

Lithography Hotspot Detection by Two-stage Cascade Classifier using Histogram of Oriented Light Propagation

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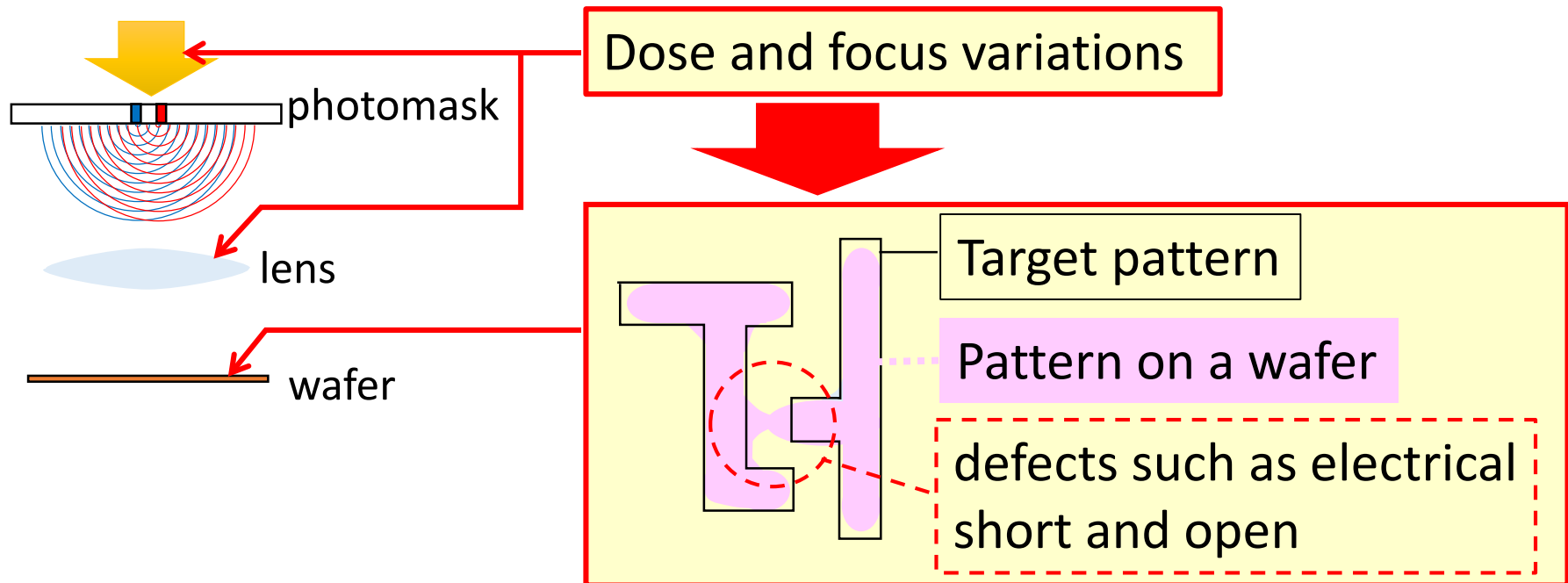
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Backgrounds

Ongoing shrinkage in the size of semiconductor devices degenerates the fidelity of the layout pattern on a wafer



It is essential to detect and repair **lithography hotspots** having high possibility of defects

Existing Methods for Hotspot Detection

1. Lithography simulation

Accurate but **time consuming**

2. Pattern matching (J. Xu et al., ICCAD2007) (Y.-T. Yu et al., DAC2012)

Cannot detect unknown hotspots that are not stored in the library

3. Machine learning (S.-Y. Lin et al., DAC2013) (T. Matsunawa et al., SPIE2015) (Y.-T. Yu et al., TCAD2015)

Train a classifier with hotspot and non-hotspot samples

Can detect unknown hotspots in reasonable time

Has not achieved sufficient accuracy

Goal & Contributions

Our goal:

To realize accurate and fast machine-learning-based hotspot detection

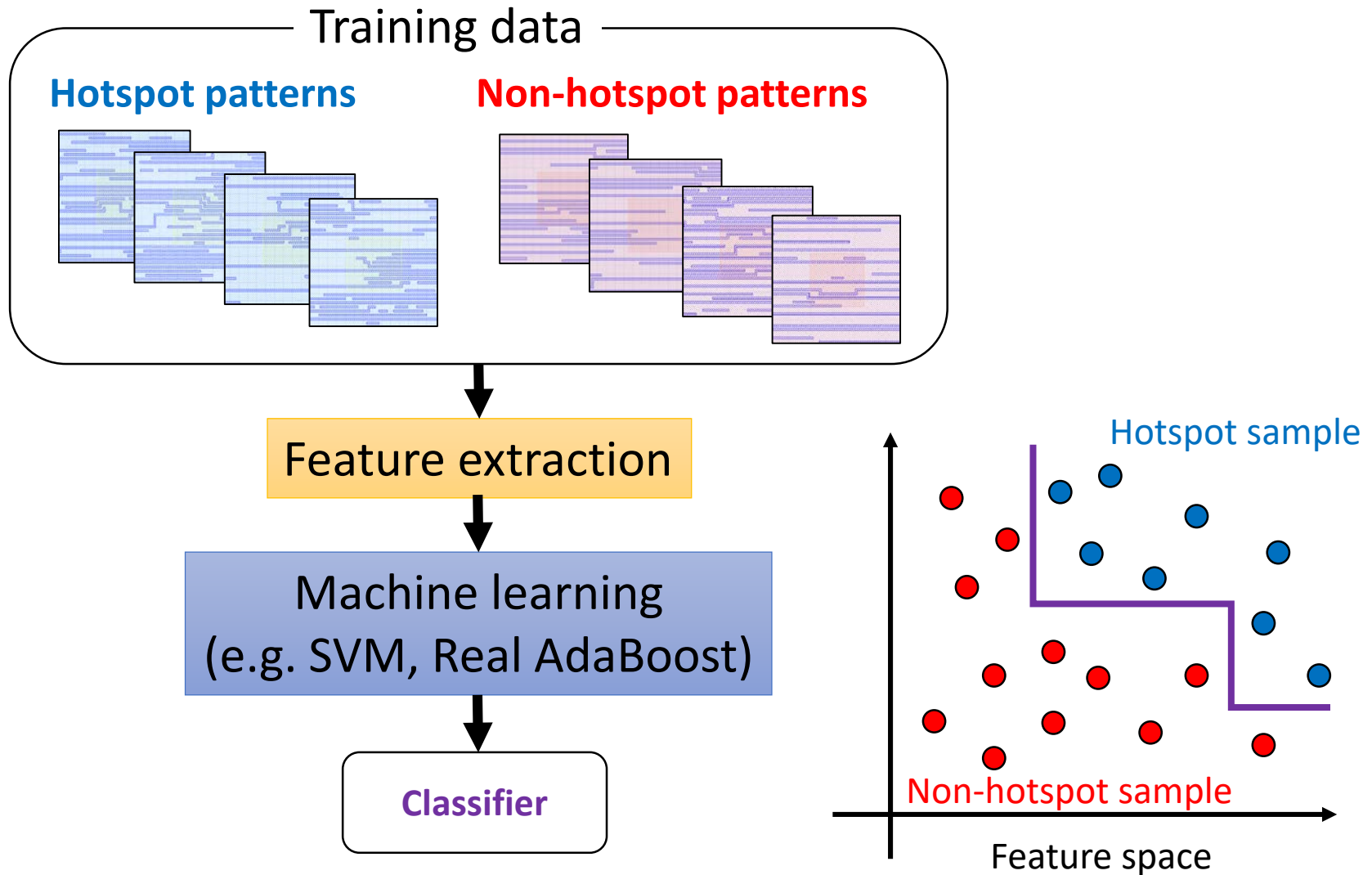
Contributions:

- Novel layout feature named as HOLP
- Two-stage cascade classifier using combination of HOLP and density-based layout feature
- Improvement of detection accuracy compared to existing methods

$$(I1) \frac{\#(\text{correctly detected hotspots})}{\#(\text{actual hotspots})} : 1.15\% \text{ improvement}$$

$$(I2) \frac{\#(\text{correctly detected hotspots})}{\#(\text{false hotspots})} : 24.4 \text{ times improvement}$$

Classifier Construction for Hotspot Detection



Existing Layout Feature

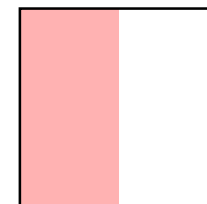
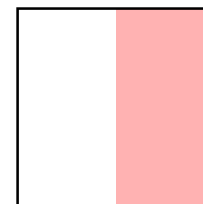
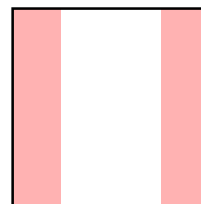
Density-based layout feature (DBLF)

(J.-Y. Wu, et al., ASPDAC2011)

Calculate the density of the layout pattern in each subregion

0.316	0.316	0.274	0	0	0	0	0	0	0
0.414	0.45	0.441	0.383	0.383	0.277	0	0	0	0
0.758	0.758	0.758	0.758	0.758	0.758	0.758	0.758	0.758	0.758
0.25	0.25	0.25	0.545	0.575	0.575	0.575	0.575	0.575	0.575
0	0	0	0.505	0.484	0.441	0.441	0.441	0.441	0.441
0.458	0.448	0.075	0.548	0.336	0.383	0.39	0.075	0.008	0.373
0.633	0.633	0.633	0.578	0.225	0.515	0.605	0.633	0.36	0.431
0.058	0.064	0.441	0.441	0.396	0.432	0.441	0.441	0.441	0.24
0.024	0.391	0.391	0.391	0.391	0.391	0.391	0.391	0.088	0.008
1	1	1	1	1	1	1	1	1	1

Cannot distinguish
different patterns of the same density



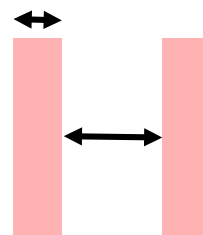
Geometry-related and lithography-process-related features

(Y.-T. Yu *et al.*, TCAD2015)

1. Classify layout patterns according to their topologies
2. Construct a classifier for each topology class

Geometry-related features such as

- pattern width
- space width



Lithography-process-related features such as

- # of corners
- DBLF

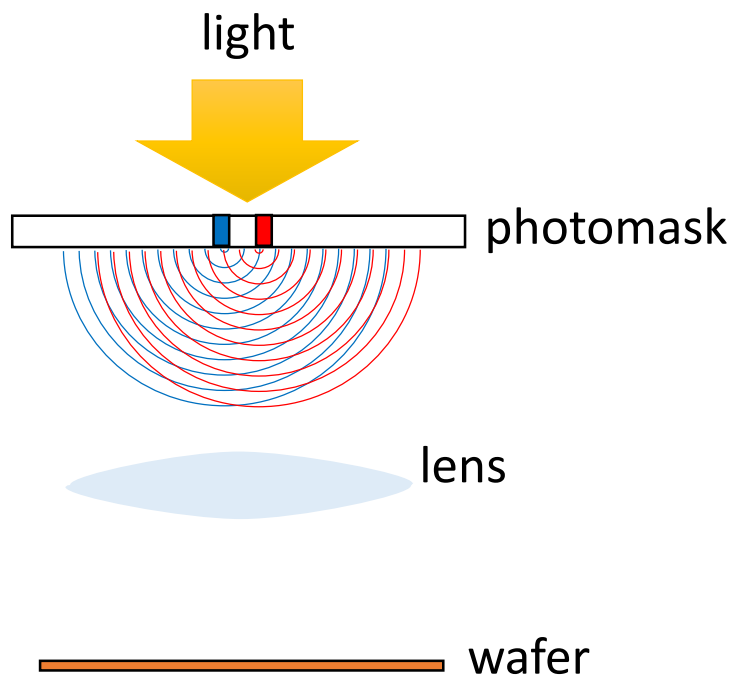
Detection accuracy is not sufficient

More suitable features are required for hotspot detection

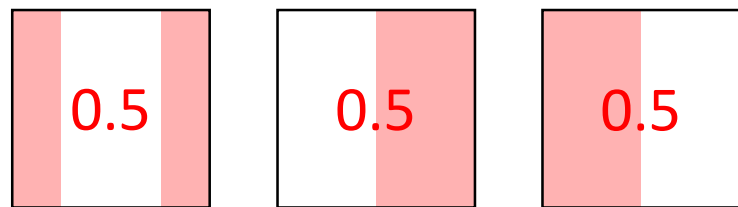
Feature of Our Proposed Classifier

Defects depend on light passing through a photomask

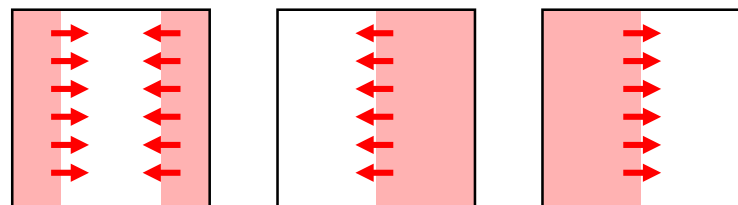
Both the amount and direction of the light are important



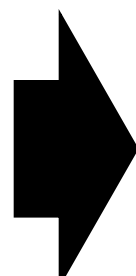
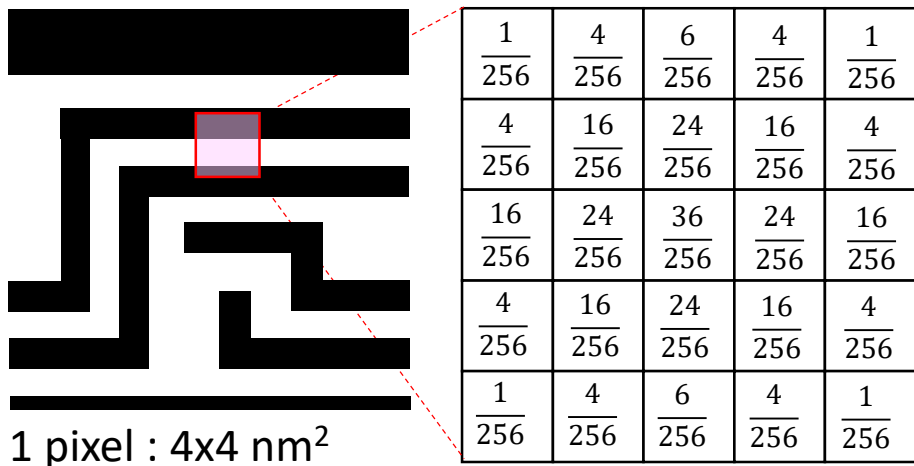
DBLF represents the amount of light passing through a photomask



