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CNN-based ship classification method incorporating SAR geometry information

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Motivation

Ship classification enhances the performance of maritime surveillance

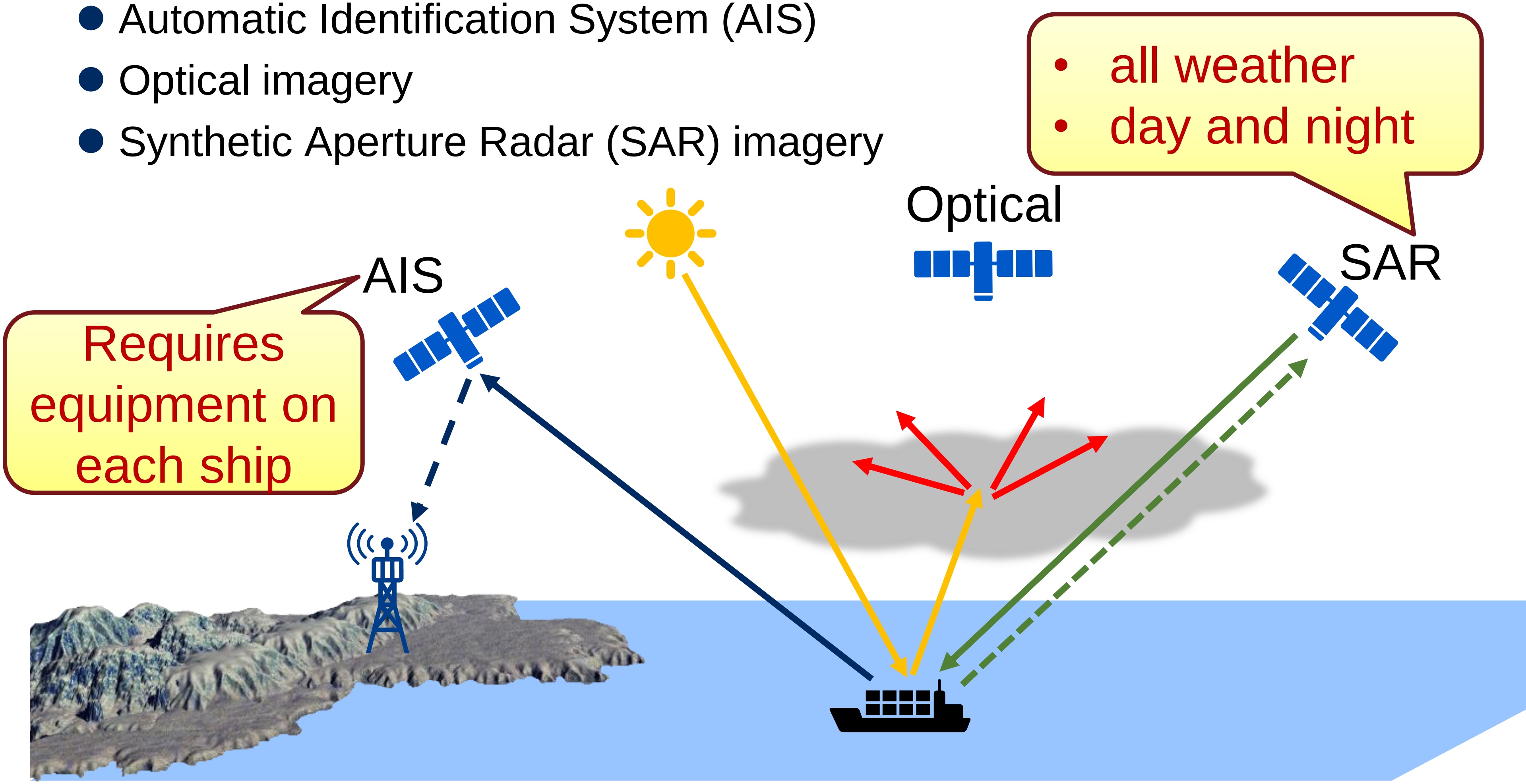
Helps in quick identification of vessels involved in illegal activities

An accurate ship classification technology is needed

Ship Monitoring from Space

3 major sources of information:

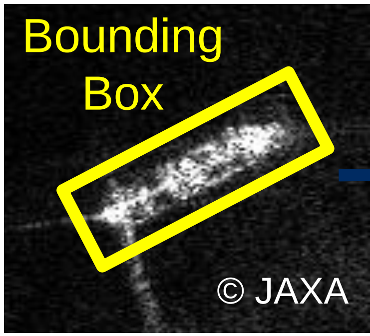
- Automatic Identification System (AIS)
- Optical imagery
- Synthetic Aperture Radar (SAR) imagery



SAR images are now preferable for ship classification

Existing SAR Ship Classification Methods

1. Hand-crafted Features (HCF)-based



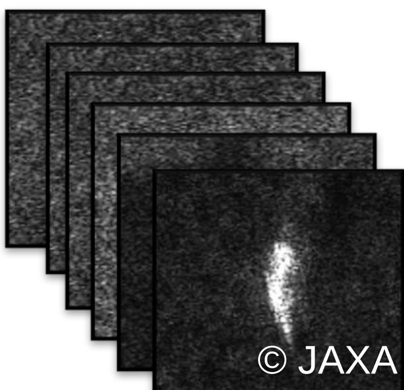
Feature* extractor → Classifier (SVM) → Class

*Length, Area, Intensity, … etc.

Pros
- Intuitive features

Cons
- Requires expert knowledge of ships

2. Convolutional Neural Network (CNN)-based



CNN → Class

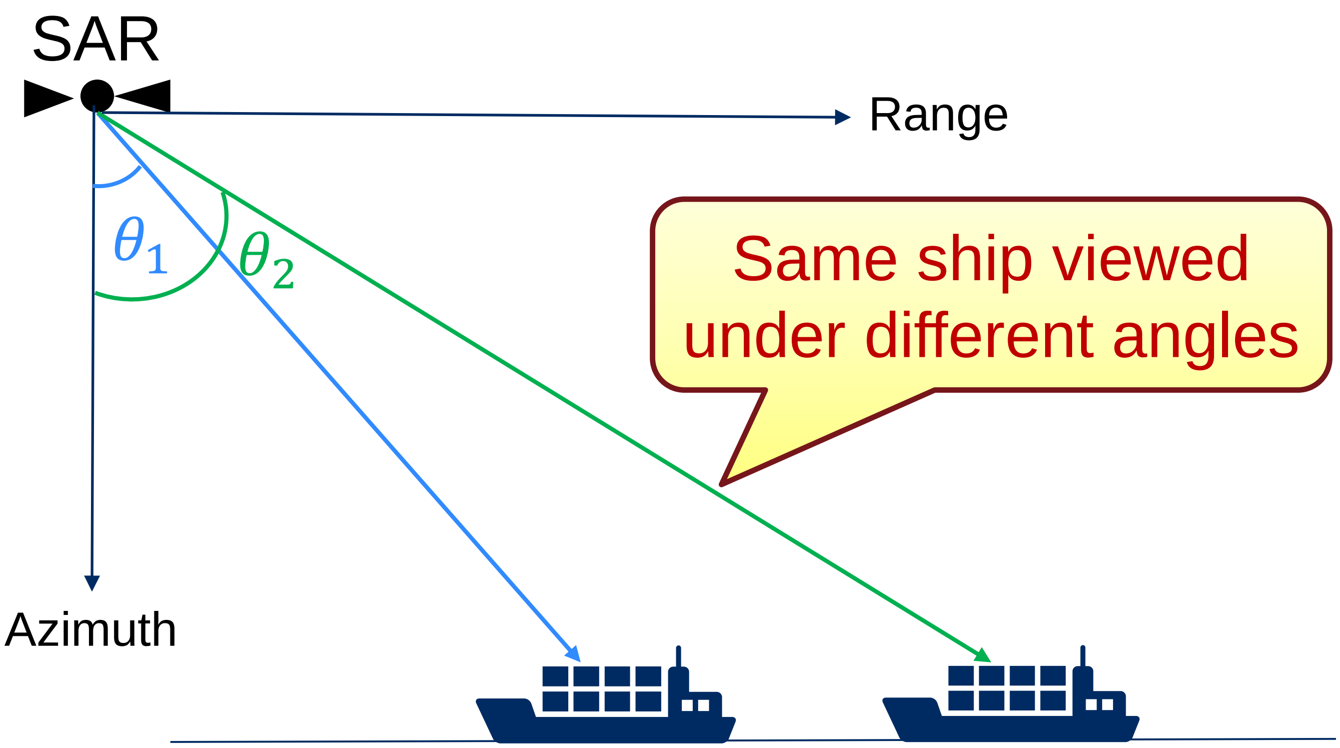
Pros
- Does not require expert knowledge

Cons
- Requires huge training data

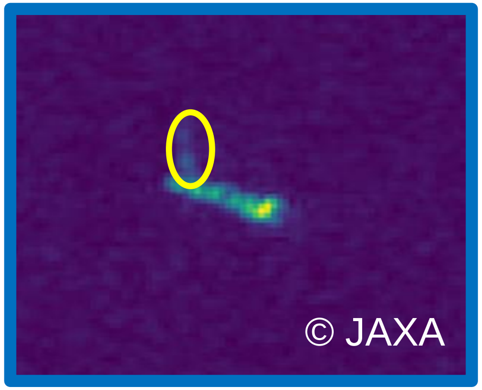
These methods classify a ship based on its appearance

Appearance of a ship varies with SAR geometry

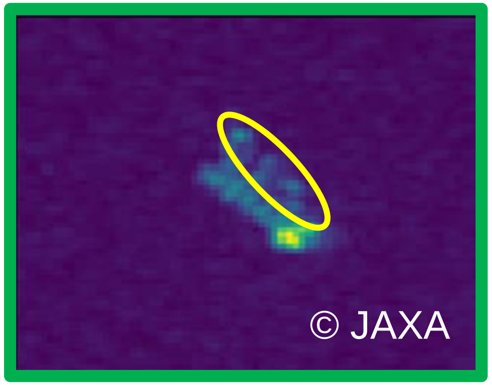
Example:



$\theta_1 = 30^\circ$



$\theta_2 = 40^\circ$



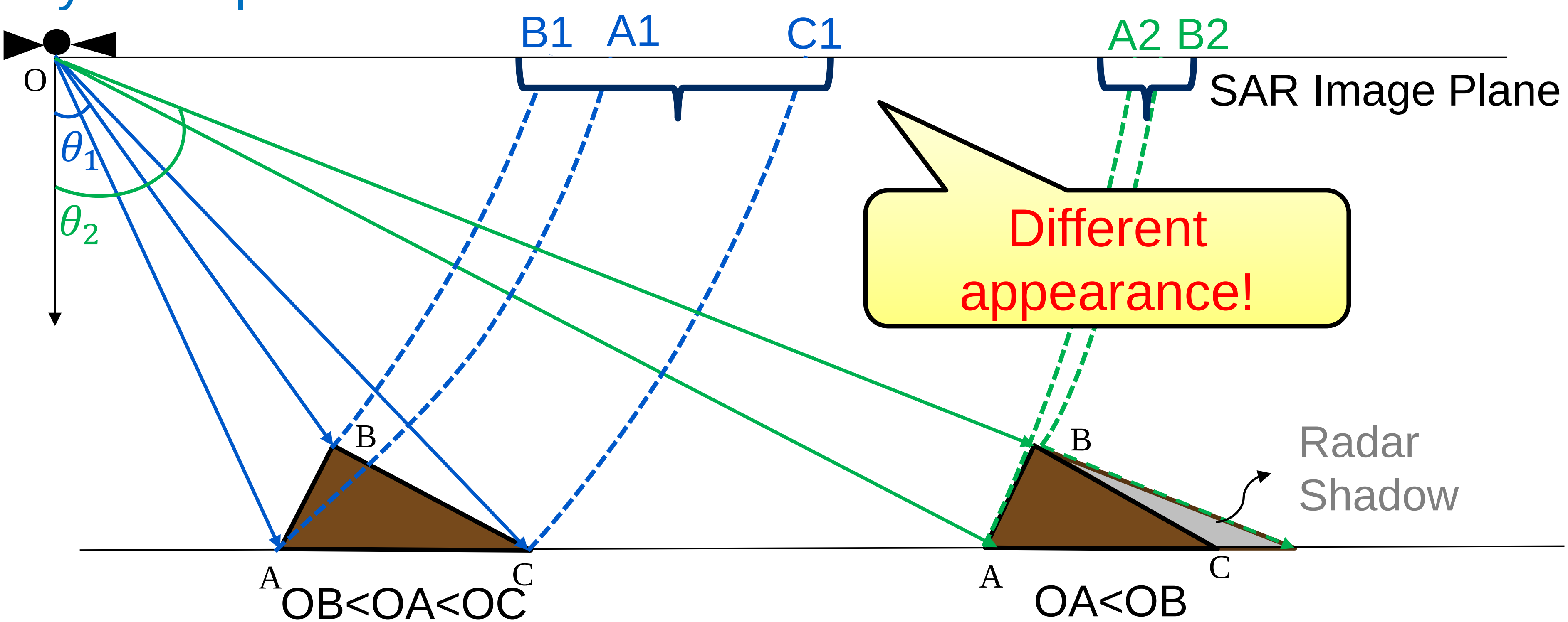
Appearance information is not sufficient to achieve robust classification

