

Overview of Projects and Rakuten Case Study

Shreya Sharma

About Me

- From India, working in Japan since Oct 2016

▪ Education

- B. Tech. in Electrical Engineering, GBPUAT Pantnagar, India
- M. Tech. in Geoinformatics Engineering, IIT Bombay, India

▪ Professional Experience

- Data Science Researcher at NEC (3 years)
- Image Processing Lab Teaching Assistant at IIT Bombay (1 year)

▪ Research Achievements

- 3 Patents
- 5 Publications in top-level remote sensing conferences- IGARSS, SPIE
- Foreign collaborations

▪ Hobbies

- Blogging
- Social Activities
 - Volunteer at Hands-on-Tokyo NGO
 - Speaker at Machine Learning Tokyo

Career Interests

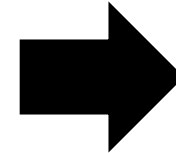
Research Interests

Computer
Vision

Image
Processing

Deep
Learning

Statistical
Analysis



Domains

Geospatial

Healthcare

E-commerce

Agriculture

Security

Overview of My Projects

Research Projects at NEC

- Ship Classification for Maritime Surveillance
- Change Detection in Time-series of Satellite Images
- Land-use Land-cover Segmentation in Large-size Satellite Images

Master's Thesis

- Hyperspectral Image Super-resolution

Academic Projects

- Dimensionality Reduction of Hyperspectral Images
- Shape Detection using Hit and Miss Transform
- Optimal Bike Path Development and Route Prediction
- Feature extraction using Active Contour Models

More Information at: <https://shreya1sharma.github.io/ShreyaSharma/projects/>

Contents

1. Ship Classification for Maritime Surveillance
2. Change Detection in Time-series of Satellite Images
3. Current Work and Challenges
4. Collaboration Activities
5. Case Study: Brain Tumor Segmentation with MRI

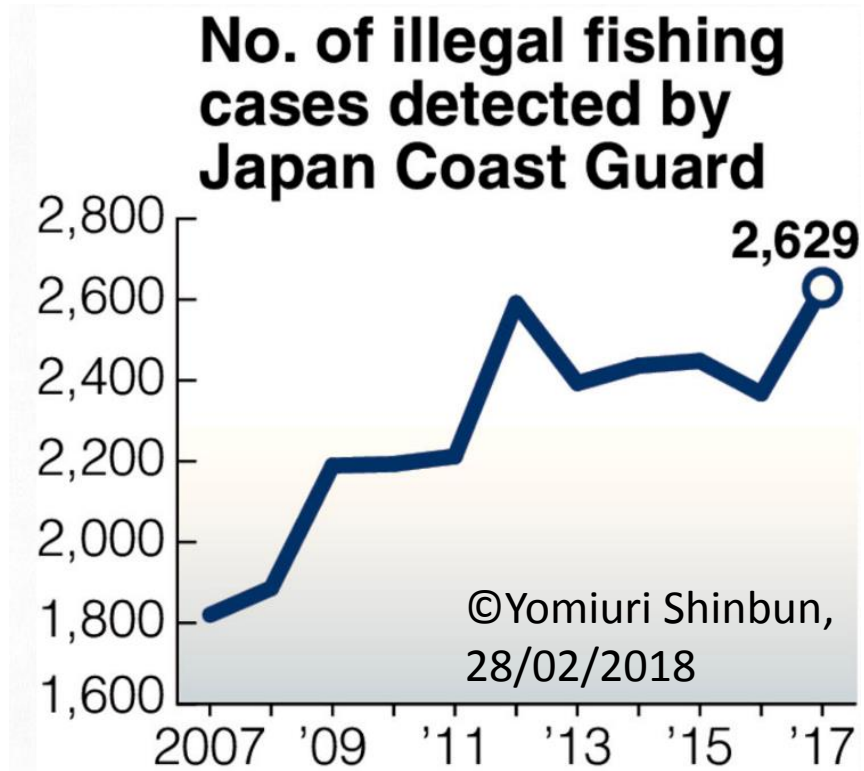
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Motivation

Ship Classification is a key application in maritime surveillance

Helps in quick identification of ships involved in illegal activities



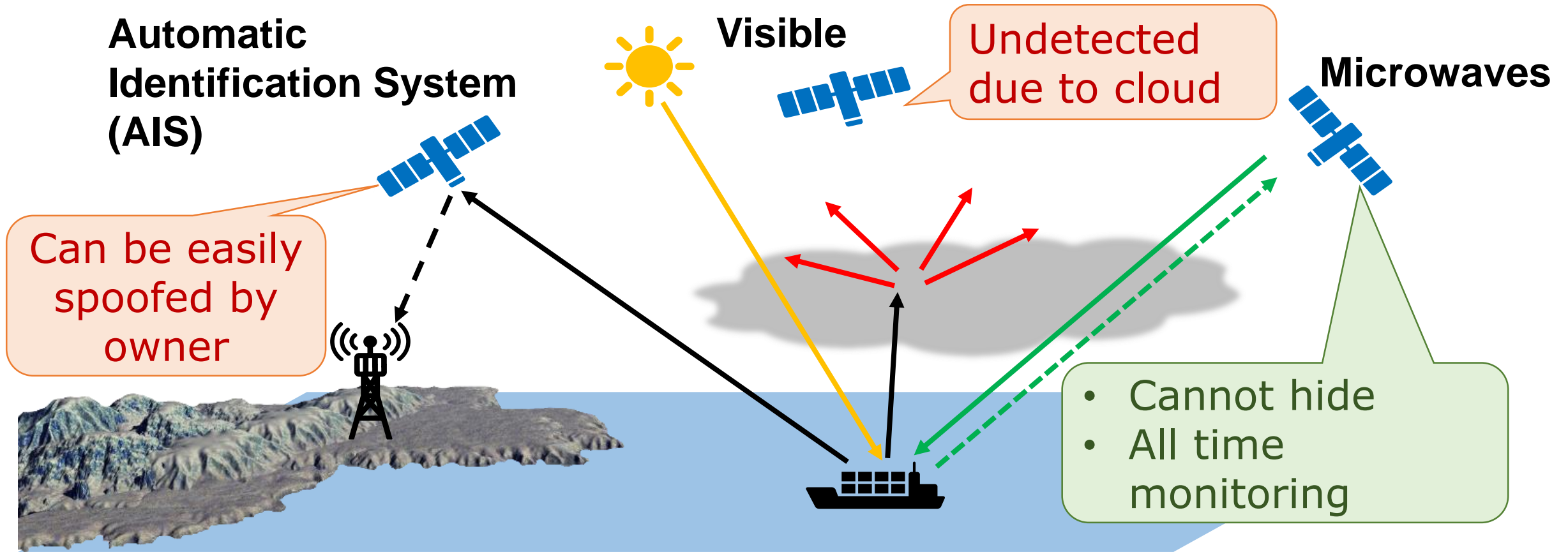
**\$US23 billion loss
worldwide per year!**



Ship Classification from Space

3 major sources of information : AIS, Visible and Microwaves

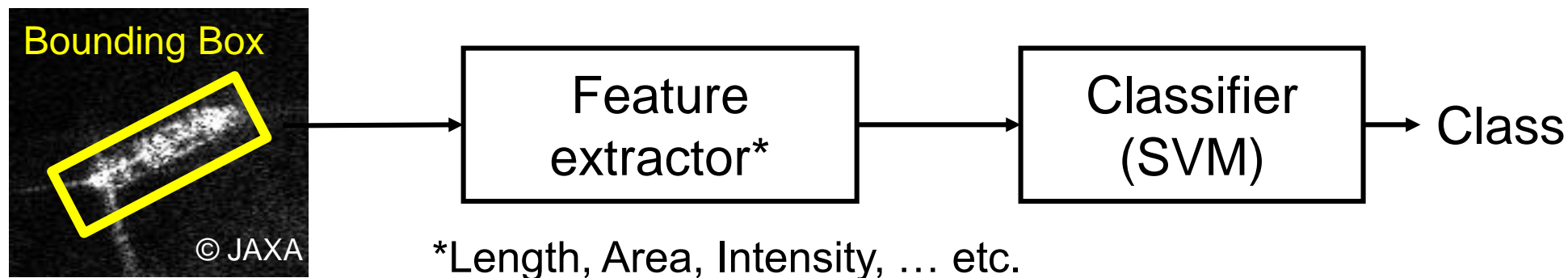
Microwaves can see ships undetected/spoofed by AIS and Visible



