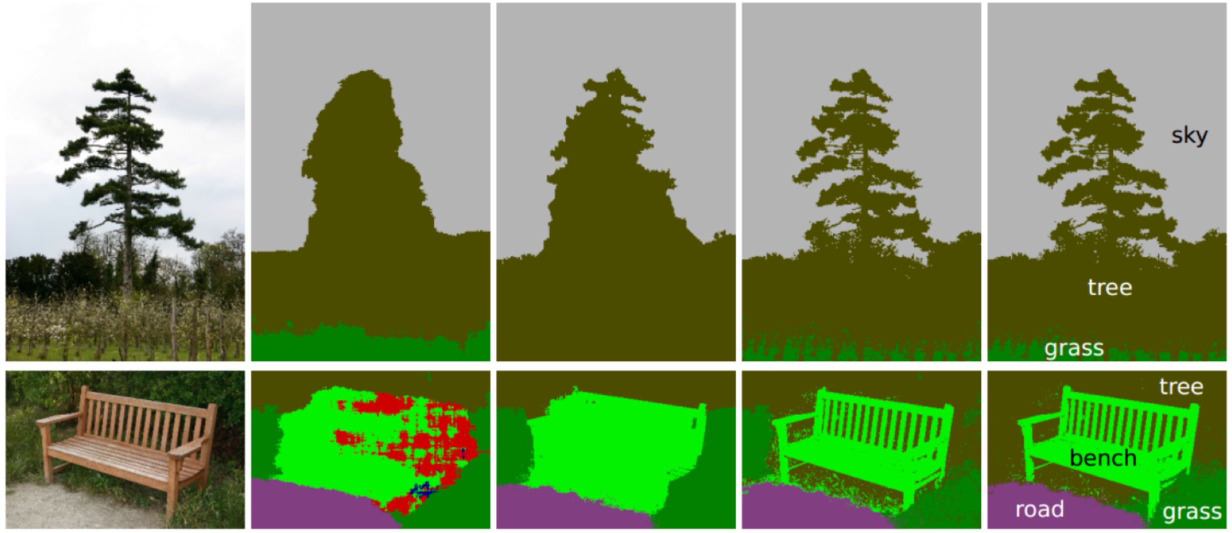
02 PROPOSED METHODS

Post-Processing

$$\theta_{i,j} = \mu(x_i, x_j)[\omega_1 \exp\boxed{(-\frac{||p_i - p_j||^2}{2\sigma_\alpha^2} - \frac{||I_i - I_j||^2}{2\sigma_\beta^2})} + \omega_2 \exp\boxed{(-\frac{||p_i - p_j||^2}{2\sigma_\gamma^2})}]$$

Kernel for position similarity and color similarity

Kernel for position similarity



(a) Image (b) Unary classifiers (c) Robust P^n CRF (d) Fully connected CRF, MCMC inference, 36 hrs (e) Fully connected CRF, our approach, 0.2 seconds

Input Image Predicted Mask 2nd iteration 5th iteration 10th iteration Ground Truth

As a post-processing technique in semantic segmentation firstly.

03 EXPERIMENTIAL RESULTS

Dataset Setup

NC2016	Carvalho	Columbia
280 samples	100 samples	180 samples
532k patches	45k patches	15k patches

For each dataset:

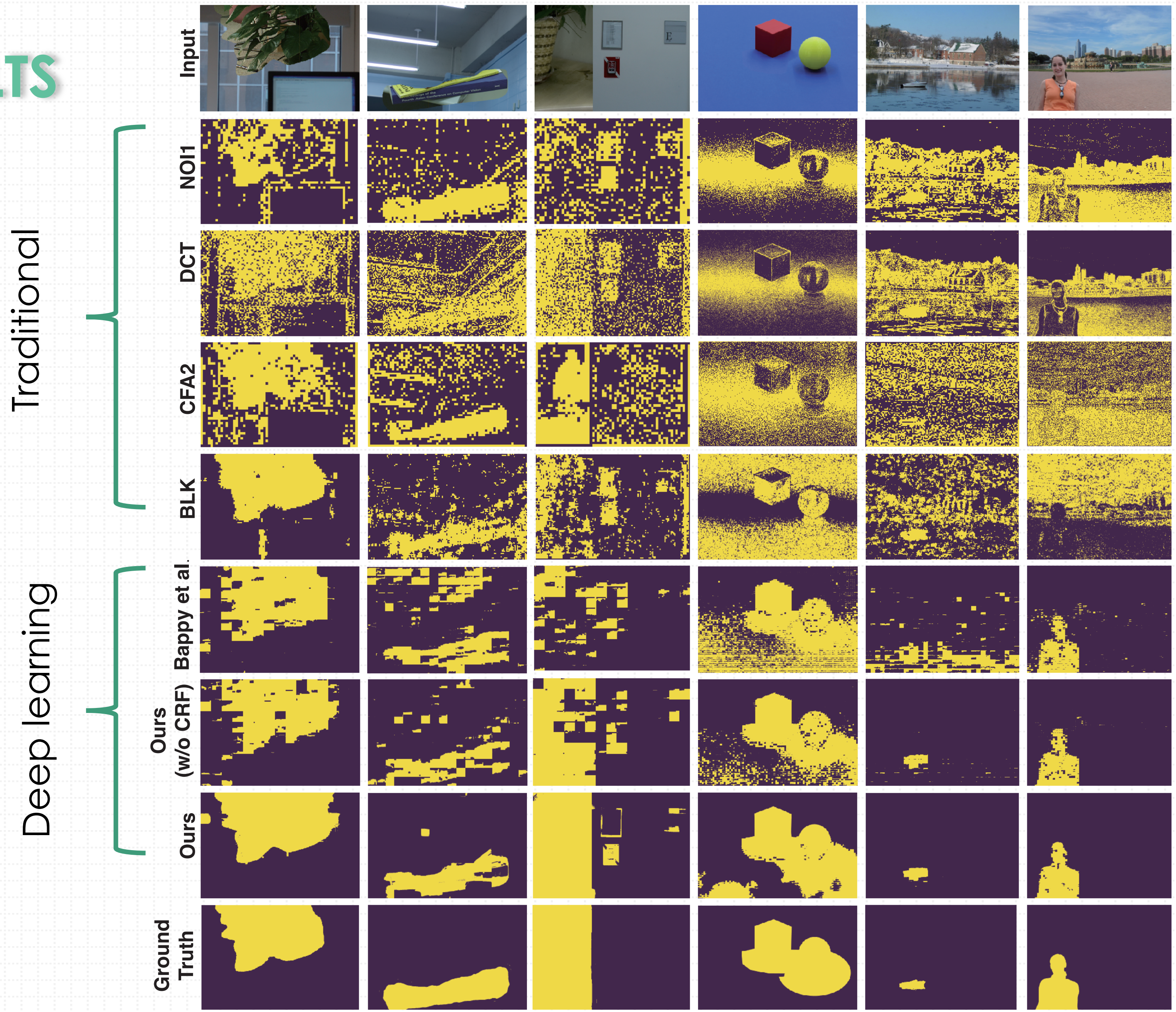
- Training: 65%
- Validation: 15%
- Testing: 30%