Relationship between Appearance and SAR geometry

Incident angle (θ) is a key SAR geometry information which directly affects the appearance of a ship

θ changes the imaging order of the major scattering points

Toy Example:

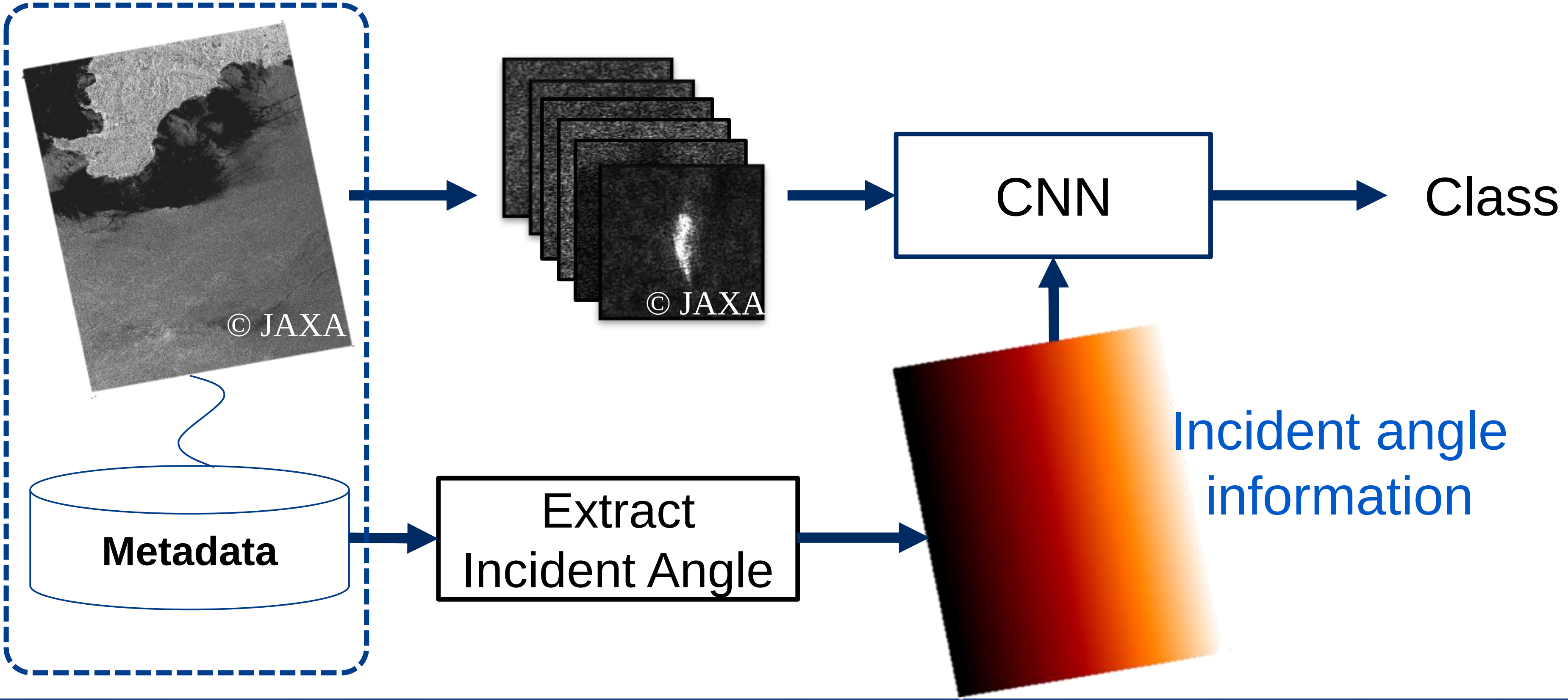


Incident angle indicates how appearance of a ship varies

Proposed Solution

Use incident angle as an additional information in a CNN

Helps the CNN to combine feature information and geometry information in feature space



CNN can follow SAR geometry changes

Representation of Incident Angle Information

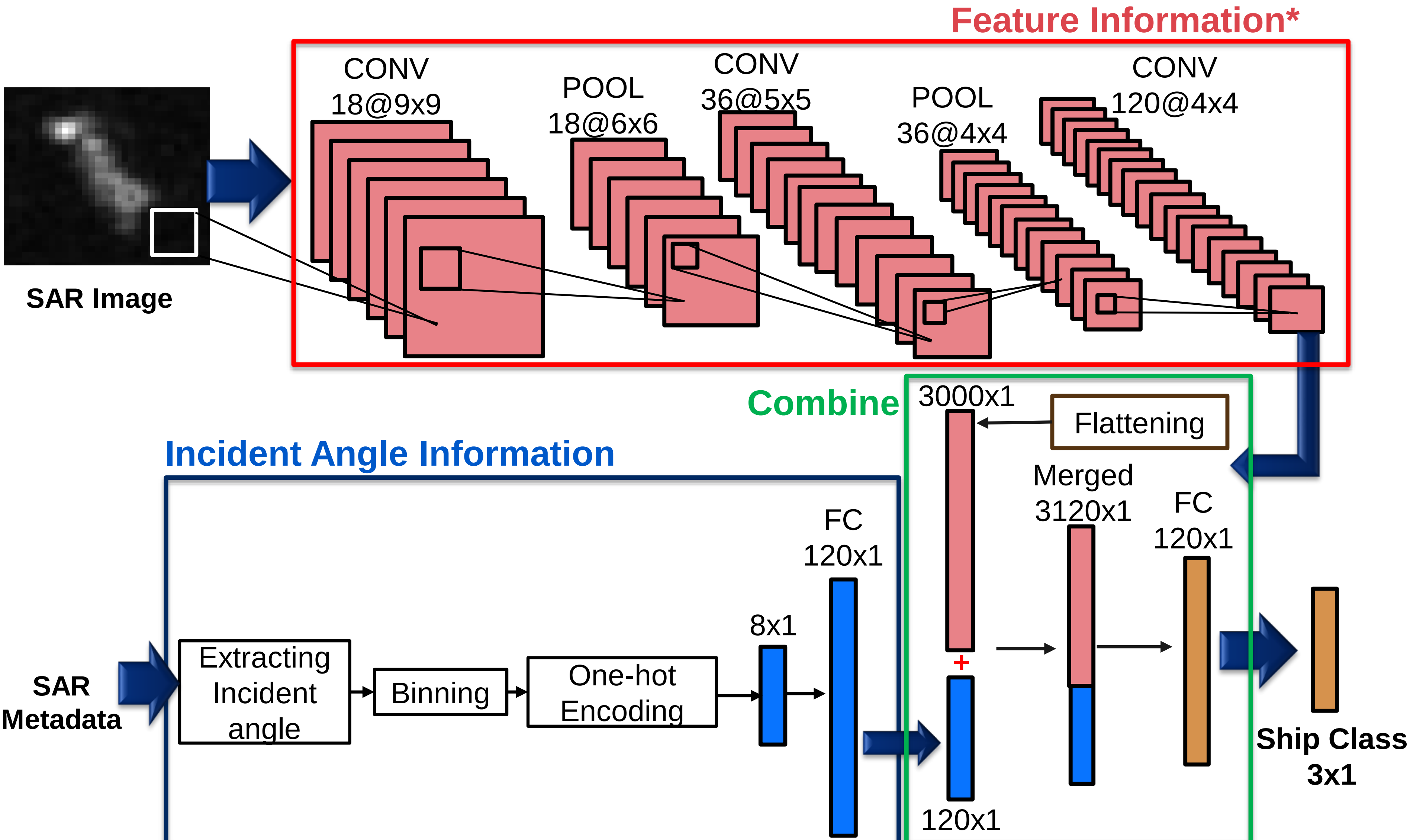
EX) Bin 1: [25° - 27°)
Bin 2: [27° - 29°)
⋮
Bin 8: [39° - 40°)

Incident Angle → Binning → One-hot encoding → Angle Info.

EX) Bin 1: 1 0 0 0 0 0 0 0
Bin 2: 0 1 0 0 0 0 0 0
⋮
Bin 8: 0 0 0 0 0 0 0 1

Binning and one-hot encoding reduces the real-valued angles to discrete labels which accelerates CNN training

Network of Proposed Method



* Bentes, C., Velotto, D. and Tings, B., "Ship classification in terrasar-x images with convolutional neural networks," IEEE Journal of Oceanic Engineering 43(1), 258-266 (2018)

Evaluation

Test 1: Classification performance

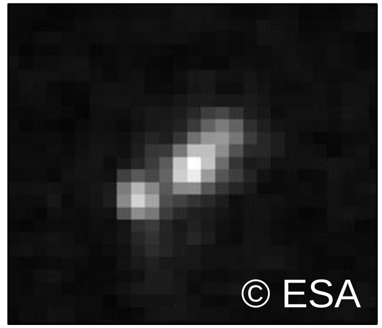
- Accuracy
- F-measure

Test 2: Dependence on training data size

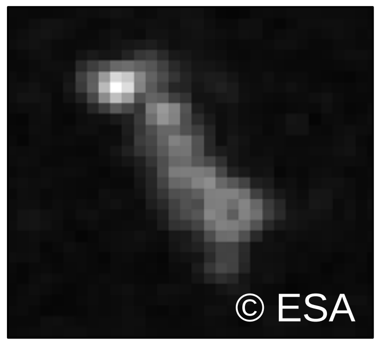
Experimental Set-up

Dataset: OpenSARShip*

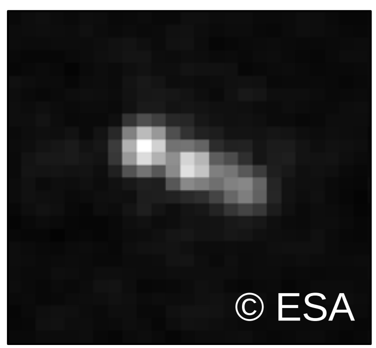
Container



Bulk-carrier



Tanker



Specifications

Satellite	Sentinel-1
Resolution	20m
Polarization	HH
Image size	128x128
No. images	200/class
Ground truth	AIS + Marine Traffic