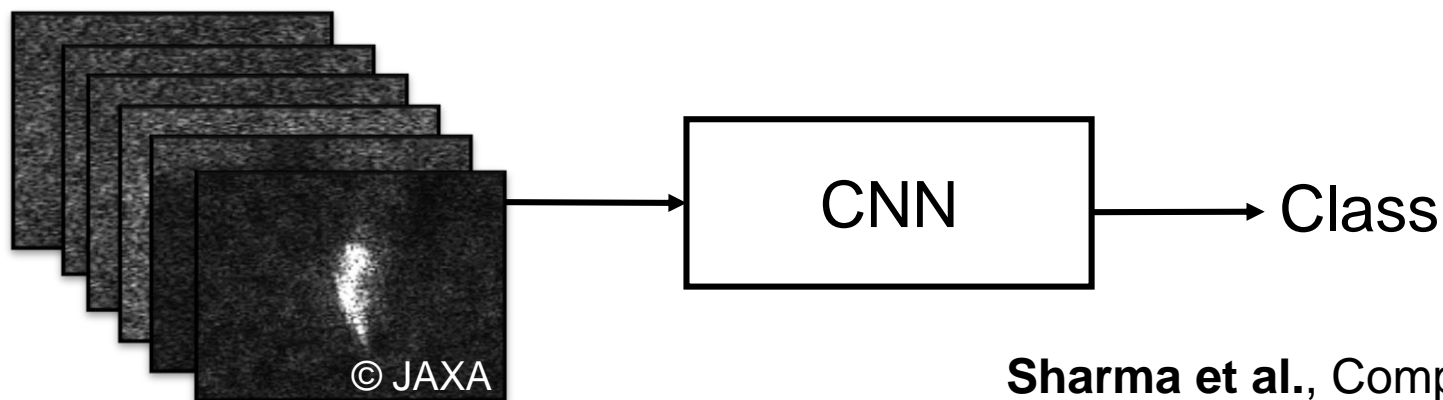
Microwave images are highly reliable for ship classification

Conventional Methods

1. Hand-crafted feature (HCF)-based



2. Convolutional Neural Network (CNN)-based



Sharma et al., Comparative Analysis of feature extraction approaches for ship classification in moderate resolution SAR imagery, IEEE IGARSS 2018.

These methods classify a ship based on its appearance in image

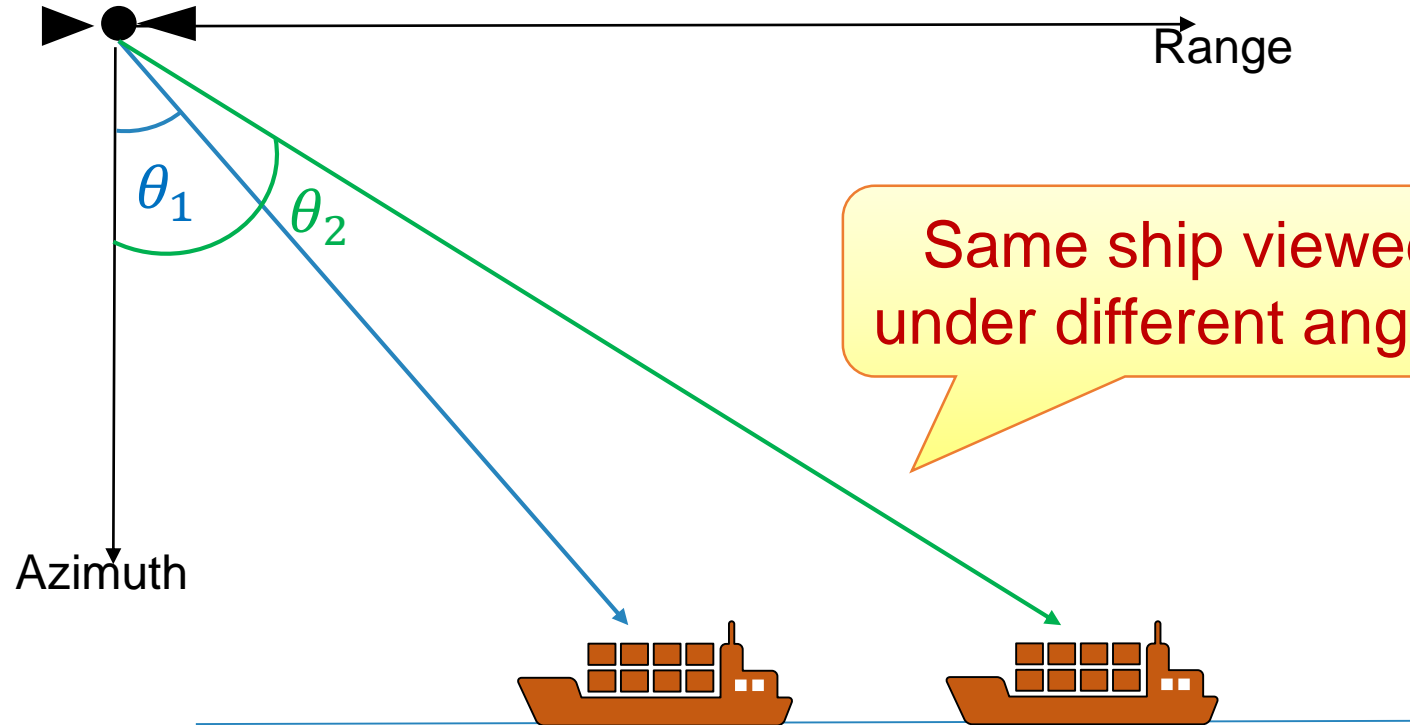
Problem

Appearance of a ship varies with satellite viewing angle

Labelled microwave images are very few to learn all possible variations

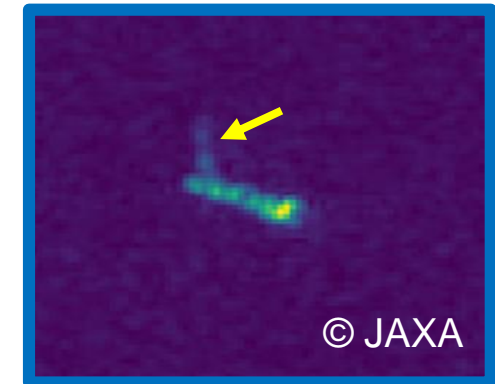
Example:

Satellite

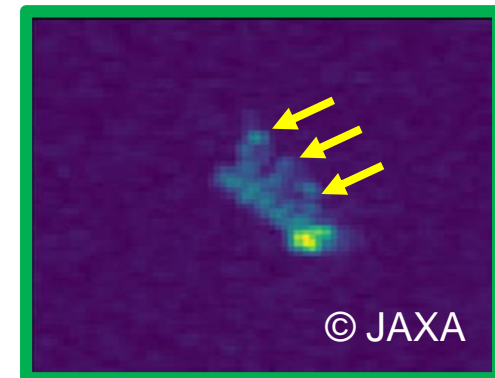


Same ship viewed
under different angles

$\theta_1 = 30^\circ$



$\theta_2 = 40^\circ$

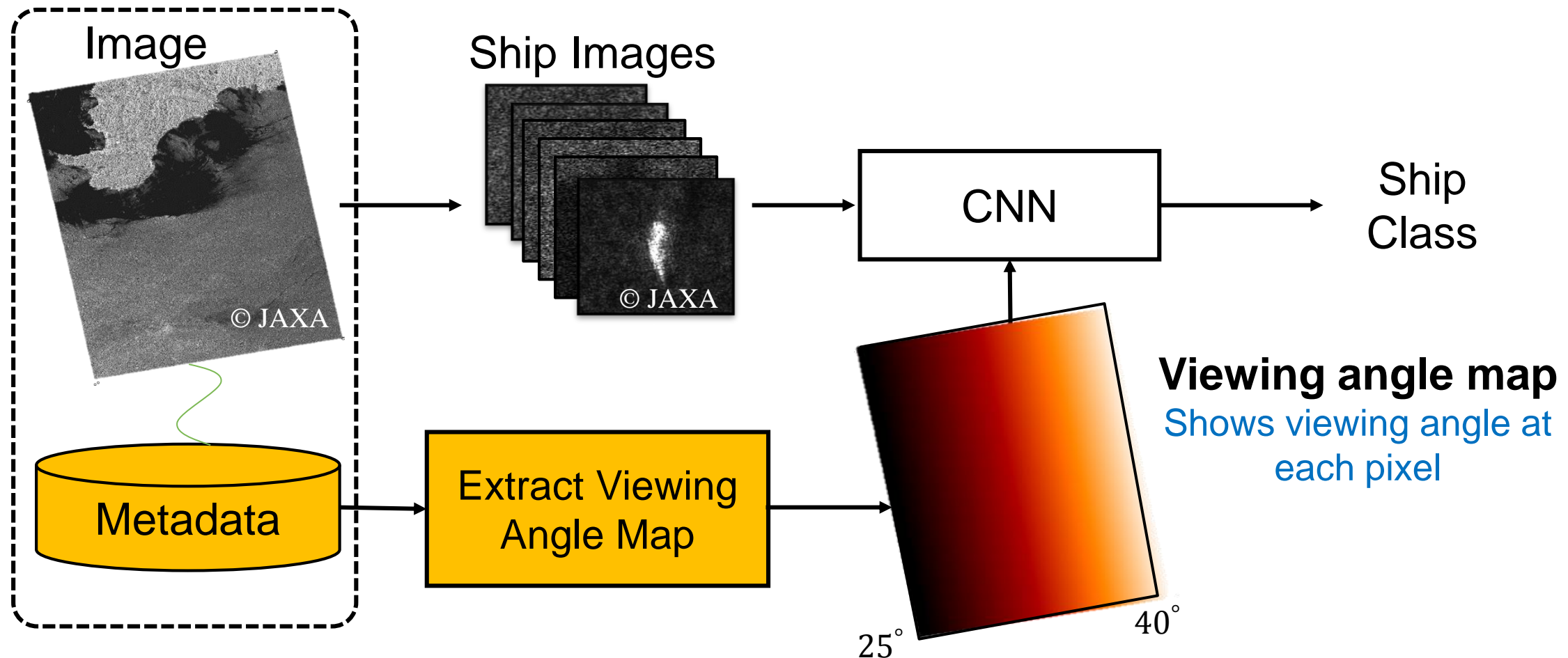


Only image information is insufficient for robust classification

Proposed Method

Use viewing angle as an additional information in a NN

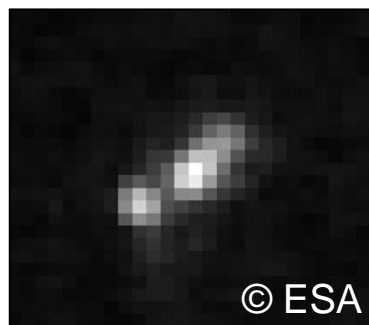
Helps the CNN to follow the appearance changes by learning a relationship



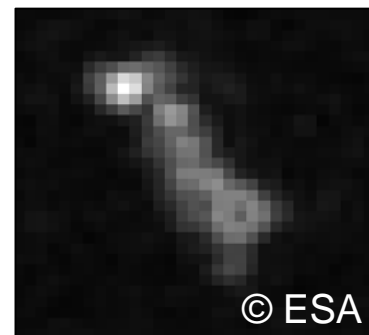
Experiments

Dataset: OpenSARShip*

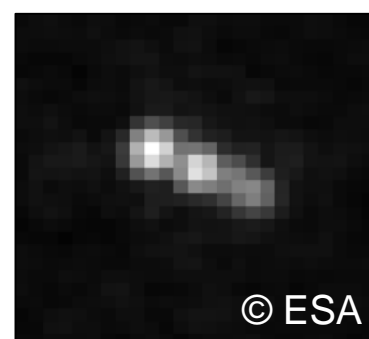
Container



Bulk-carrier



Tanker



Specifications

Satellite	Sentinel-1
Resolution	20m
Image size	128 x 128
No. images	200 per class
Ground truth	AIS + Marine Traffic