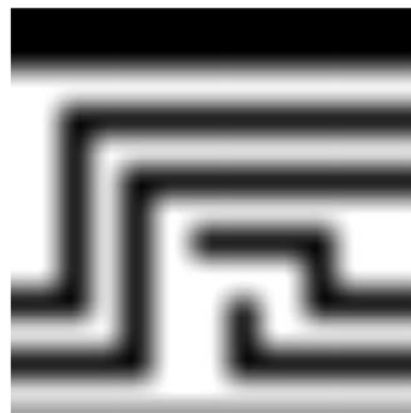
We propose a novel layout feature representing the direction of light propagation



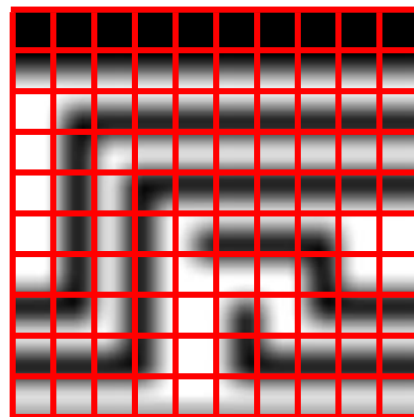
Histogram of Oriented Light Propagation (HOLP)



1. Gaussian blur



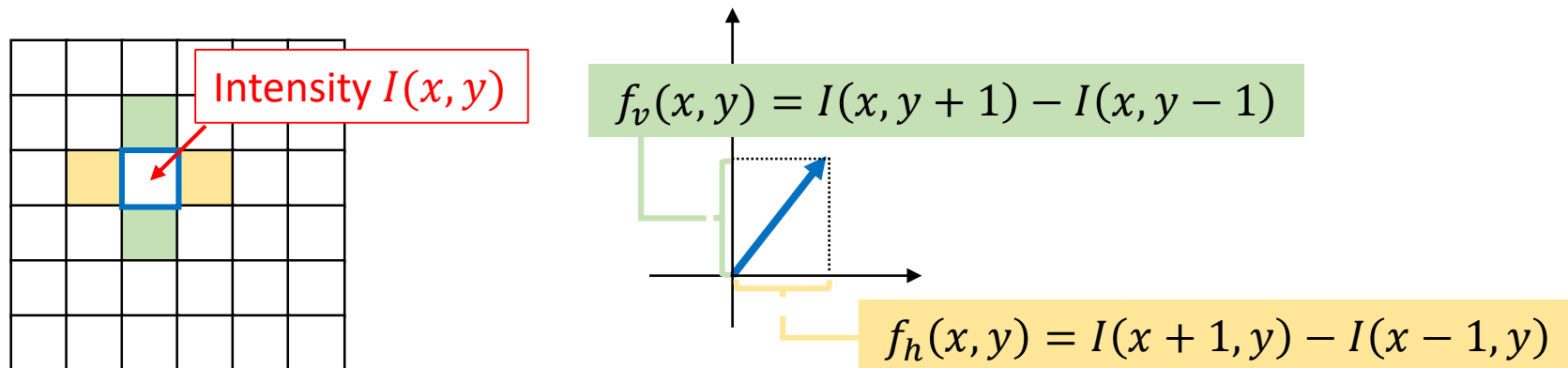
2. Division into 10x10 blocks



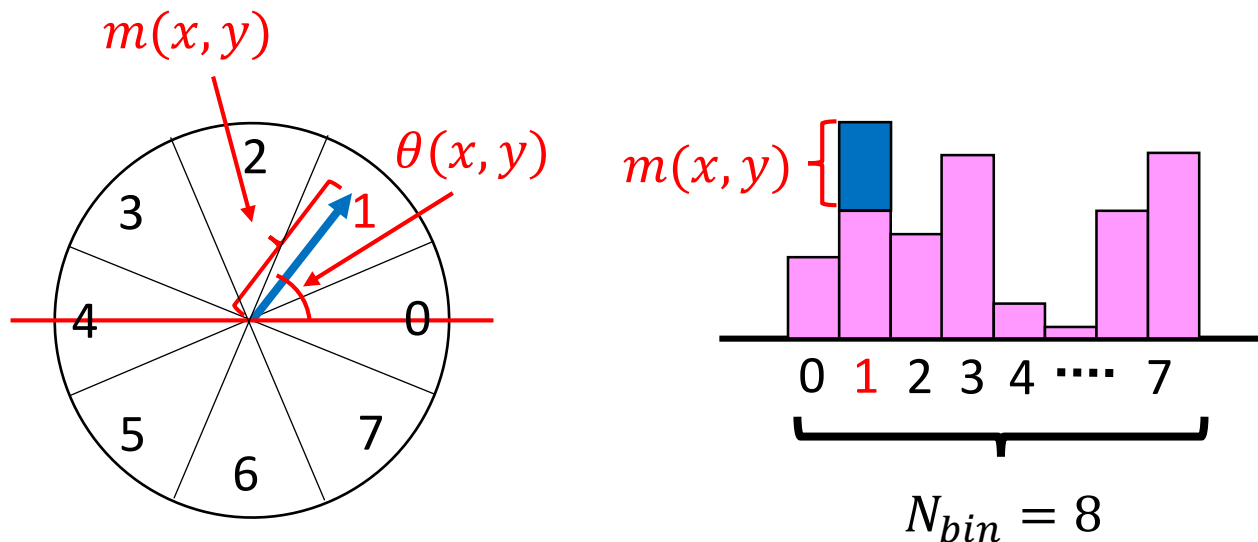
3. Calculation of HOG-like feature



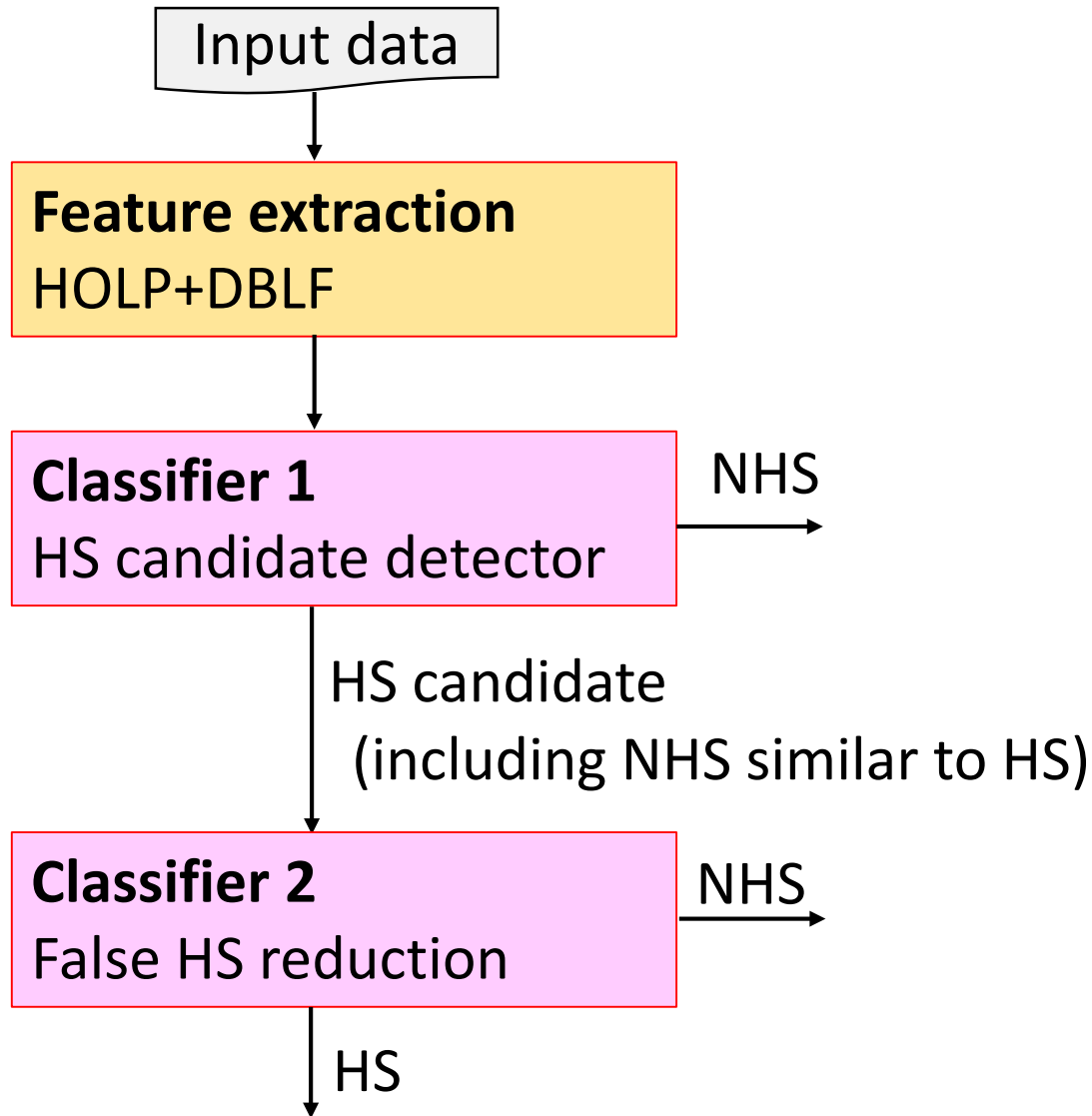
Calculation of HOG-like feature



The histogram of each block is calculated by voting $m(x, y)$ to the bin corresponding to $\theta(x, y)$ for all pixels of the block