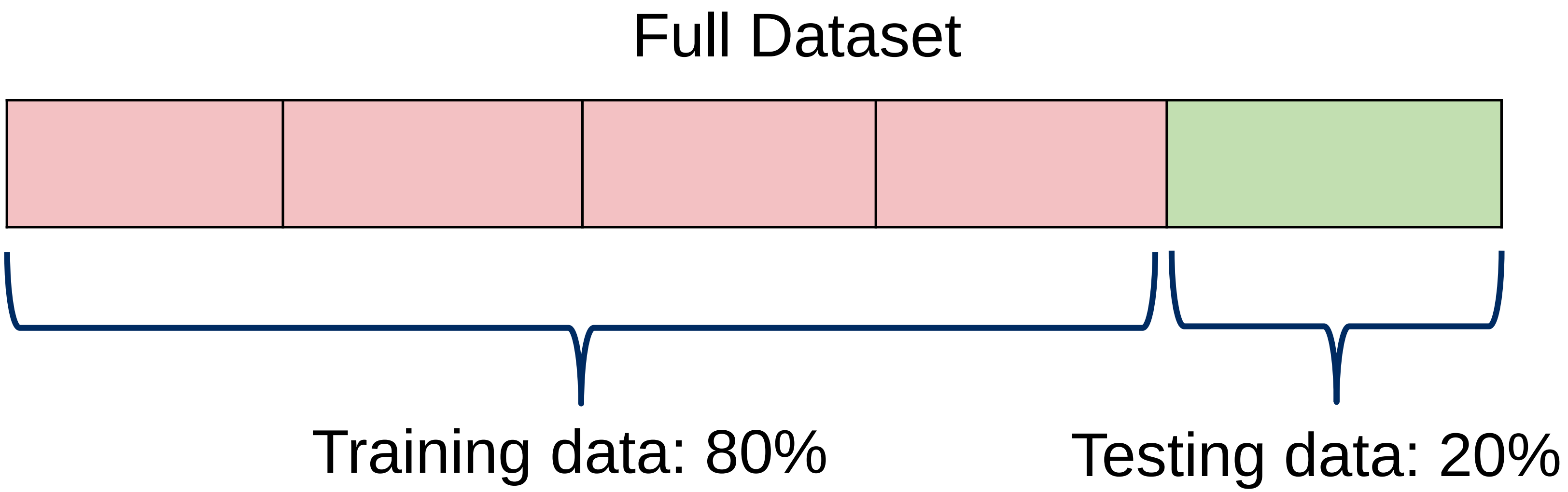
Conventional Methods

HCF	10 Features + SVM
CNN	w/o incident angle

*Huang, L et al., "OpenSARShip: A dataset dedicated to Sentinel-1 ship interpretation," IEEE Journal of Sel. Top. in App. Earth Obs. and Rem. Sen. 11(1), 195-208 (2018).

Network Training and Testing

- Five-fold cross-validation

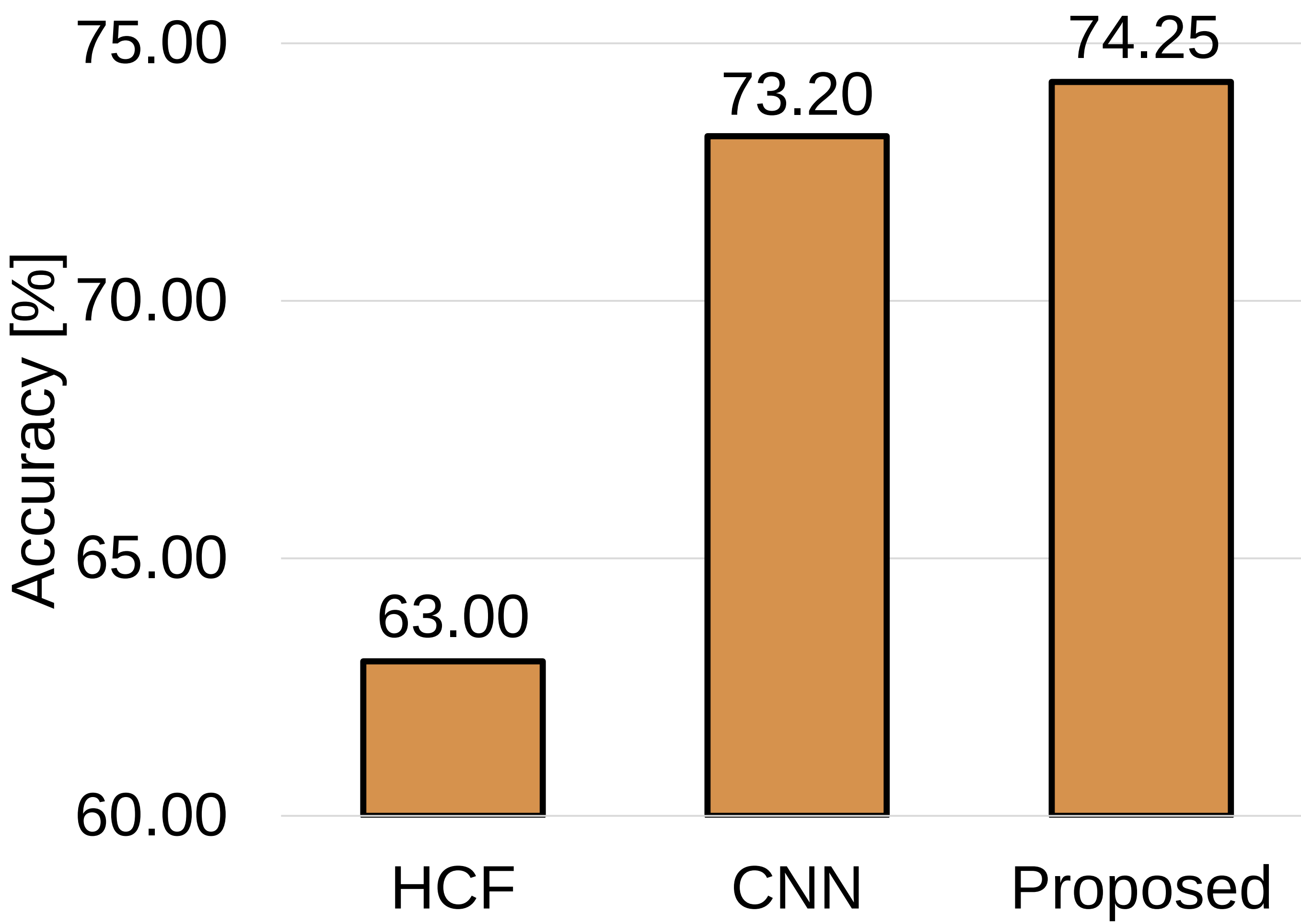


- Training data split into: 80%, 66%, 50%, 25%, 20% of full dataset to evaluate the effect of training data size

- 10 initial random seeds

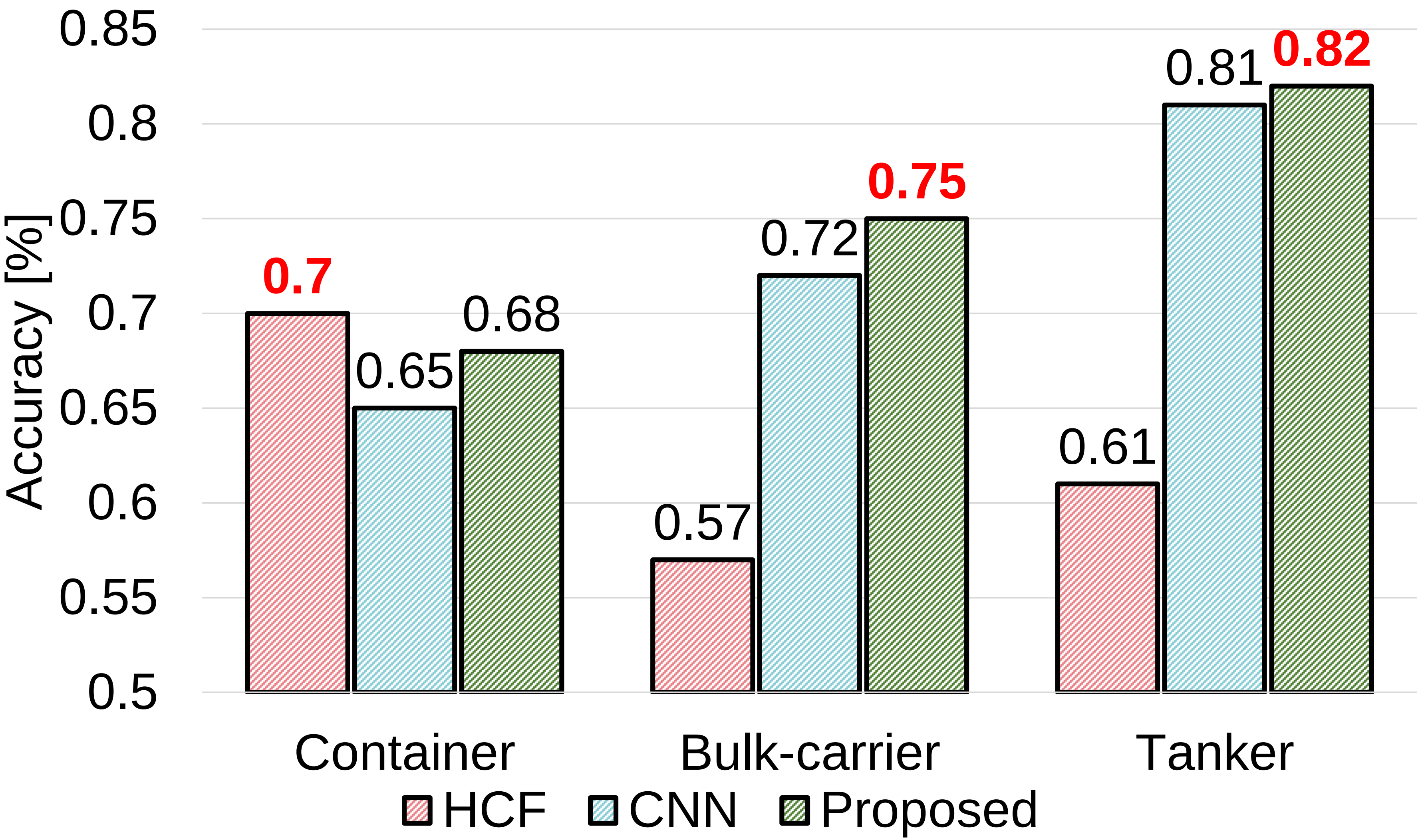
Result 1: Classification Accuracy (Overall)