Conventional Methods

HCF	10 Features + SVM
CNN	w/o incident angle

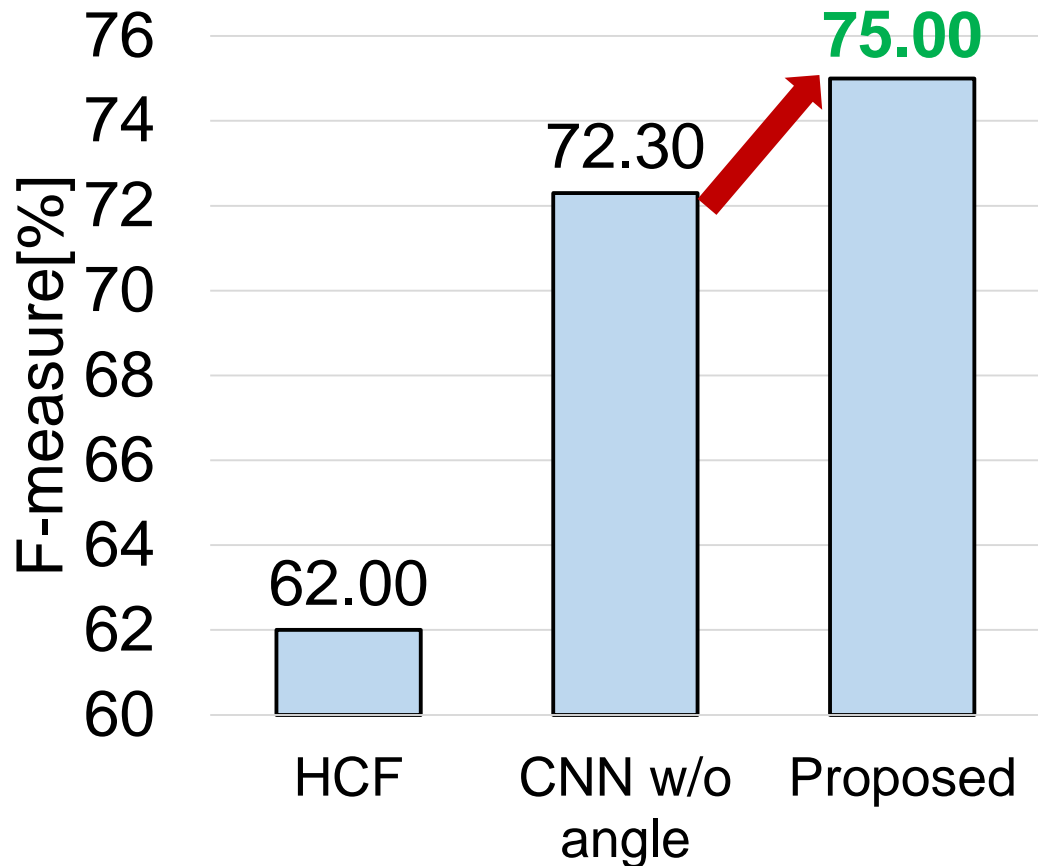
Metrics

f-measure	Higher is better
#training data needed	Lower is better

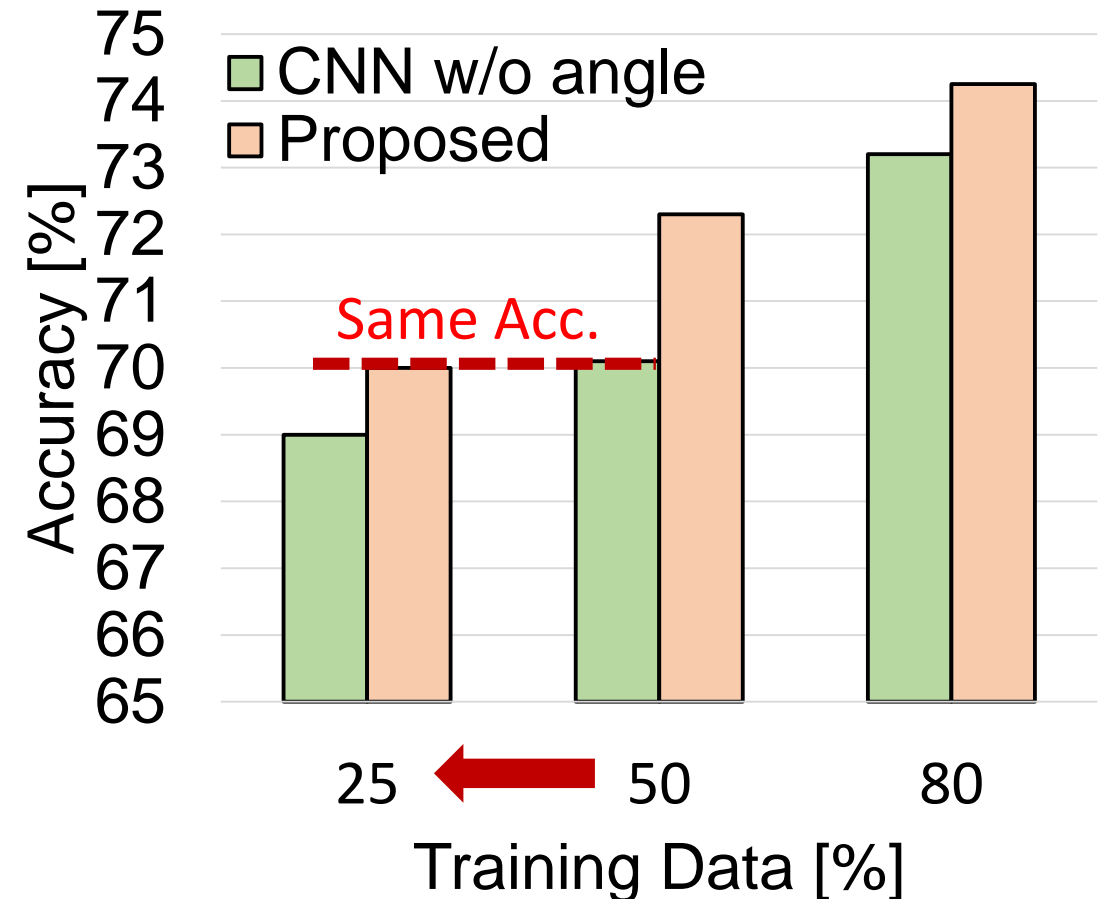
*Huang, L et al., "OpenSARShip: A dataset dedicated to Sentinel-1 ship interpretation," IEEE Journal of Sel. Top. in App. Earth Obs. and Rem. Sen. 11(1), 195-208 (2018).

Results

4.2% improvement in
f-measure



25% reduction in
training data requirement



Proposed method outperforms the conventional methods

Demo Example

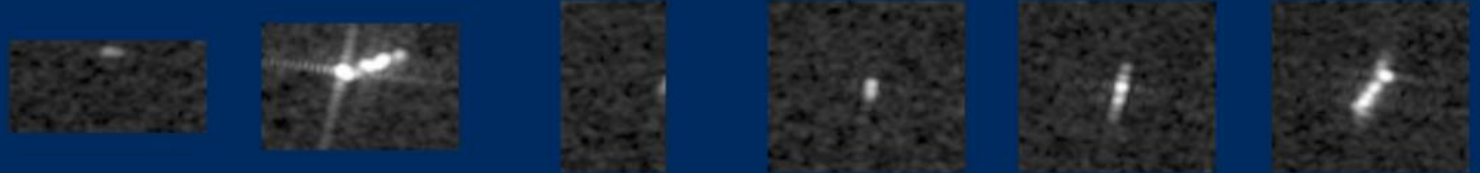
Presented at International Geosciences and Remote Sensing Symposium '19

Ship Detection Result

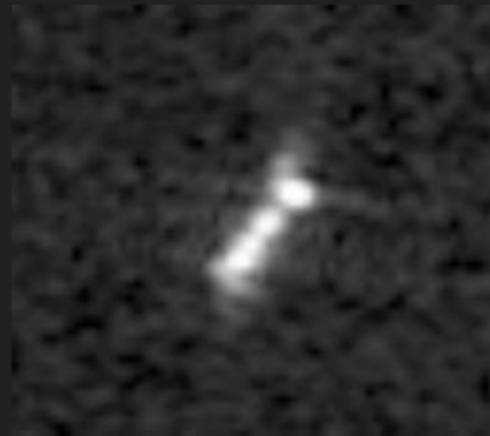
Result Image



Detected ships



Unknown ship



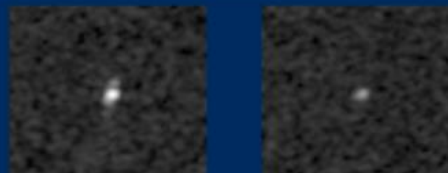
カテゴリ	確率 [%]
Container Ship	21%
Bulk Carrier	55%
Tanker	24%

緯度:139.74
経度:35.39
長さ:267 幅:67
画像上座標 (x,y) = (143, 577)