Two-stage Cascade Classifier for Hotspot Detection

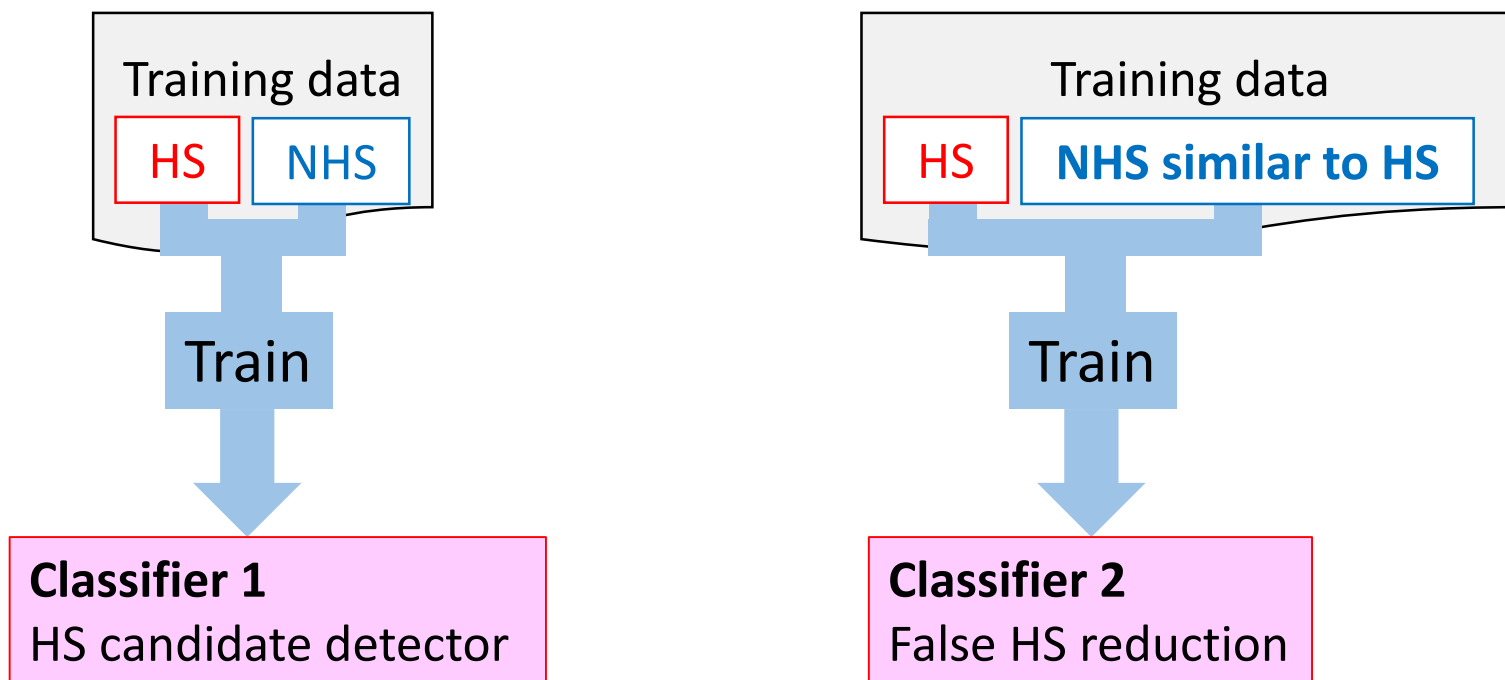


Training of Two-stage Classifier

We employed Real-AdaBoost-based classifier

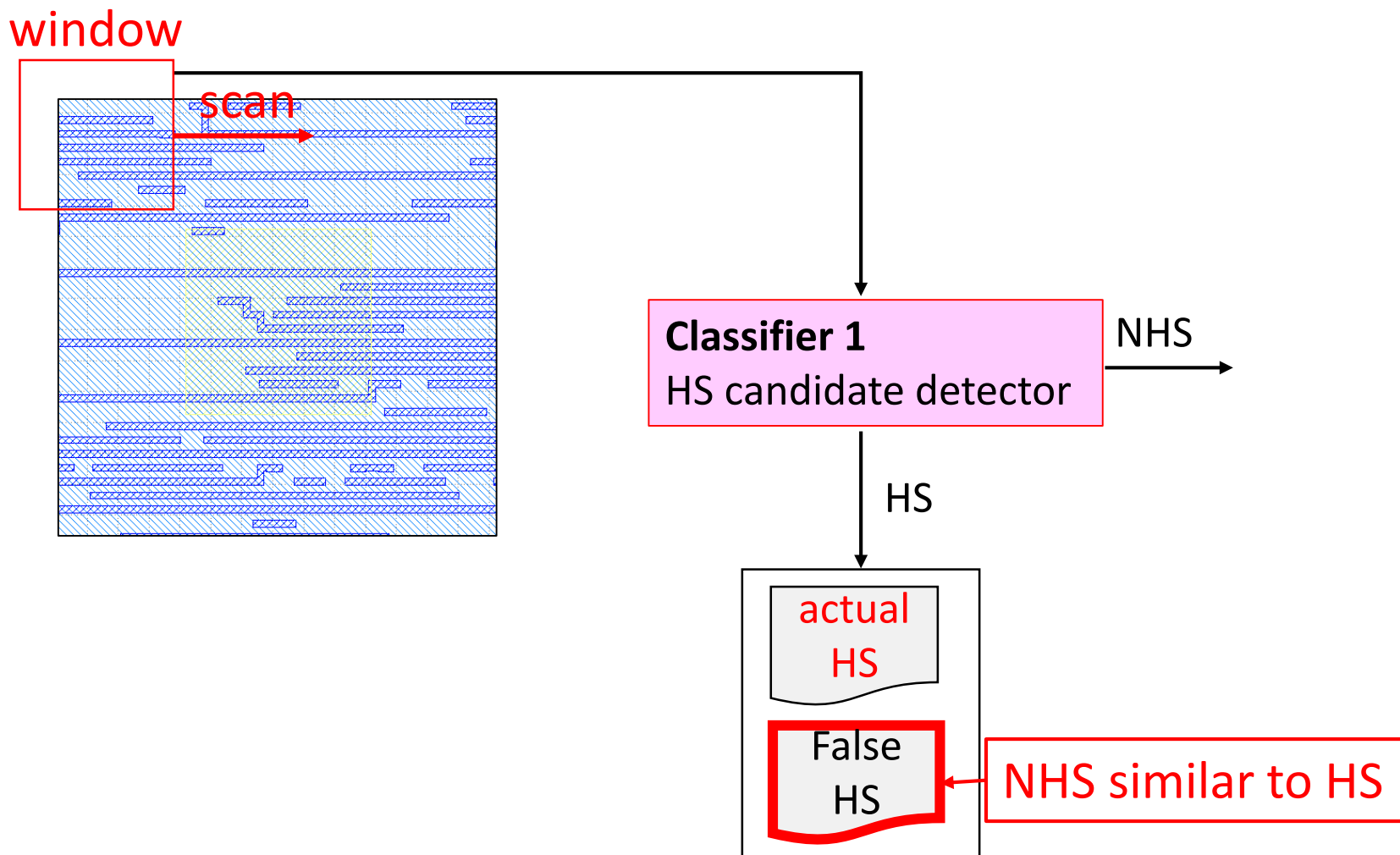
Weak classifiers are decision trees