Results are averaged over 10 initial seed values



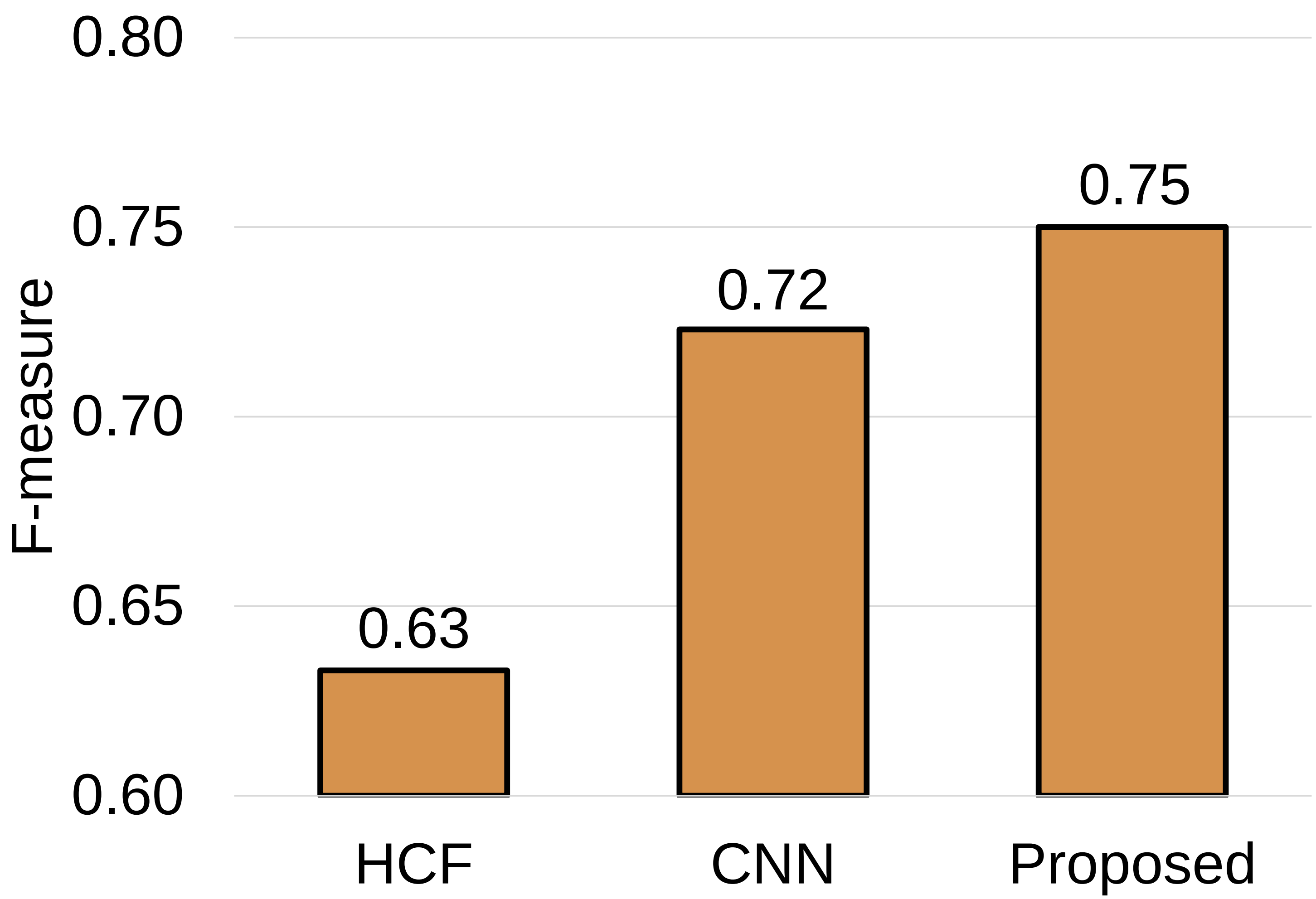
Proposed method outperforms the conventional methods

Result 2: Classification Accuracy (Each class)



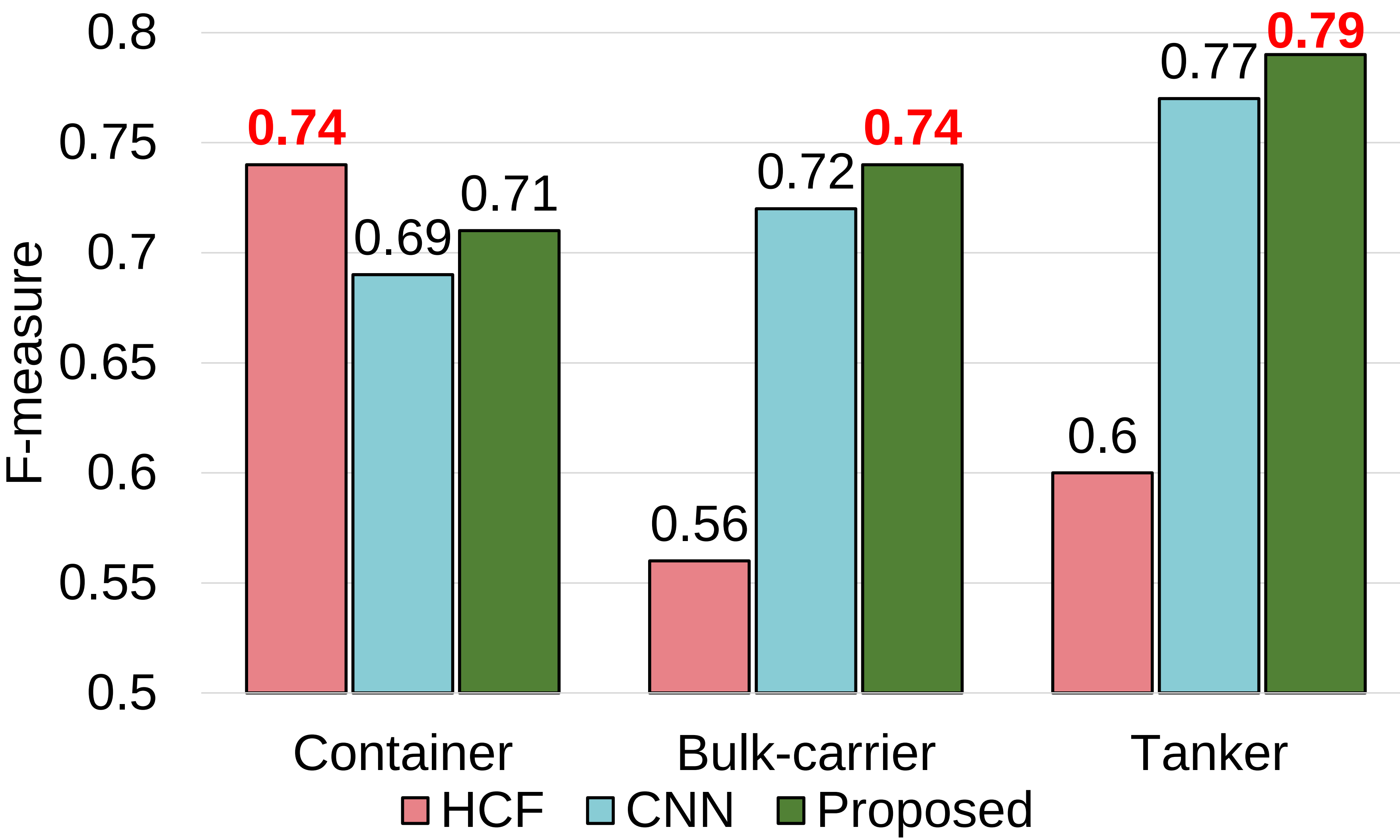
Accuracy of bulk-carrier and tanker has improved

Result 3: F-measure (Overall)



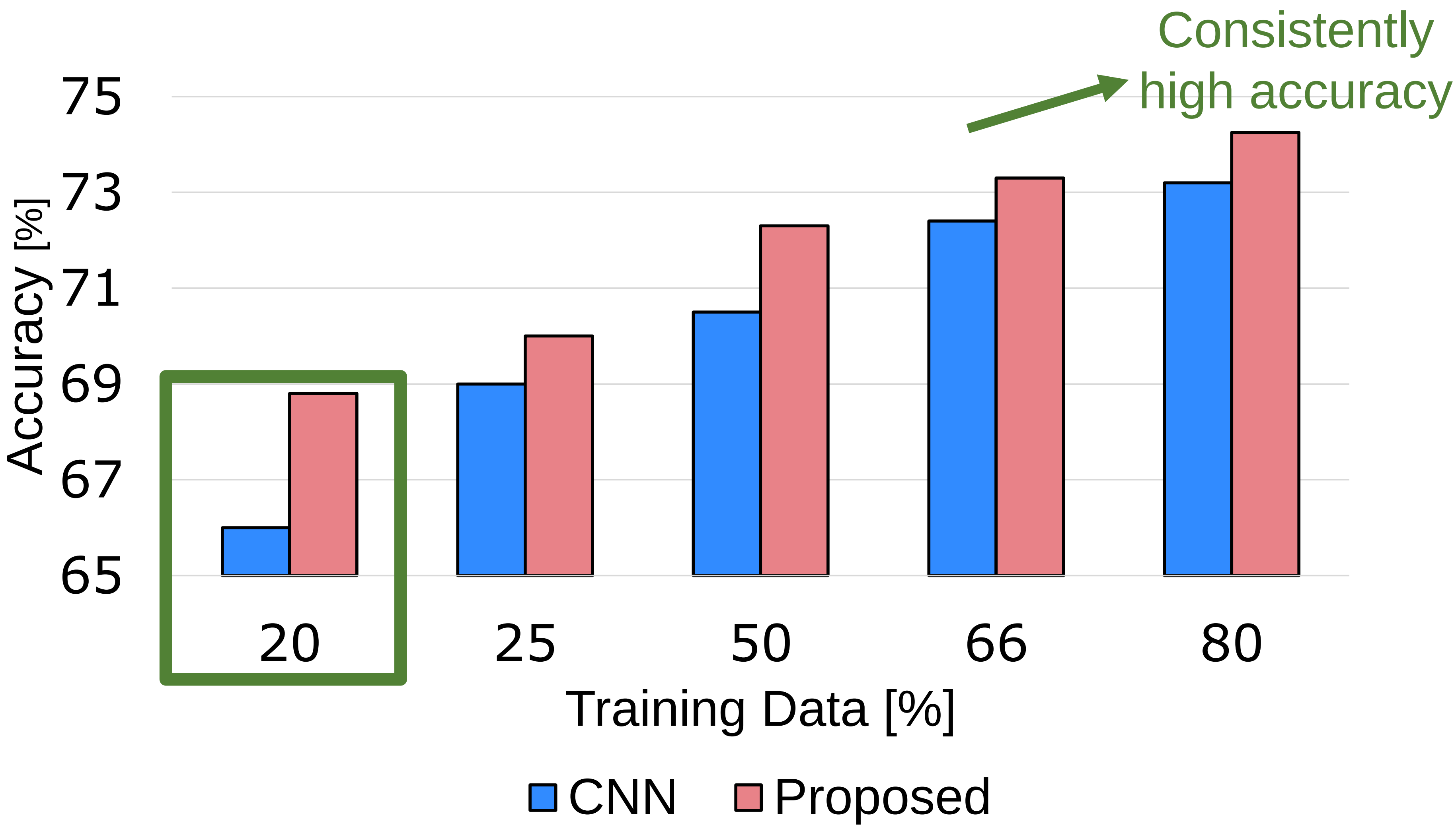
Proposed method achieves the best overall f-measure

Result 4: F-measure (Each class)



Proposed method outperforms in bulk-carrier and tanker

Result 5: Effect of Training Data Size



Proposed method requires less training data for high accuracy

Conclusion

- A CNN-based ship classification method incorporating SAR geometry information is proposed

- The proposed method uses incident angle information to separate feature information and geometry information