Orchestrating a brighter world

NEC



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Motivation

Change detection enables us to **understand dynamics** of Earth

Dubai Coastal Expansion

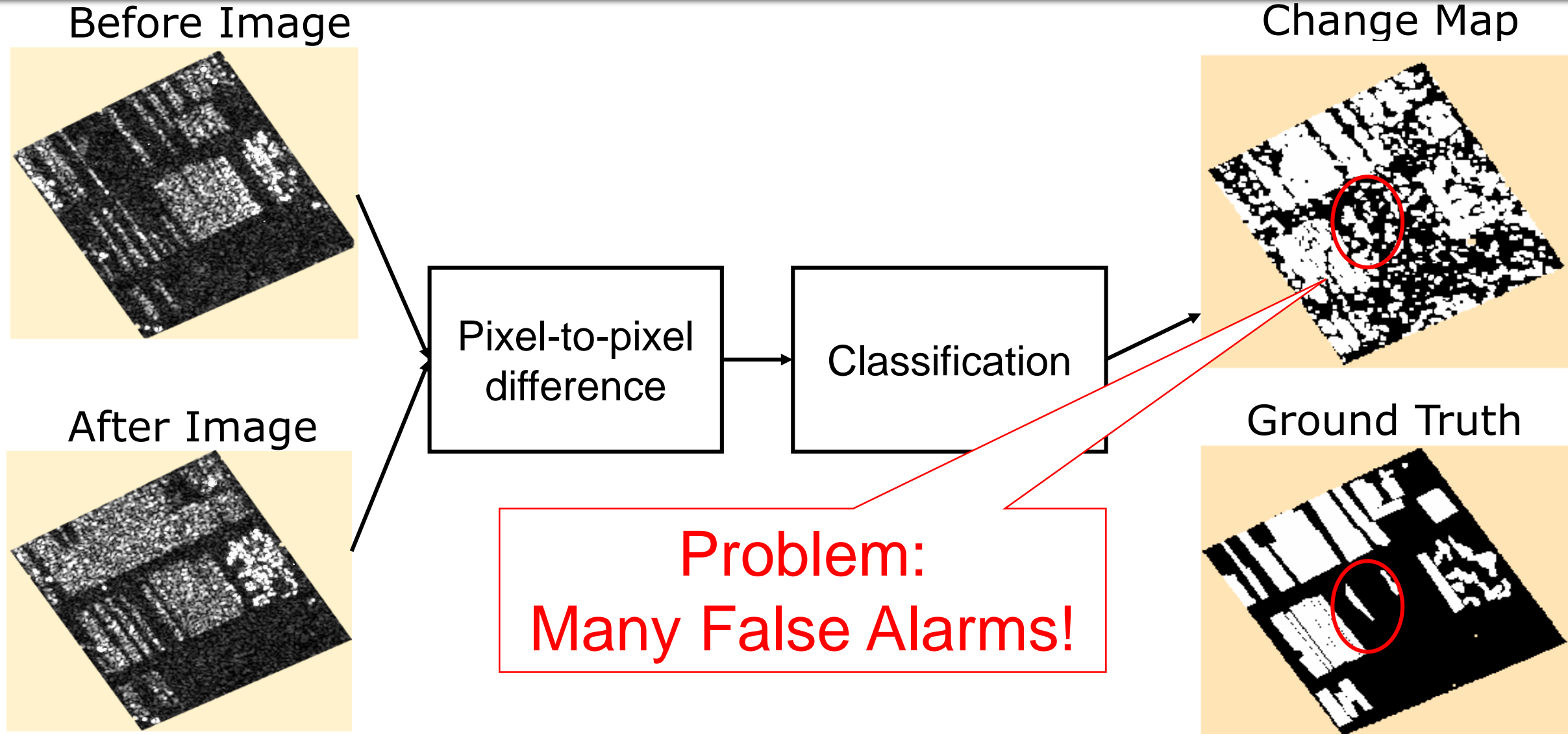


Saudi Arabia Irrigation



Conventional Method

Based on pixel-to-pixel difference followed by classification



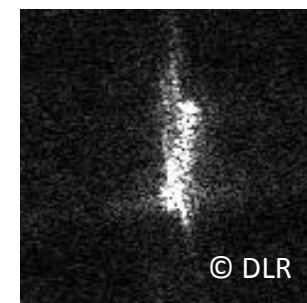
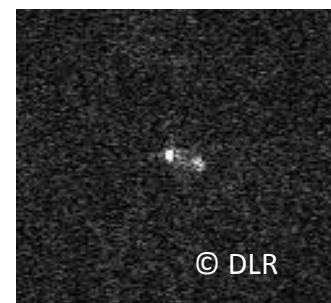
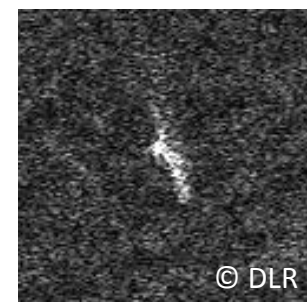
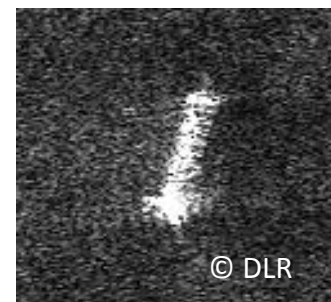
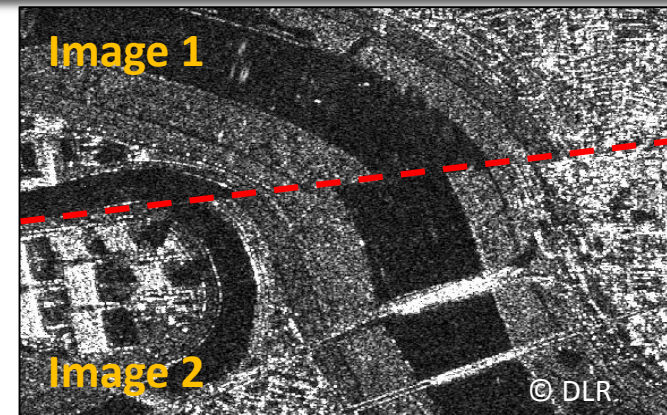
Problem

Pixel-to-pixel difference-based method cause many false alarms

- **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



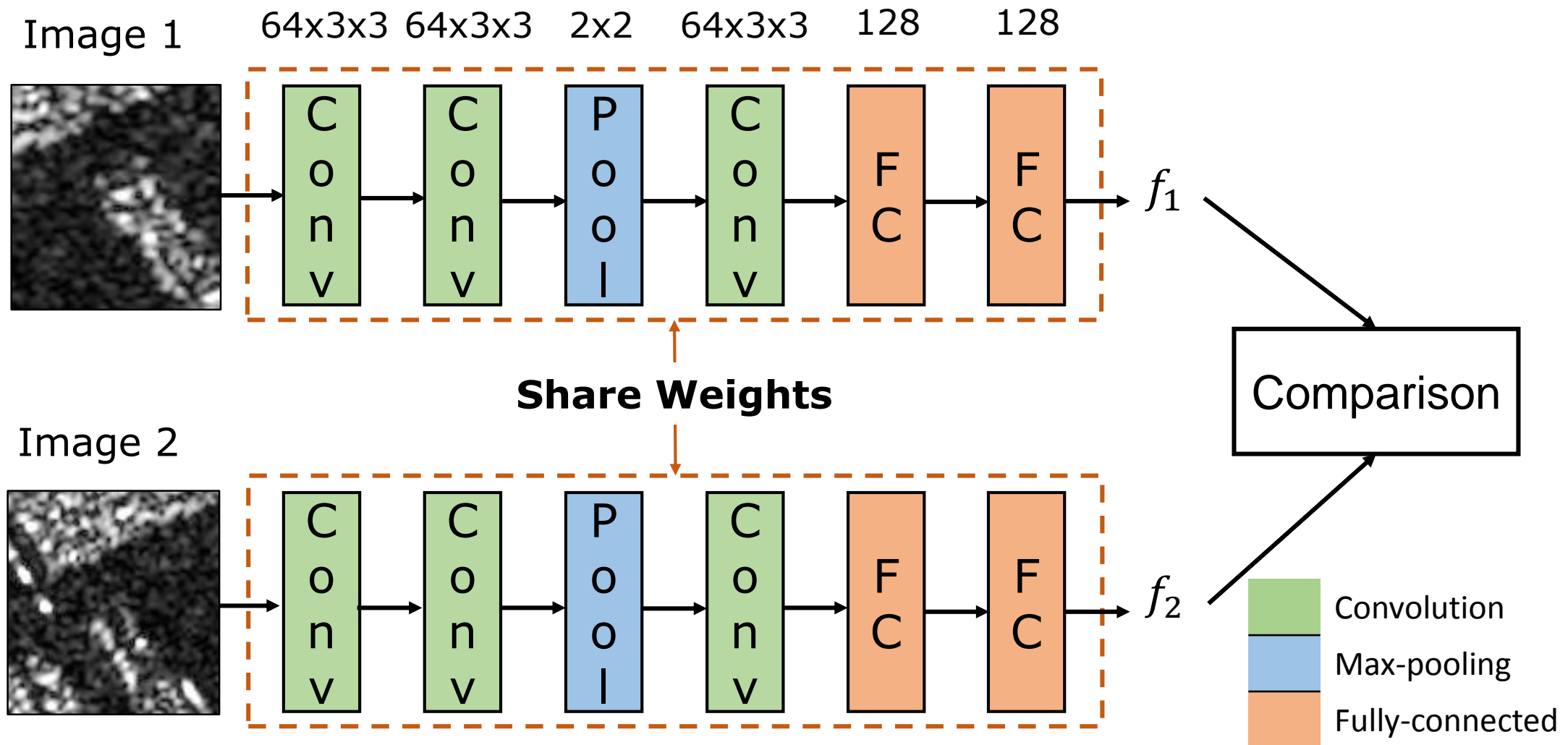
Low change
detection accuracy



Solution

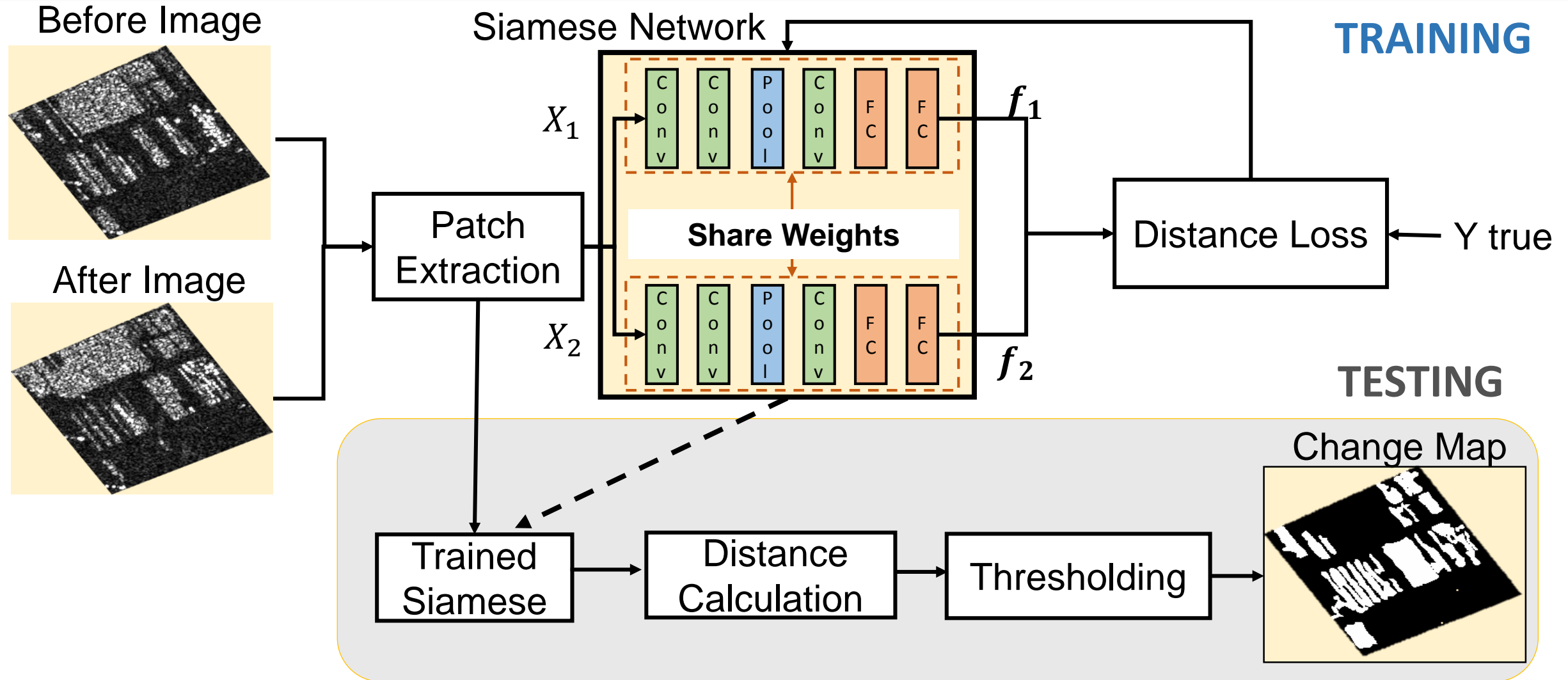
Feature-to-Feature difference method is robust to the conditions