- Depth: 1--3
- #classifiers: 10--200

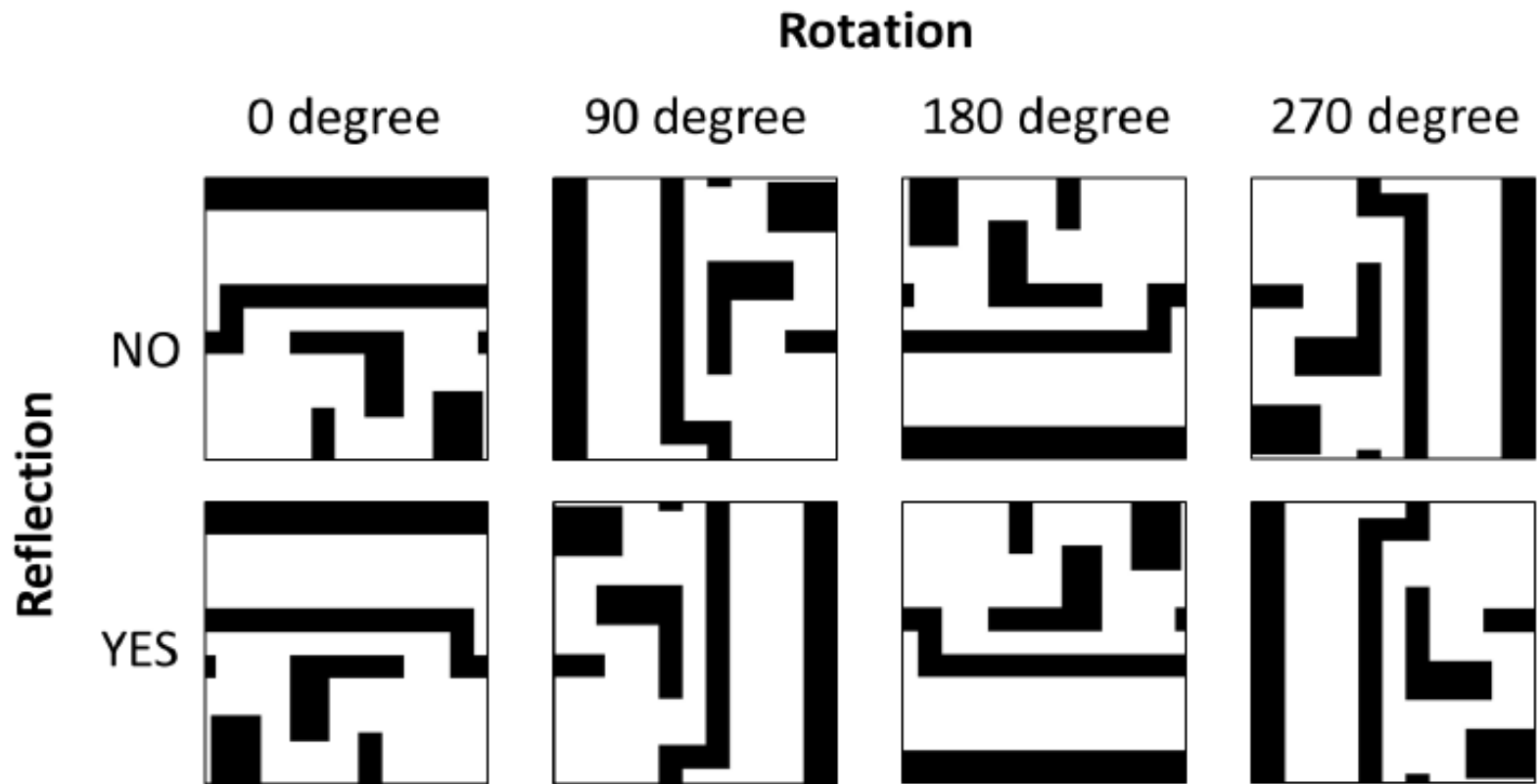


Extraction of NHS similar to HS

Training data



Transformation of Training Data



Experiments

Implementation: the C++ language and CUDA.