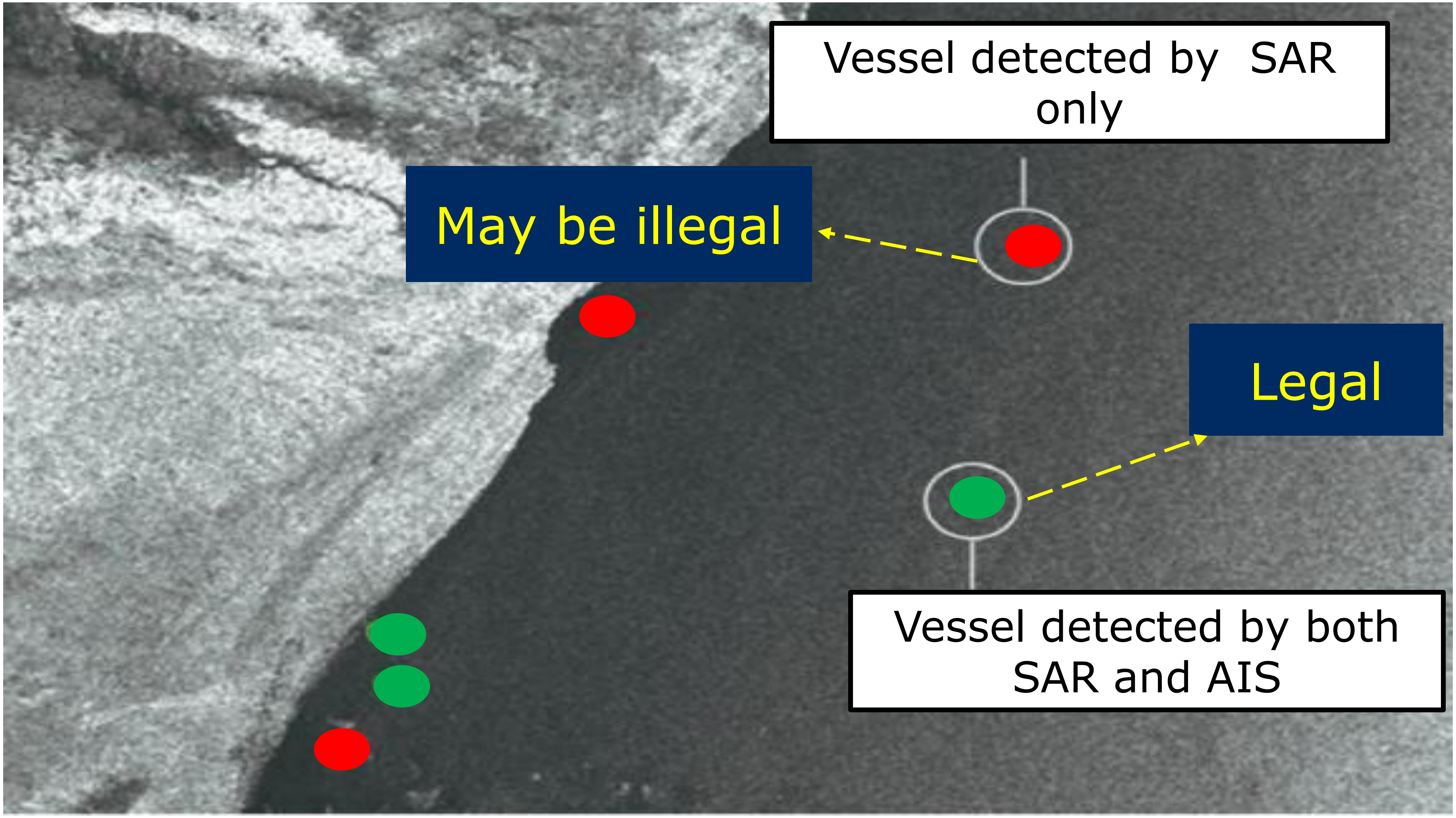
- The proposed method outperforms the CNN without incident angle information by **1.05%** and HCF method by **11.25%**

- The proposed method achieves best f-measure for bulk-carrier and tanker but fails in container

- The proposed method requires **25% less** training data as compared to the conventional CNN method

Appendix

A1: AIS + Synthetic Aperture Radar (SAR)



A SAR image can be used in conjunction with AIS data to detect illegal vessels in ocean

A2: Hand-crafted Features*

Feature	Formula
Length	L
Width	W
Perimeter	$2 \times (L + W)$
Area	$L \times W$
Shape Complexity	$P/4\pi A$ P: Perimeter
Compactness	$P/2\pi L$
Elongatedness	L/W
Aspect Ratio	W/L
Centroid X	$\frac{M_{10}}{M_{00}}$ M_{ij}: Image Moment
Centroid Y	$\frac{M_{01}}{M_{00}}$ M_{ij}: Image Moment

*Lang, H., Zhang, J., Zhang, X. and Meng, J., "Ship classification in SAR image by joint feature and classifier selection," IEEE Geoscience and Remote Sensing Letters 13(2), 212-216 (2016).

Published in the 66th Conference of the Remote Sensing Society of Japan
http://www.rssj.or.jp/eng/activity/meeting-of-the-remoto-sencing-society-of-japan/66th_spring/

Very High Resolution SAR Change Detection with Siamese Networks

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Motivation

To develop change detection technology using Earth Observation data

For quick and detailed monitoring of important economic areas

Example:

Multi-temporal SAR Images

Change Detection System

Change Detection Maps

Trends in the target area

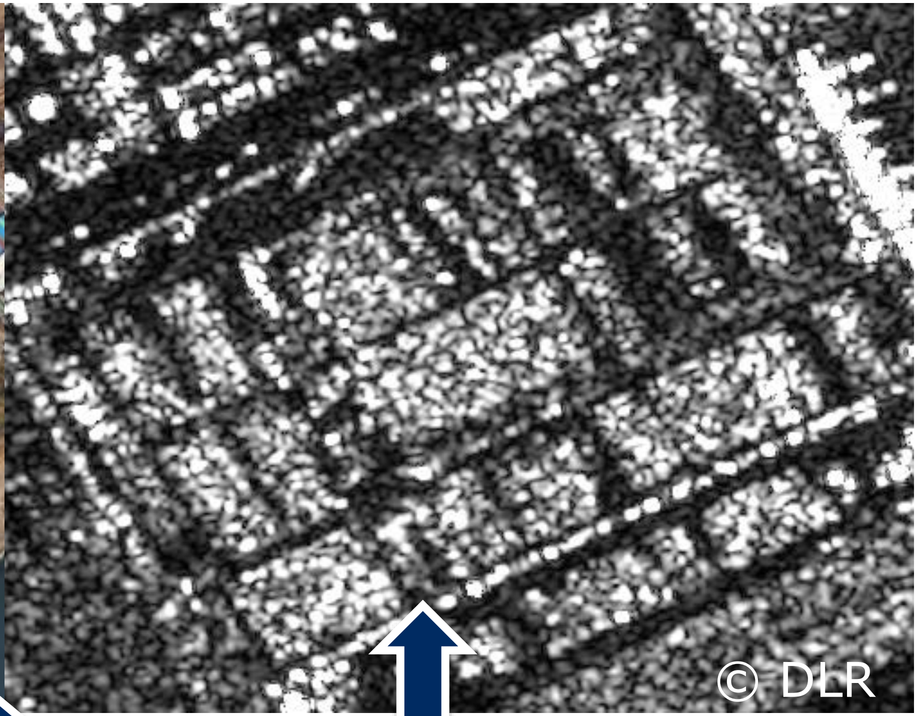
Comparison

Ground Truth

Optical Image v/s SAR Image

Optical Image

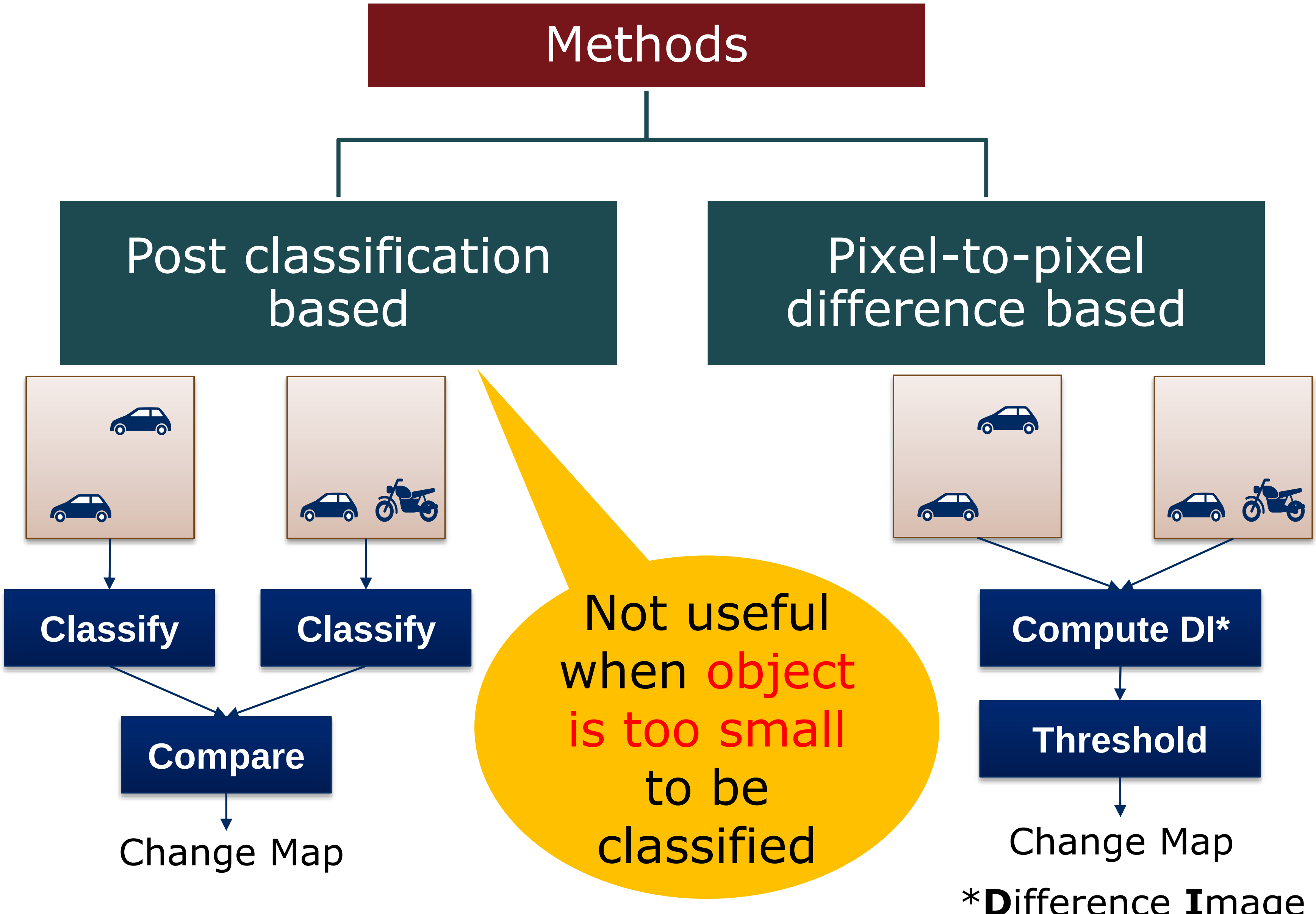
SAR Image



- Nadir-view imaging
- Passive sensing – day only
- Cannot image over clouds

- Side-view imaging
- Active sensing – day/night
- Can image over clouds

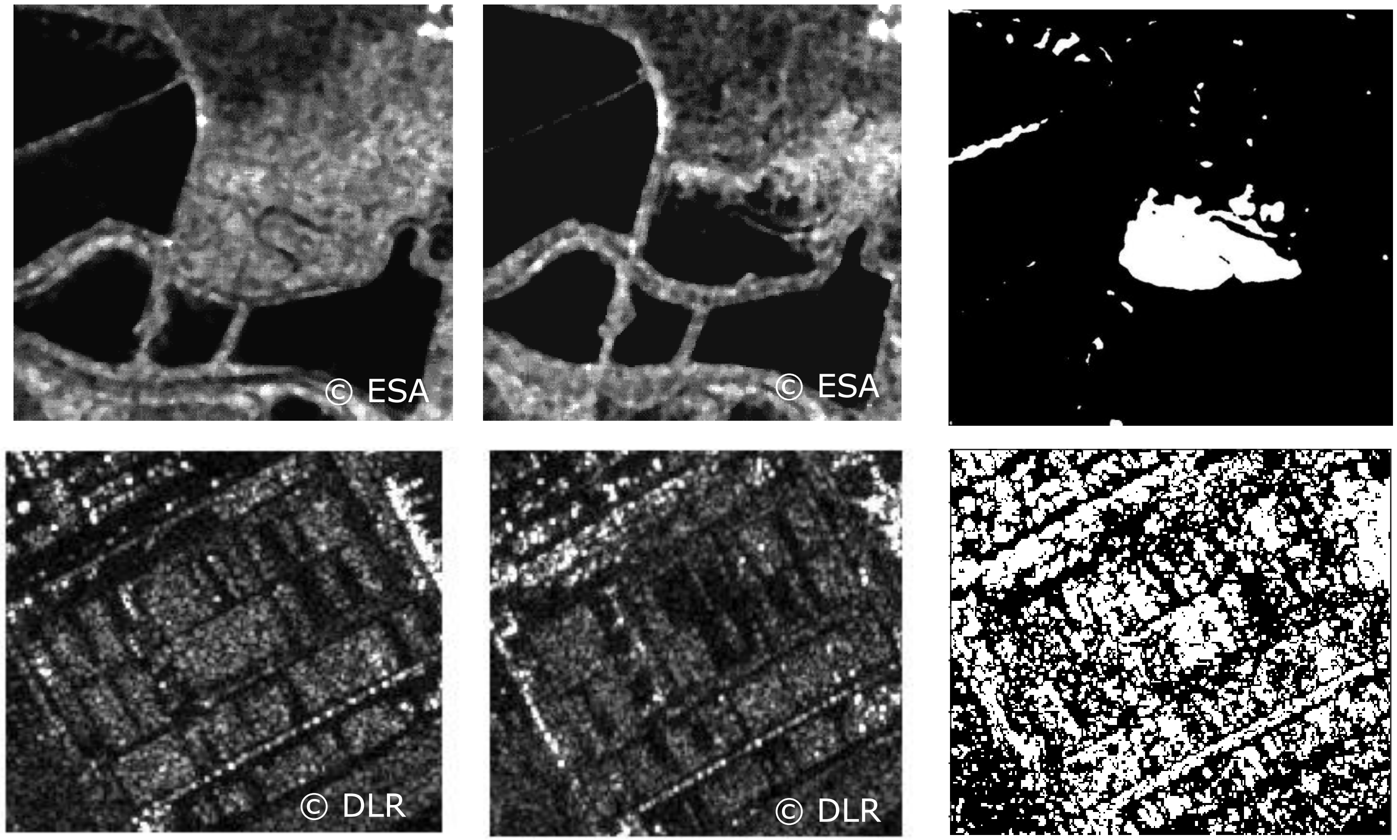
SAR Change Detection Methods



Low Resolution v/s Very High Resolution (VHR) SAR CD

Pixel-to-pixel difference method works well for low resolution SAR

	Image 1	Image 2	Change Map
Low Resolution			
High Resolution			



We need a change detection method for VHR SAR

Problem In VHR SAR Change Detection

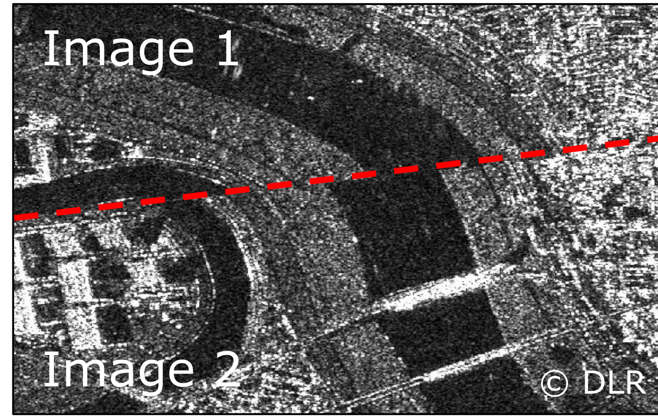
Pixel-to-pixel difference method cause many false changes in VHR

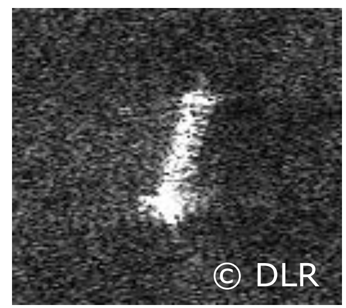
Camera Jitter
- causes co-registration error

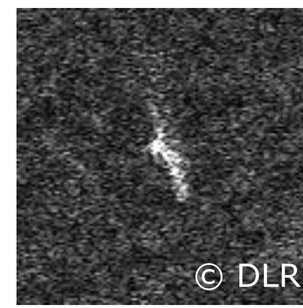
Speckle
- characteristic property in SAR
- causes noisy background

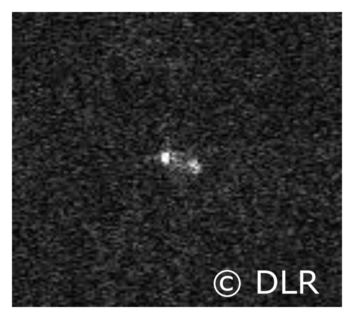
Camouflage
- non-defined shape and boundary
- difficulty to detect small and moving objects

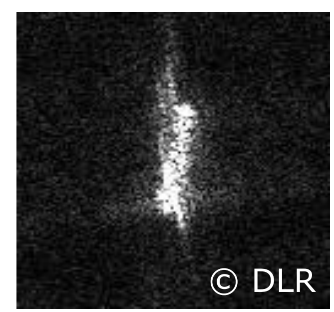
Low change detection accuracy







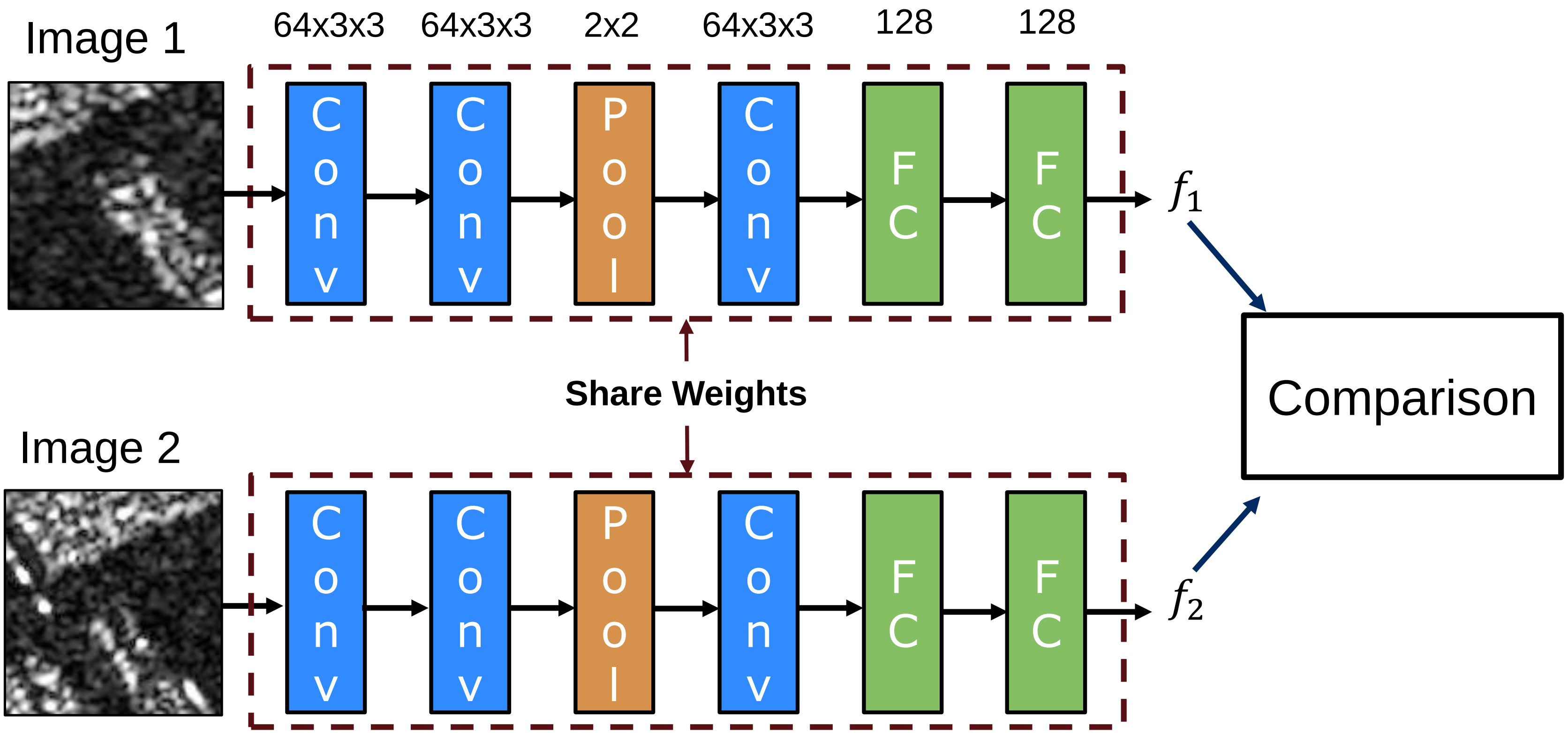




Solution

Feature-to-Feature difference method is robust to the conditions

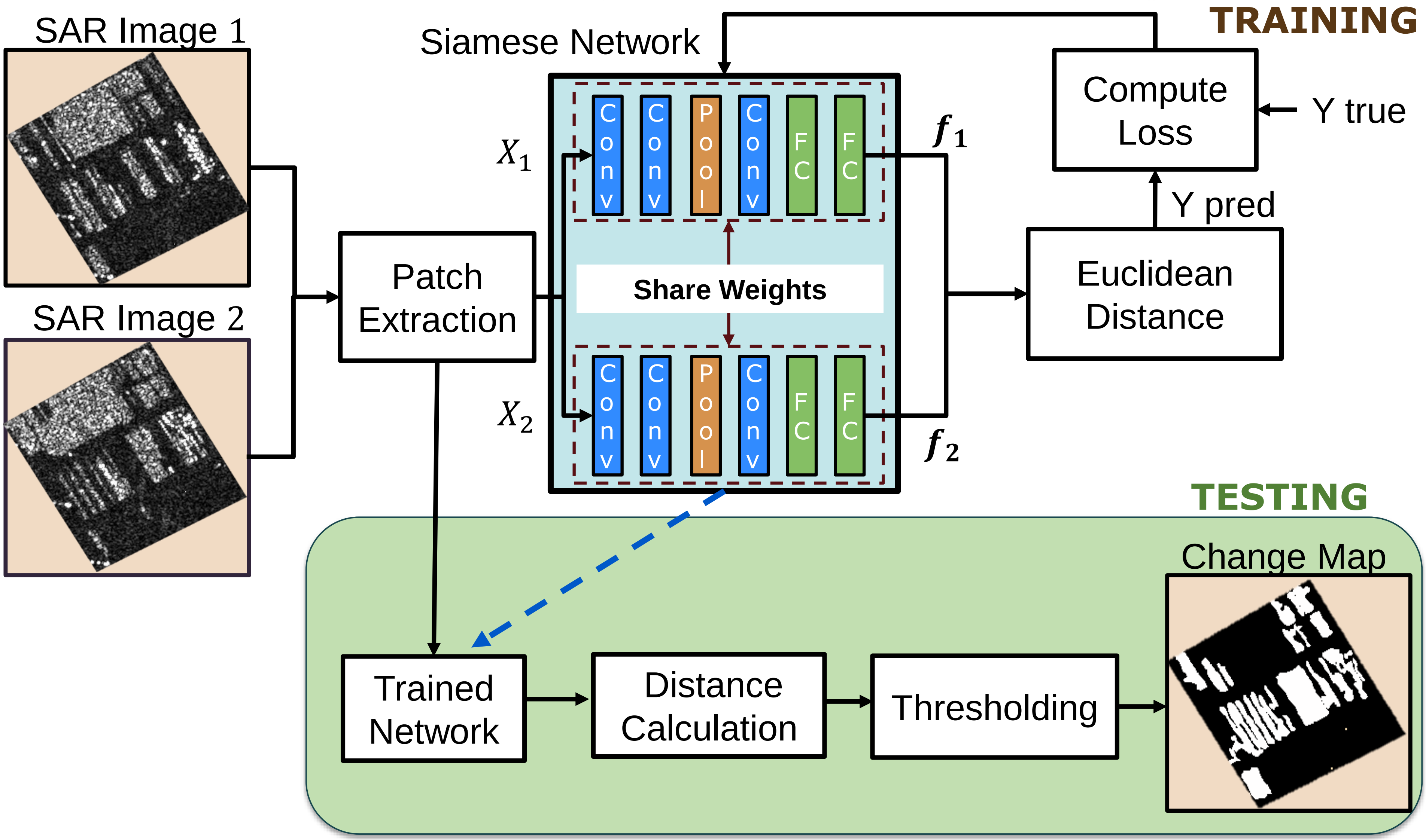
Siamese network has been widely used for feature comparison