Siamese network has been widely used for feature comparison



Proposed Method

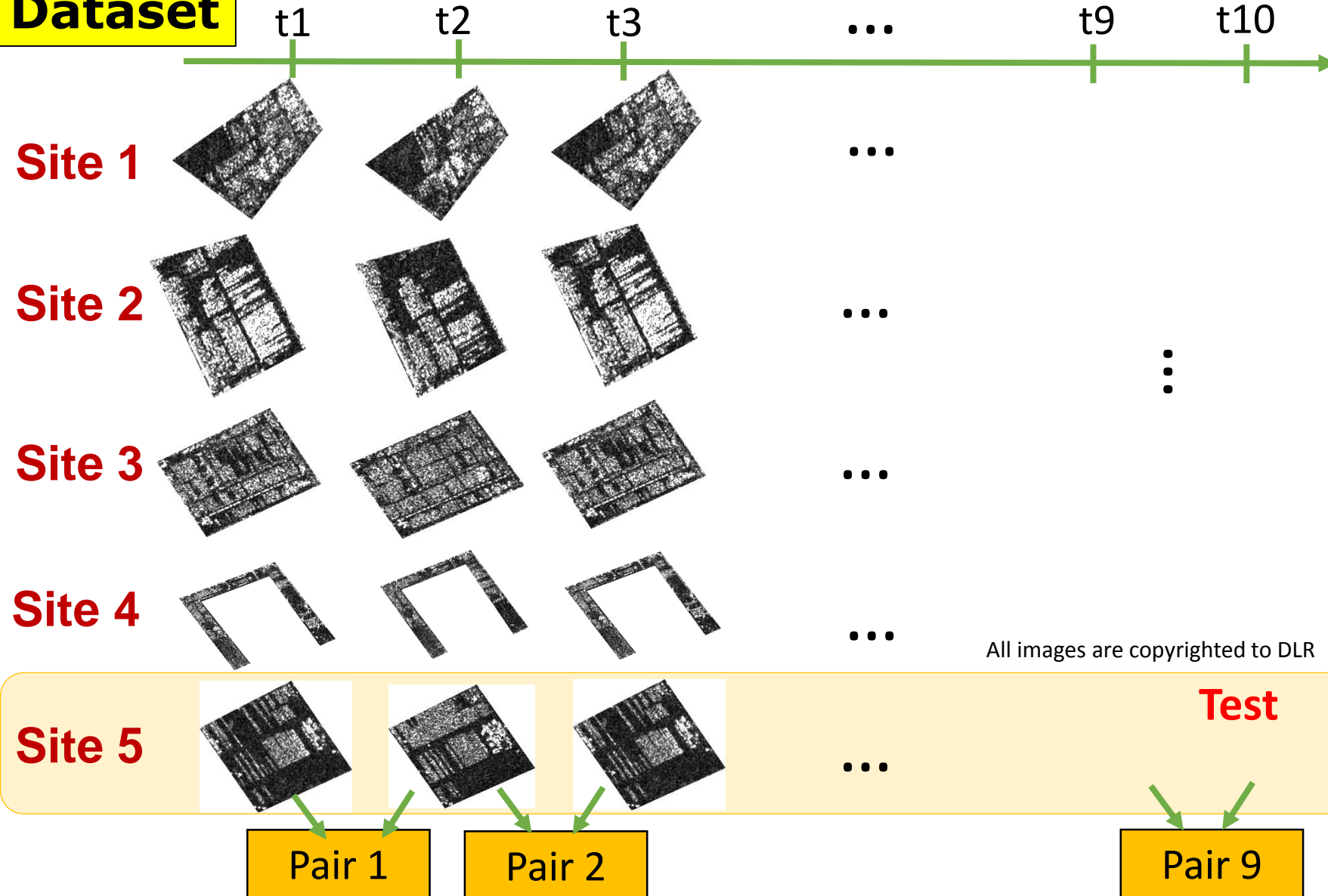
Transform the images into features and compute difference between features



Sharma et al., Very high resolution SAR change detection with Siamese Networks, The 66th Academic Conference of the Remote Sensing Society of Japan, 2019.

Experiments : Parking Lot Monitoring

Dataset



Specifications

- TerraSAR-X satellite
- 1m resolution

Baselines:

- PCA-K [1]
- SAE-K [2]

Evaluation Metrics

- f-measure
- Change Maps

[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.

Result [1/2] : f-measure

Proposed method improves f-measure by 15% over baselines



Result [2/2] : Change Maps

Proposed method produces visually better change maps

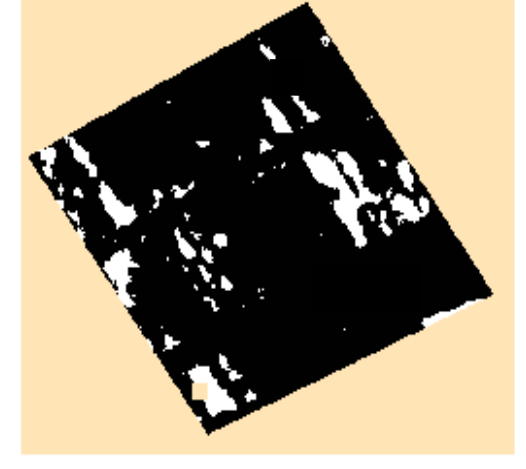
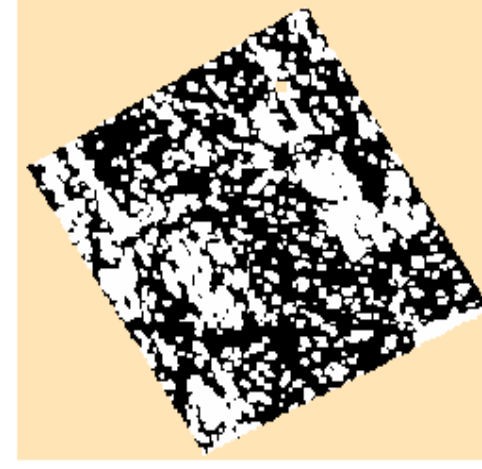
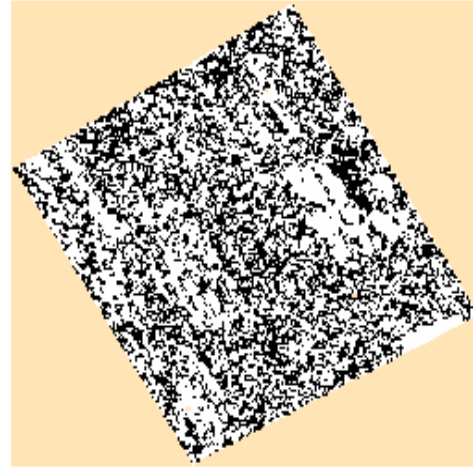
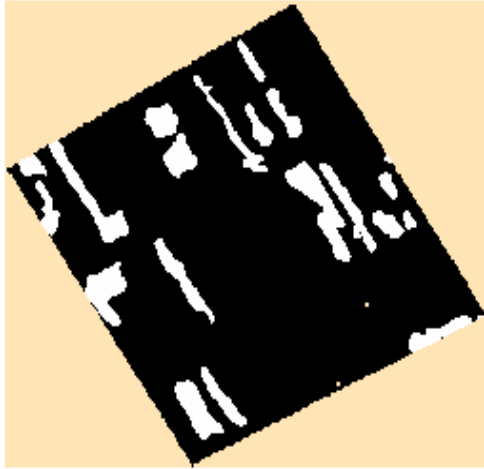
Ground Truth