03 EXPERIMENTAL RESULTS

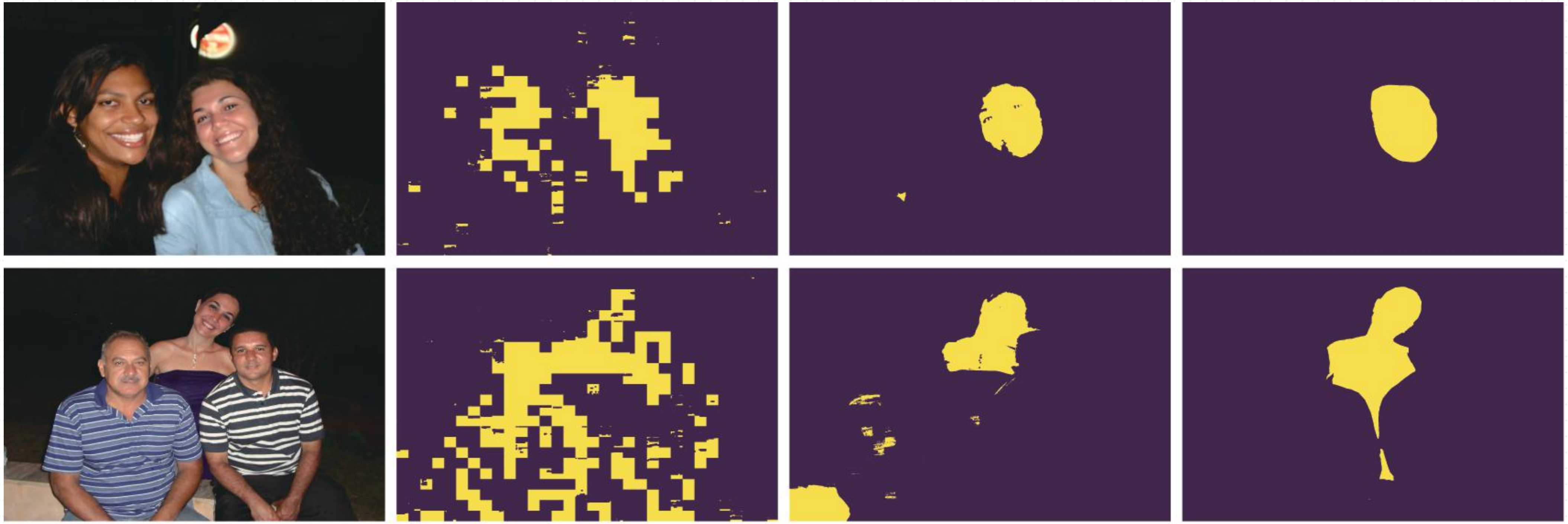
Metrics	Methods	NC2016[58]	Carvalho[59]	Columbia[60]
F_1	MFCN* [6]	0.5707	0.4795	0.6117
	Bappy et al.[15]	0.6242	0.3102	0.5270
	Ours(w/o CRF)	0.7174	0.4236	0.5956
	Ours	**0.7900**	**0.5006**	**0.6482**
MCC	MFCN*[6]	0.5703	0.4074	0.4792
	Bappy et al.[15]	0.6257	0.1882	0.5074
	Ours(w/o CRF)	0.7101	0.3309	0.5557
	Ours	**0.7847**	**0.4379**	**0.6403**

Bappy et al: Bappy, J.H., Roy-Chowdhury, A.K., Bunk, J., Nataraj, L., Manjunath, B.: **Exploiting spatial structure for localizing manipulated image regions.** ICCV,2017

MFCN: Salloum, Ronald, Y.R., Kuo, C.C.J.: Image splicing localization using a multi-task fully convolutional network arXiv preprint arXiv:1709.02016 (2017)



03 EXPERIMENTAL RESULTS on Carvalho Dataset



Probe Image | Bappy et al. | Ours | Ground Truth

Carvalho dataset exploits subtle inconsistencies in the color of the illumination of images. This can be though as a global feature. Our method can detect the spliced region by comparing the patches with global feature while Bappy et al. only detect the local region

03 EXPERIMENTAL RESULTS (Evaluation)

	Bappy et al.[15]	Ours
NC2016 dataset [58]	95.89%/89.53%	**97.81%/89.60%**
Carvalho dataset[59]	68.57%/53.80%	**83.69%/75.10%**
Columbia dataset [60]	85.02%/77.95%	**89.72%/83.90%**

The evaluation of classification/segmentation results on three different datasets.

03 EXPERIMENTAL RESULTS (Evaluation)

Global Network

Local Network

Loss Function

Post-Processing

	F_1 Score	*MCC*
Ours w/o CRF (Label)	0.5467	0.5305
Ours w/o CRF (Mask)	0.5956	0.5557
Ours w/o smooth term	0.6416	0.5863
baseline	0.5270	0.5074
Ours (0.25:1)	0.6287	0.6224
Ours (0.5:1)	0.6281	0.5255
Ours (2:1)	0.6258	0.6204
Ours (1:1)	**0.6482**	**0.6403**

Publication:

X. Cun and **C.-M. Pun**, “Image Splicing Localization via Semi-Global Network and Fully Connected Conditional Random Fields,” *Proceedings of European Conference on Computer Vision (ECCV) Workshops*, 2018.

THANK YOU!