However, Siamese network is not yet implemented for VHR SAR

Proposed Siamese Network for VHR SAR

Euclidean distance-based loss is used for feature comparison



Experimental Evaluation

Application

- Parking Lot Monitoring

Baselines:

- PCA + Kmeans [1]
- Sparse AE + Kmeans [2]

Evaluation Metrics

- f-measure
- ROC-AUC

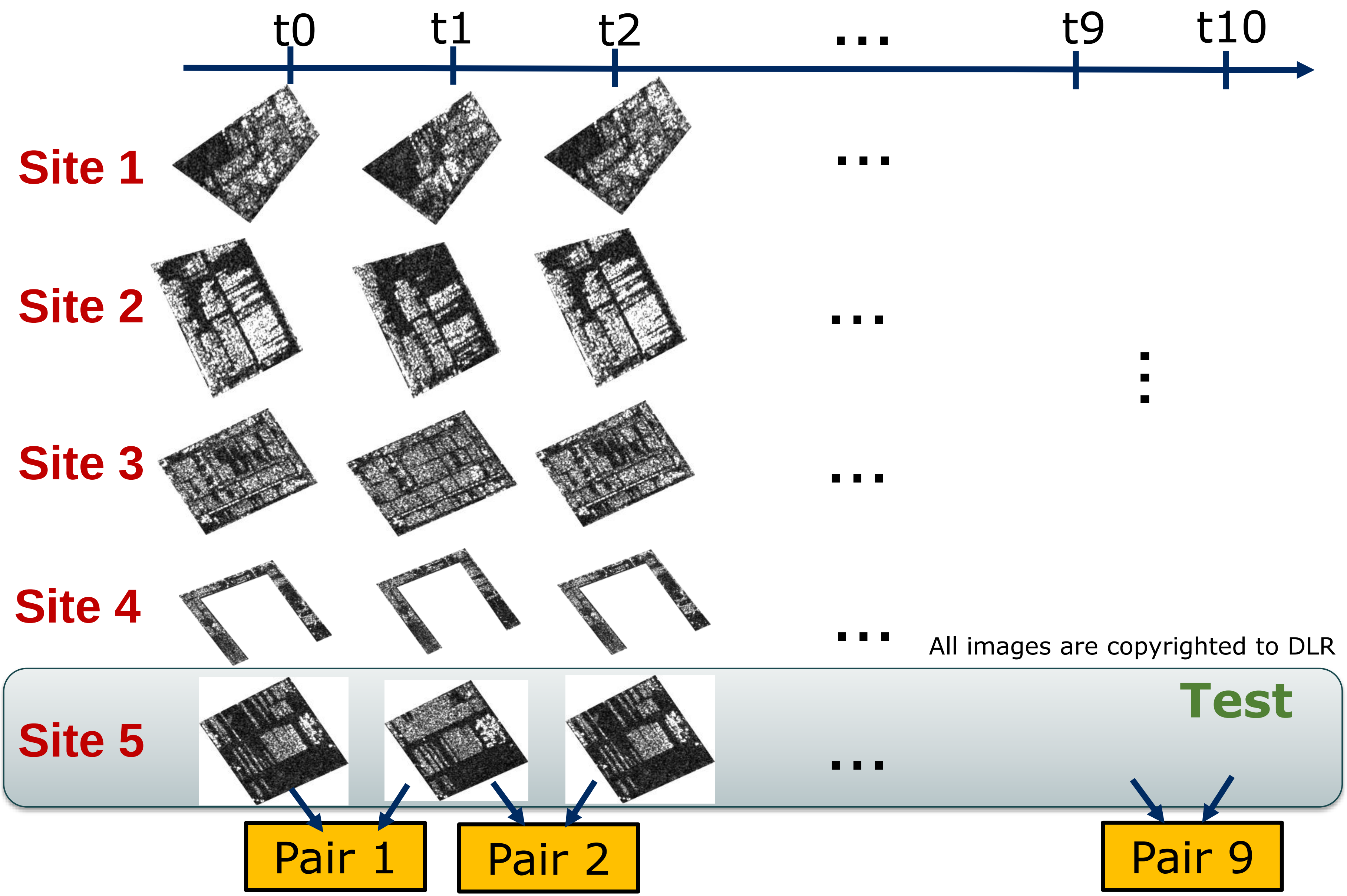
[1] T. Celik: Unsupervised change detection in satellite images using principal component analysis and k-means clustering, IEEE Geoscience and Remote Sensing Letters, vol. 6, no. 4, pp. 772-776, 2009.

[2] M. Gong., H. Yang, and P. Zhang: Feature learning and change feature classification based on deep learning for ternary change detection in SAR images, ISPRS Journal of Photogr. and Remote Sensing, no.129, pp.212-225, 2017.

Specifications

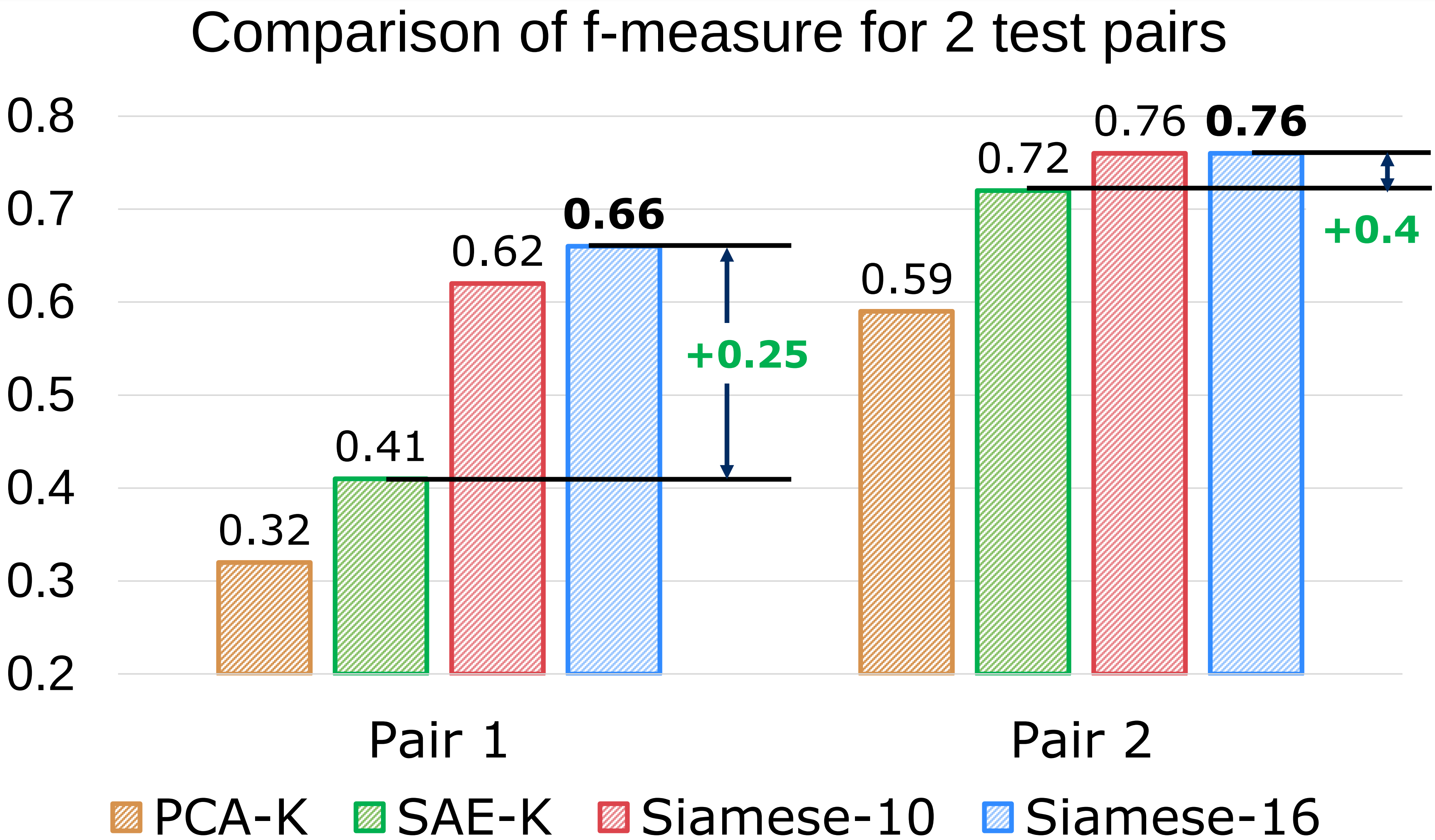
Satellite	TerraSAR-X
Resolution	1m
Polarization	HH
No. of parking sites	5
No. of images/site	10
No. of pairs/site	9
Patch sizes	10x10, 16x16
Ground Truth (GT)	Manual interpretation