PCA-K

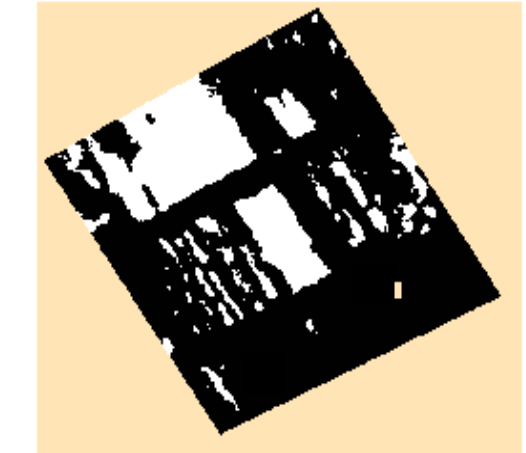
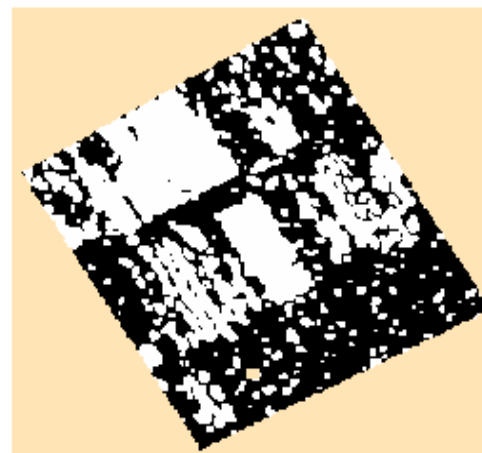
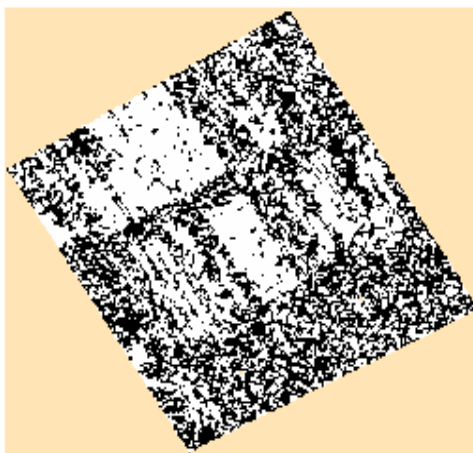
SAE-K

Proposed

Pair 1



Pair 2



Result [2/2] : Change Maps

Proposed method produces visually better change maps

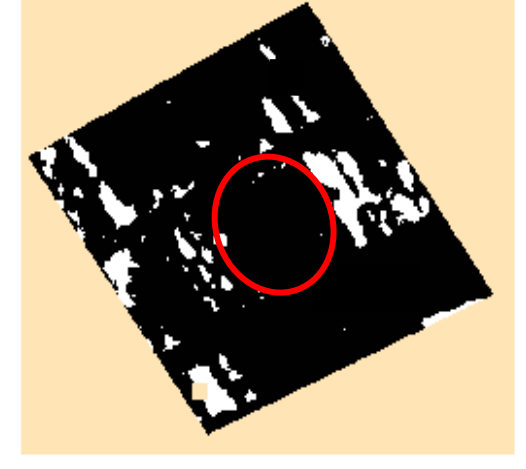
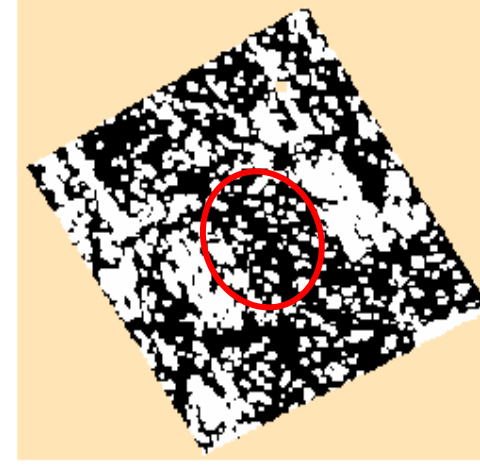
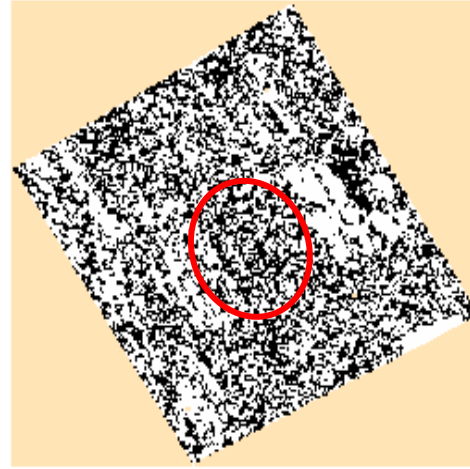
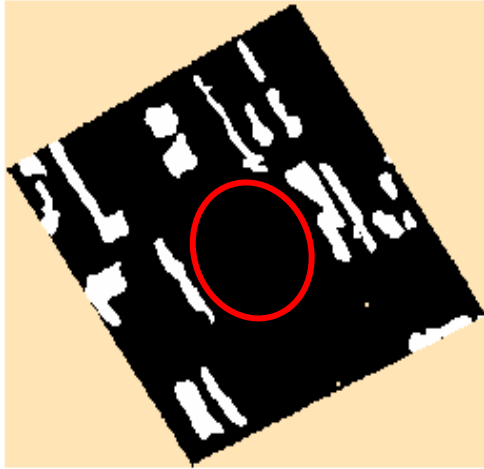
Ground Truth

PCA-K

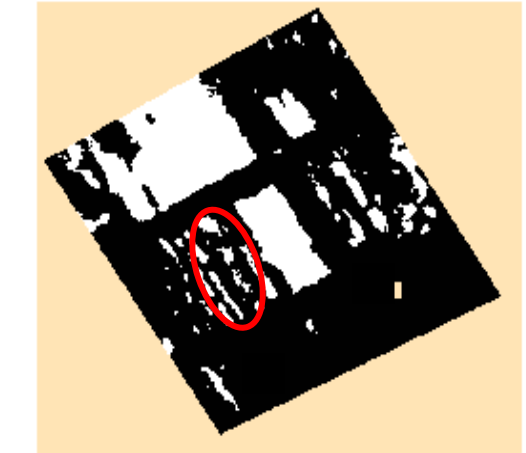
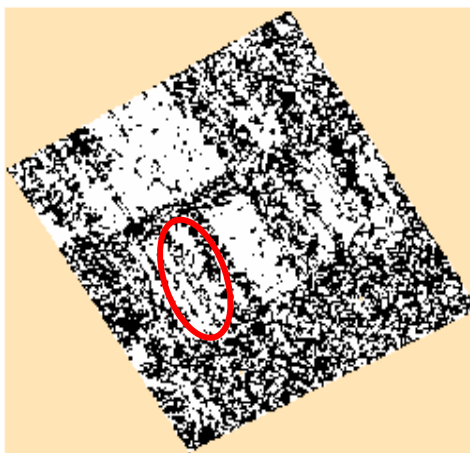
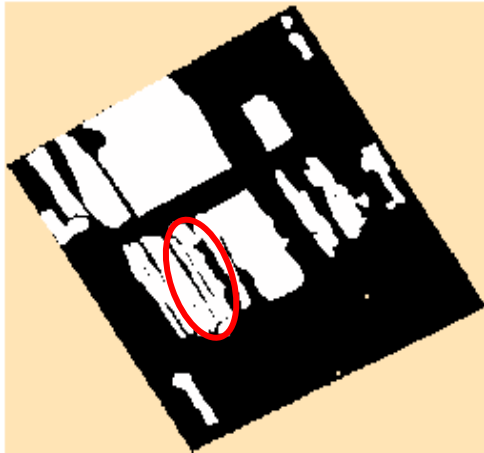
SAE-K