Platform:

- a CORE i7-4771 3.5 GHz processor,
- 32 GB memory,
- NVIDIA GeForce GTX 780 (for HOLP and DBLF extraction)

Resolution: $4 \times 4 \text{ nm}^2 = 1 \text{ pixel}$

The area to calculate HOLP: $640 \times 640 \text{ nm}^2$ (10 x 10 blocks)

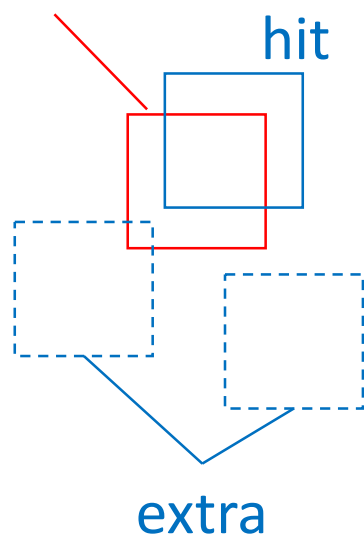
The area to calculate DBLF: $1280 \times 1280 \text{ nm}^2$ (10 x 10 blocks)

ICCAD-2012 CAD contest dataset

data	Training layout data			Test layout data			process
	Name	#hs	#nhs	Name	#hs	area (μm^2)	
data1	MX_benchmark1_clip	99	340	array_benchmark1	226	12,516	32nm
data2	MX_benchmark2_clip	174	5,285	array_benchmark2	499	106,954	28nm
data3	MX_benchmark3_clip	909	4,643	array_benchmark3	1,847	122,565	28nm
data4	MX_benchmark4_clip	95	4,452	array_benchmark4	192	82,010	28nm
data5	MX_benchmark5_clip	26	2,716	array_benchmark5	42	49,583	28nm

Detection Accuracy

Actual hotspot



hit:

if a region sufficiently close to an actual hotspot area

extra (false alarm):

otherwise

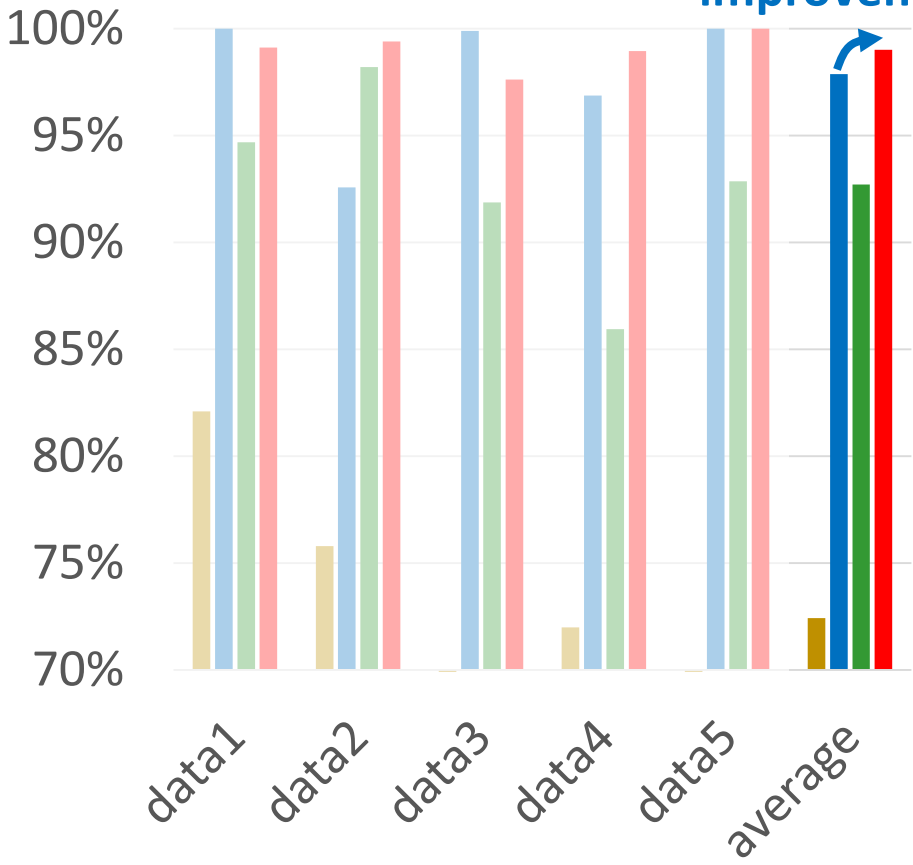
The objective is to maximize the following two indices:

$$(I1) \text{ accuracy} = \frac{\#hits}{\#(actual\ hotspots)}$$

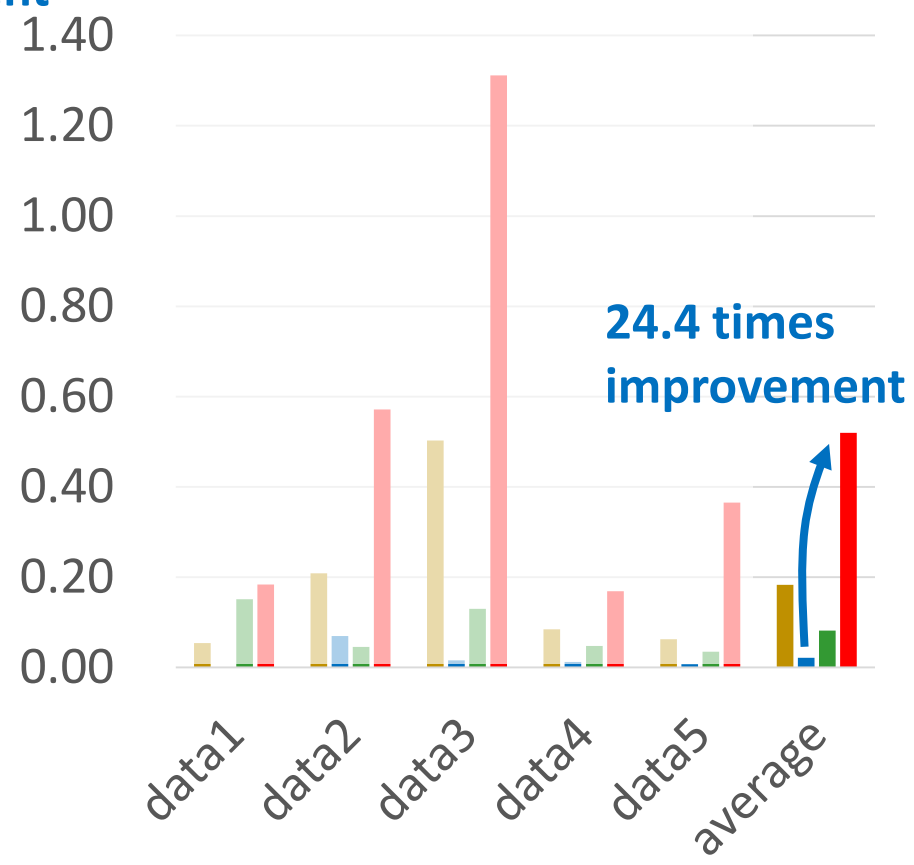
$$(I2) \frac{\#hits}{\#extras}$$

Comparison of Detection Performance

Accuracy **1.15% improvement**



#hits/#extras

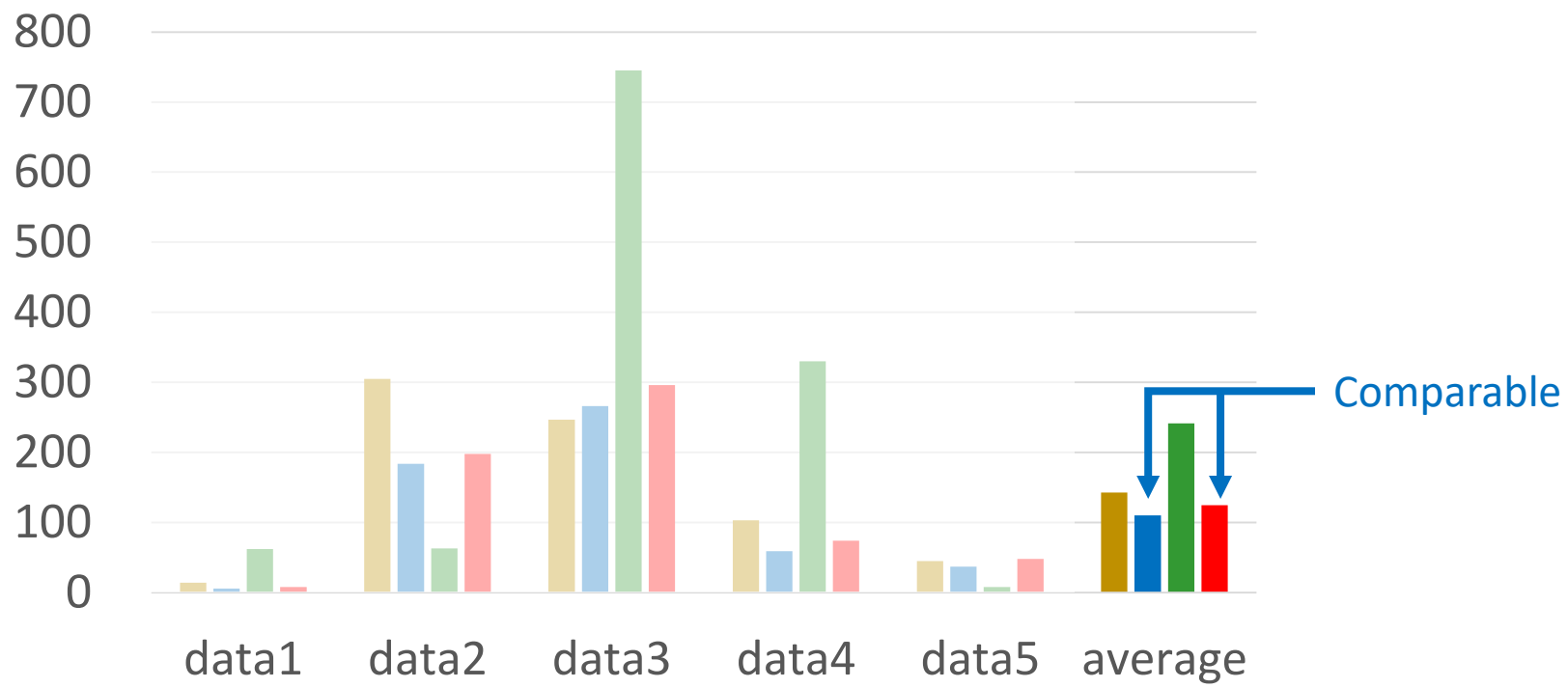


■ S.-Y. Lin et al., DAC13
■ Y.-T. Yu et al., TCAD15

■ Matsunawa et al., SPIE15
■ Ours

Comparison of Runtime

Runtime [sec.]



■ S.-Y. Lin et al., DAC13
■ Y.-T. Yu et al., TCAD15

two 2.3 GHz CPUs,
64 GB memory

■ Matsunawa et al., SPIE15
■ Ours

2.66 GHz quad-core CPU,
8 GB memory

3.5 GHz processor,
 32 GB memory,
 NVIDIA GeForce GTX 780

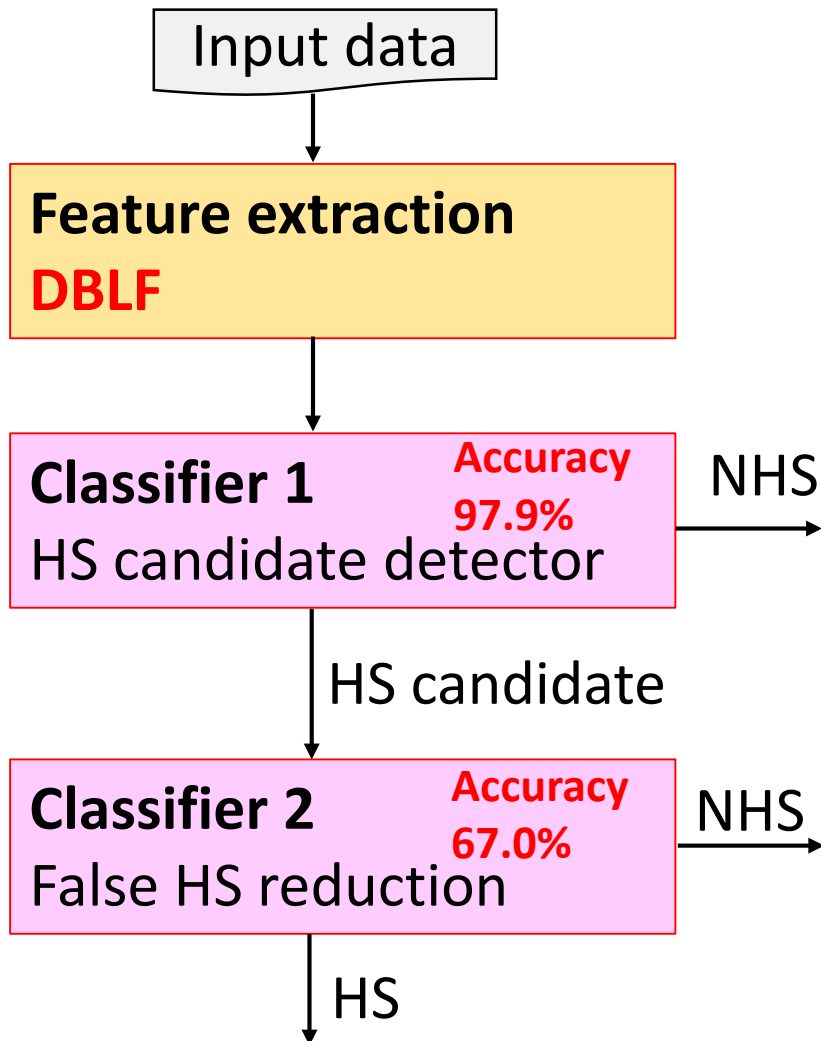
Conclusions

- We proposed a cascade classifier that uses HOLP and density-based layout features for hotspot detection and realized fast and more accurate hotspot detection.
- In future work, we will try to further reduce the execution time by selectively applying the proposed cascade classifier only to hotspot candidates detected by a rough and fast detector