Dataset

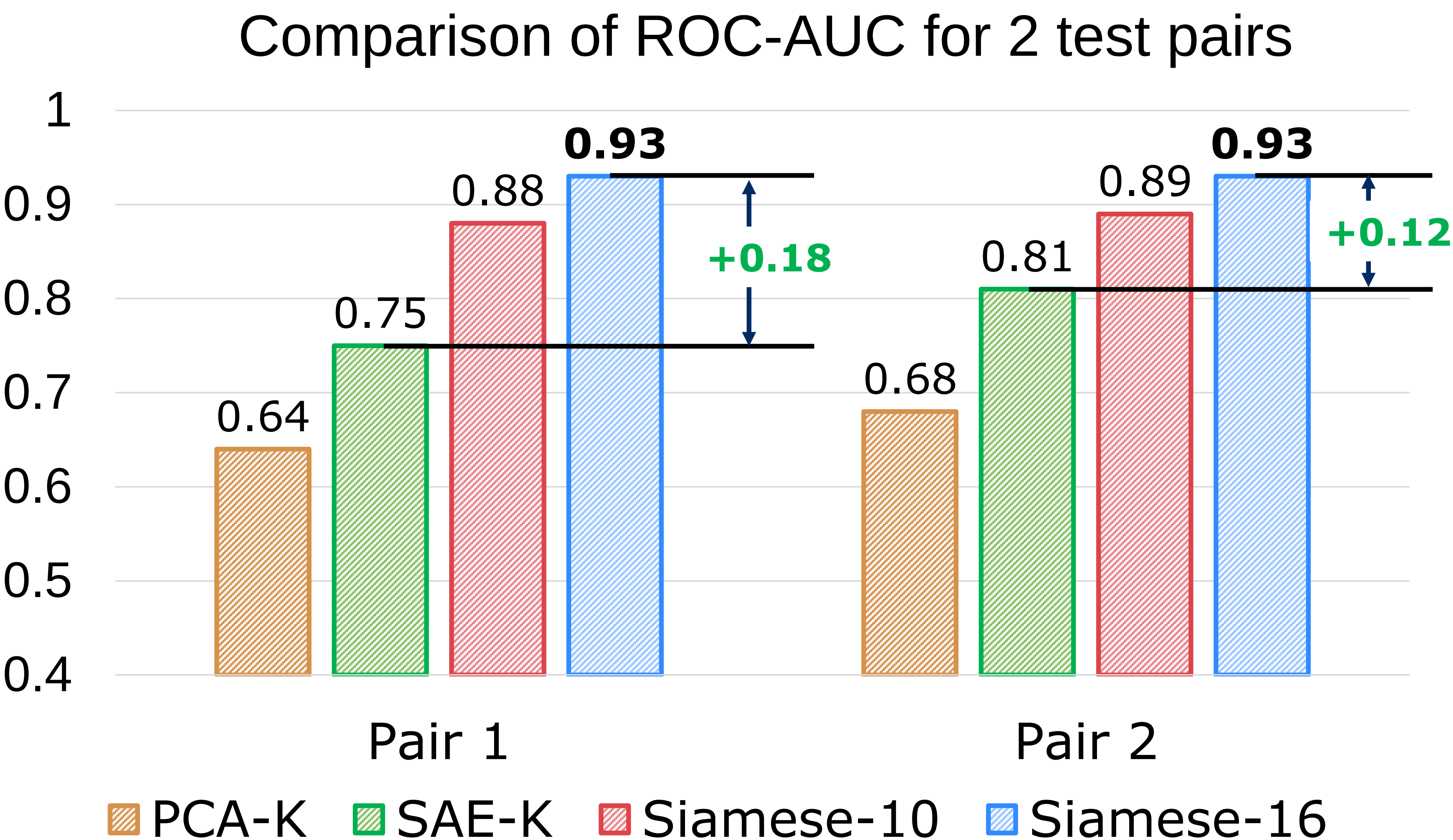

t0
t1
t2
...
t9
t10
Site 1
Site 2
Site 3
Site 4
Site 5
Test
Pair 1
Pair 2
Pair 9
All images are copyrighted to DLR

Result [1/4] : f-measure

Siamese networks outperforms the conventional methods



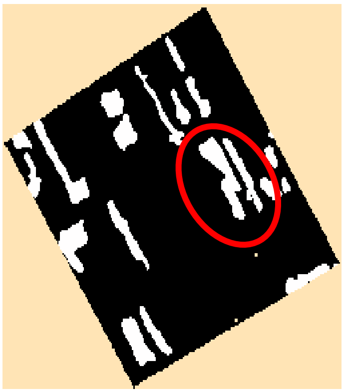
Siamese networks outperforms the conventional methods



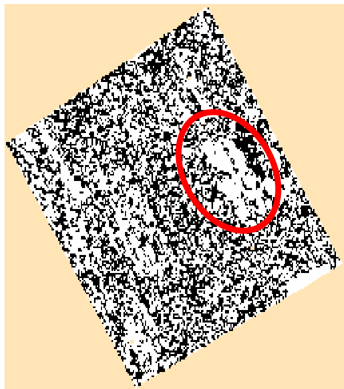
Result [3/4] : Change Maps

Siamese networks produce visually better change maps

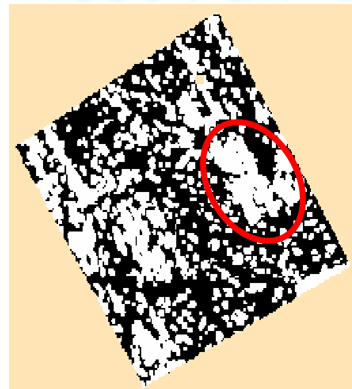
Test Pair 1



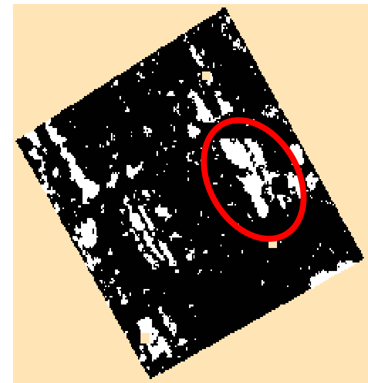
GT



PCA-K



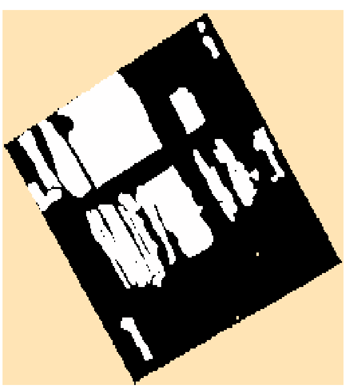
SAE-K



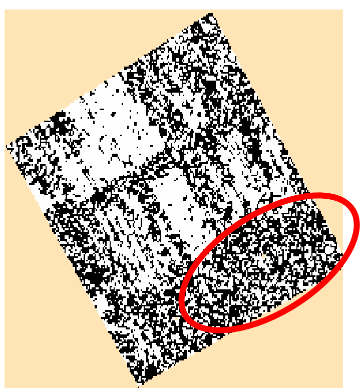
Siamese-10

Siamese-16

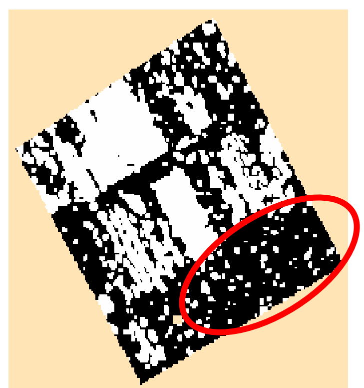
Test Pair 2



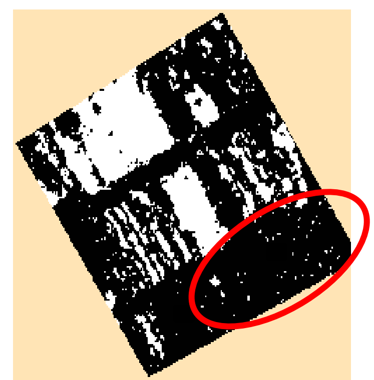
GT



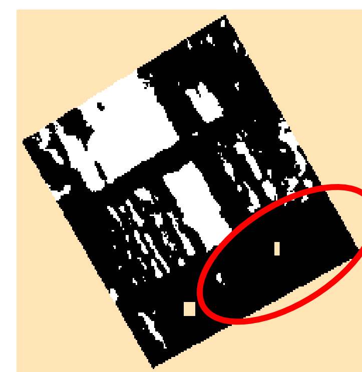
PCA-K



SAE-K



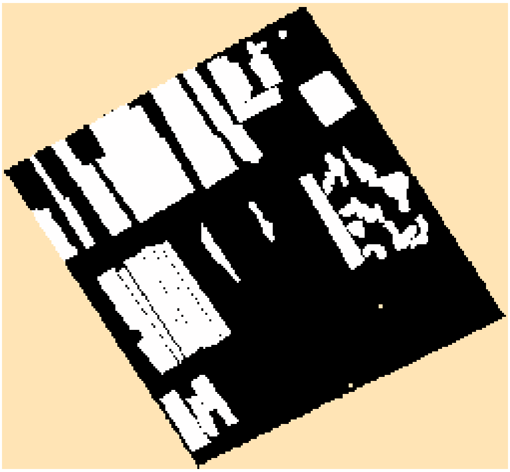
Siamese-10



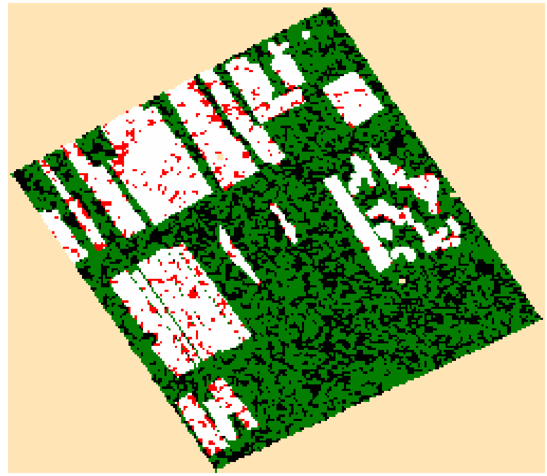
Siamese-16

Result [4/4] : Colorized Change Map

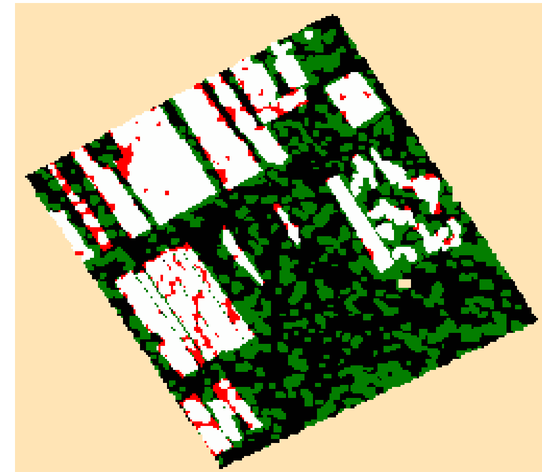
Siamese networks reduce the number of false positives



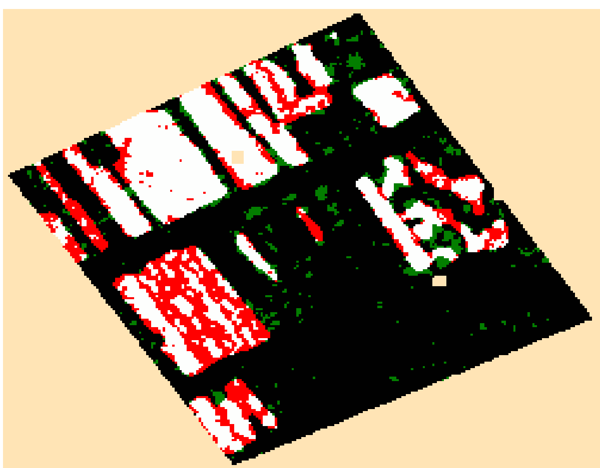
GT



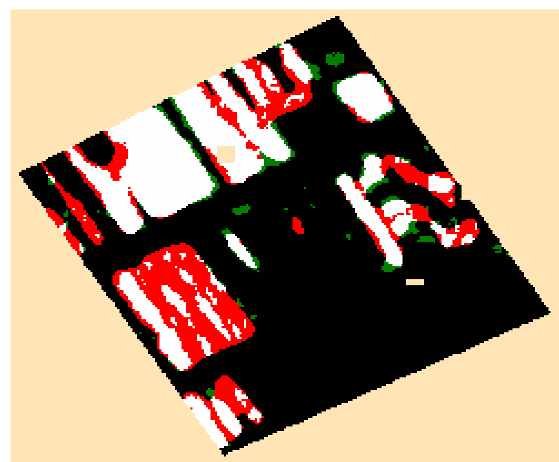
PCA-K



SAE-K



Siamese-10



Siamese-16

Legend
TP, TN,
FP, FN

Conclusion

- Proposed Siamese neural network for change detection in VHR SAR
- Proposed network is trained with Euclidean distance loss function
- Evaluated for parking lot monitoring using 1m resolution SAR images
- Proposed network outperforms the conventional methods both in f-measure and ROC-AUC
- Proposed network produces visually better change maps
- Proposed network reduces number of false positives
- Future work
  - reduce number of false negatives
  - ternary change detection

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