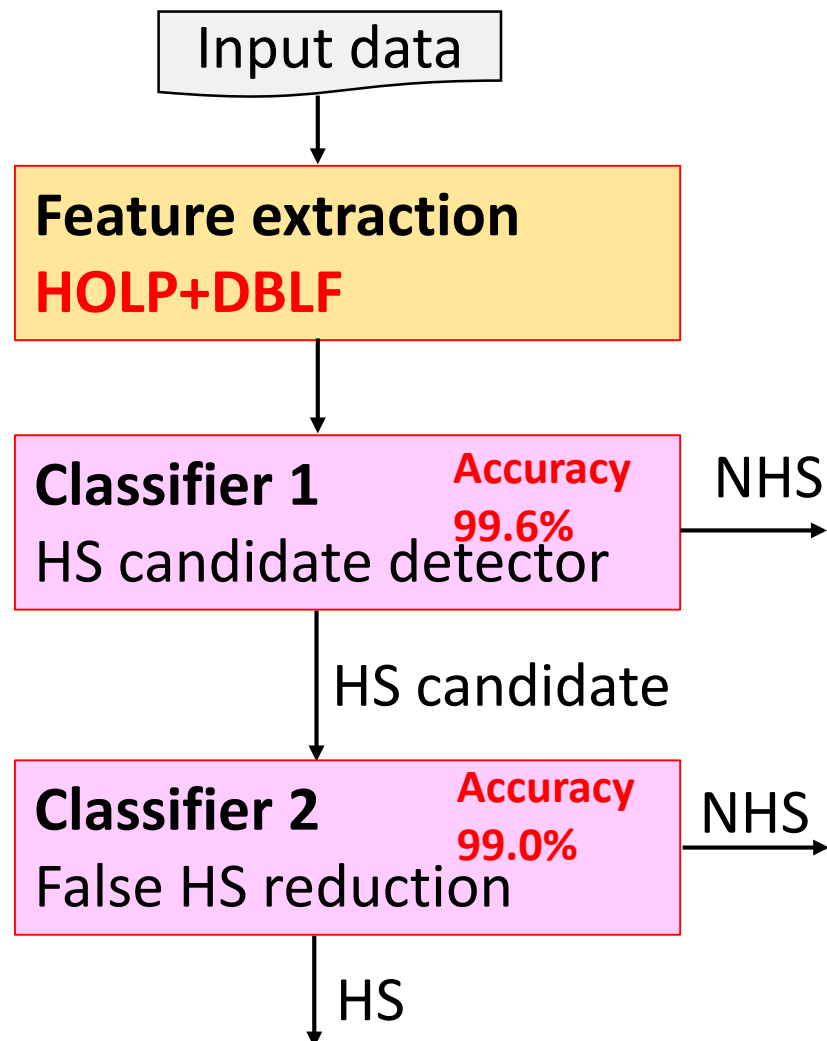
Thank you for your attention!

Accuracy Improvement by HOLP

Two-stage classifier using DBLF

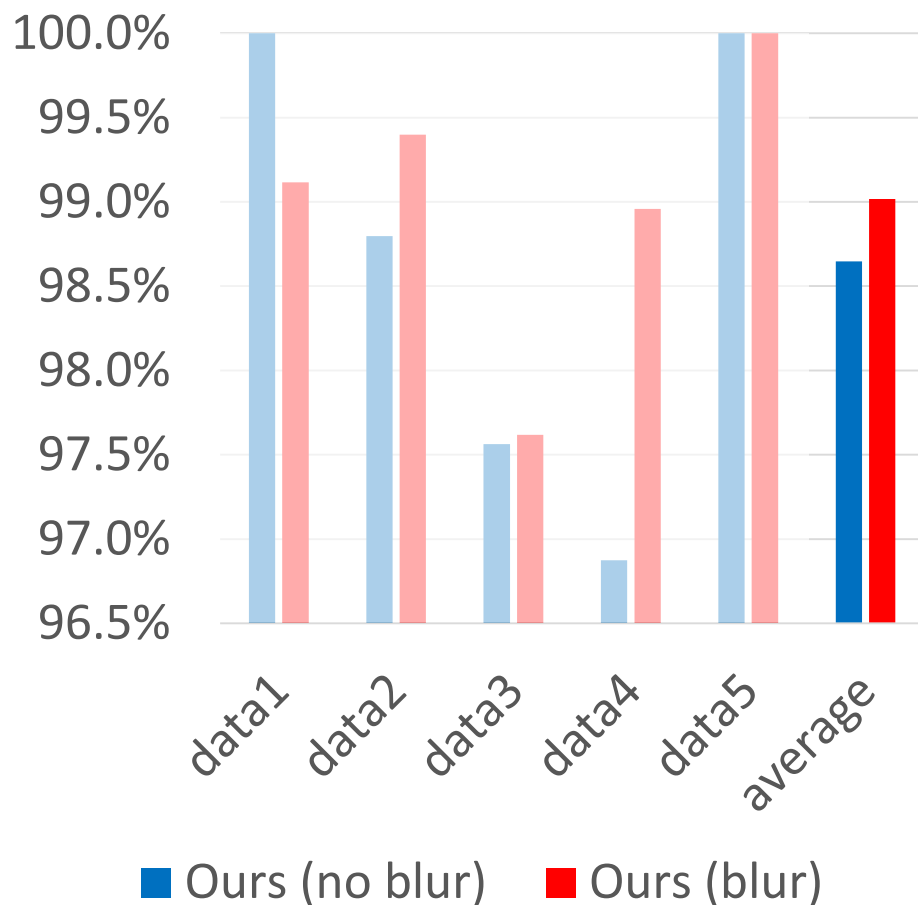


Two-stage classifier using HOLP and DBLF (Proposed method)

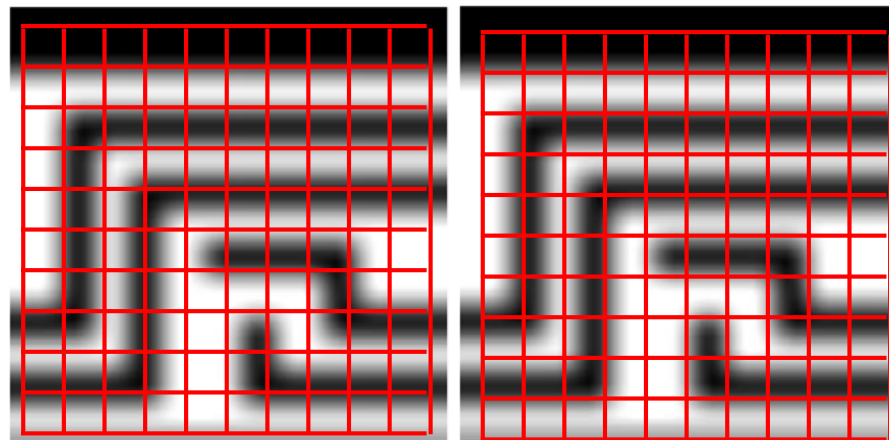


Effects of Gaussian Blur

Accuracy



More robust to small shift of input layout pattern



Parameters of Our Experiments

Value	Description
128 nm	Amount of a shift in scanning layout data
640 nm	Side length of a region for HOLP calculation
160	Side length of a pixel is 4 nm
10	Number of blocks in a side for HOLP calculation
3.3 nm	Standard deviation of Gaussian filter
8	Number of bins of histogram in a block
1280 nm	Side length of a region for DBLF
10	Number of blocks in side for DBLF calculation