Proposed

Pair 1



Pair 2



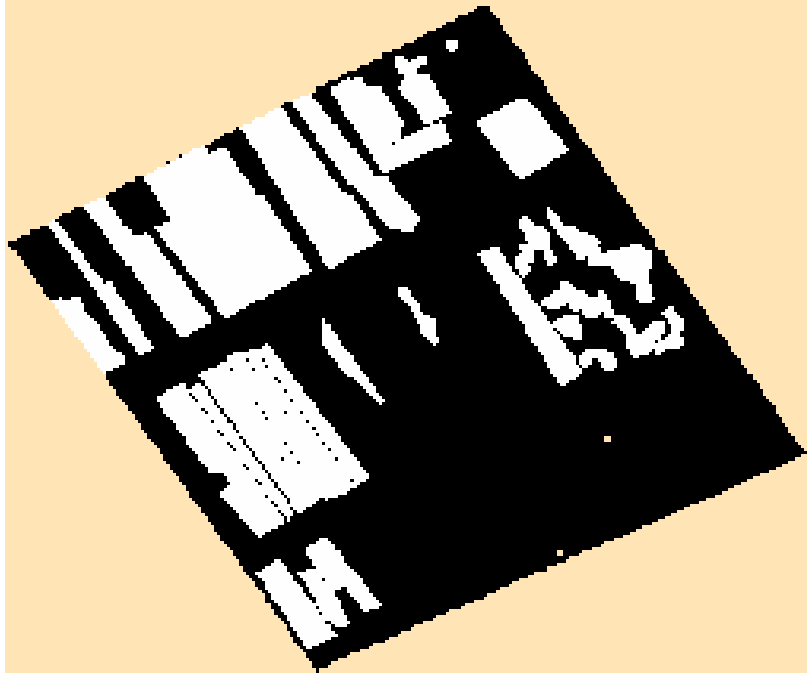
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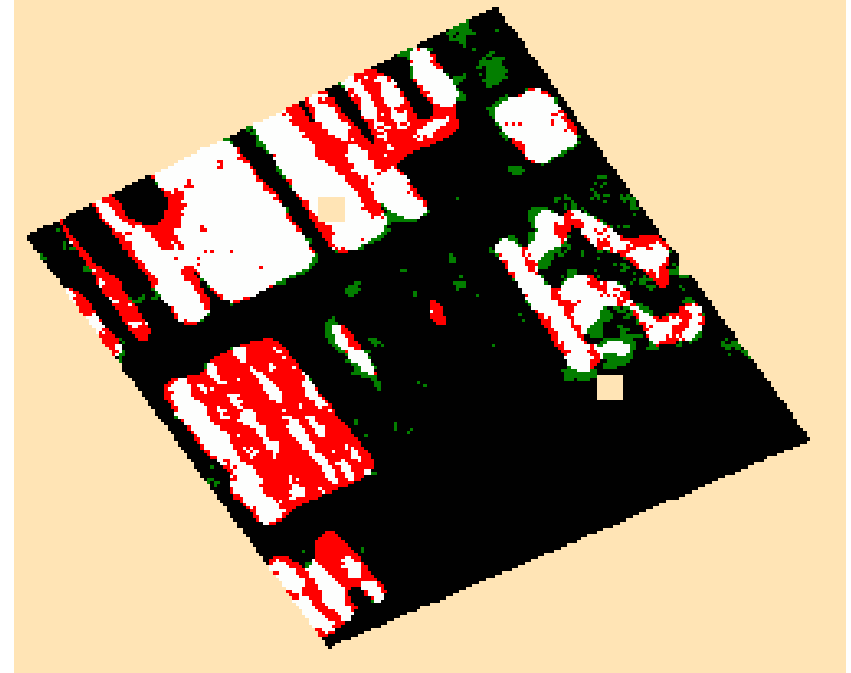
Current Work: Improving Proposed Network

False Negatives show that many foreground areas are undetected

Ground Truth



Colorized Change Map



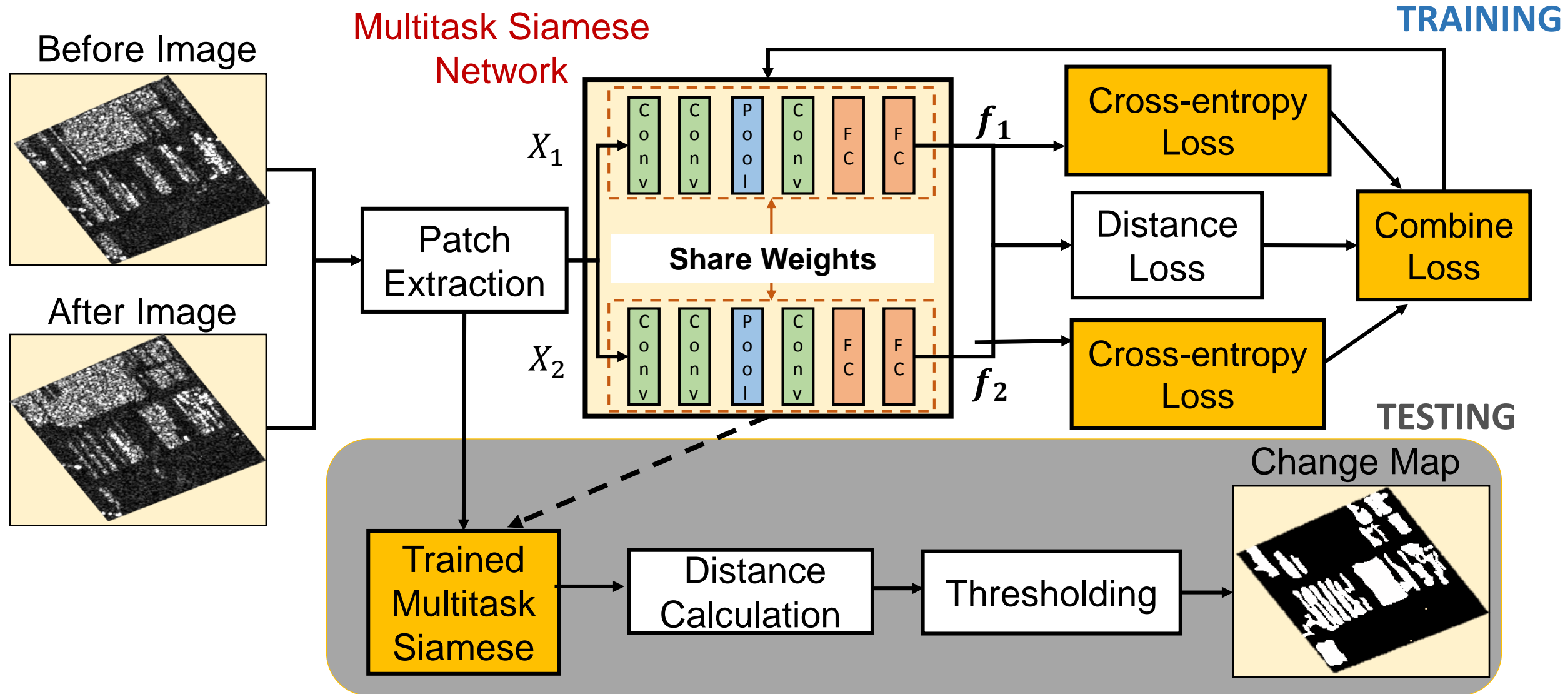
Legend: TP, TN, FP, FN

Research Question: Can we improve the detection of foreground?

- Use additional information about foreground and background

Multitask Siamese Network

Add foreground classification task as a support to change detection task



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Collaboration Activities

Actively initiated several foreign and domestic collaborations

Institute

Outcome

European Remote Sensing Firm

Exhaustive feedback from an expert and knowledge of remote sensing business model

INRIA France

Built strong connection with foreign academia on ship classification project

University of Trento Italy

Built strong connection with foreign academia on change detection project

NEC Labs Europe

Initiated cross-lab collaboration opportunity

AIST Japan

Special lecture series by renowned professor and created business opportunity

Kyushu University

Feedback on the current change detection project and obtained useful references

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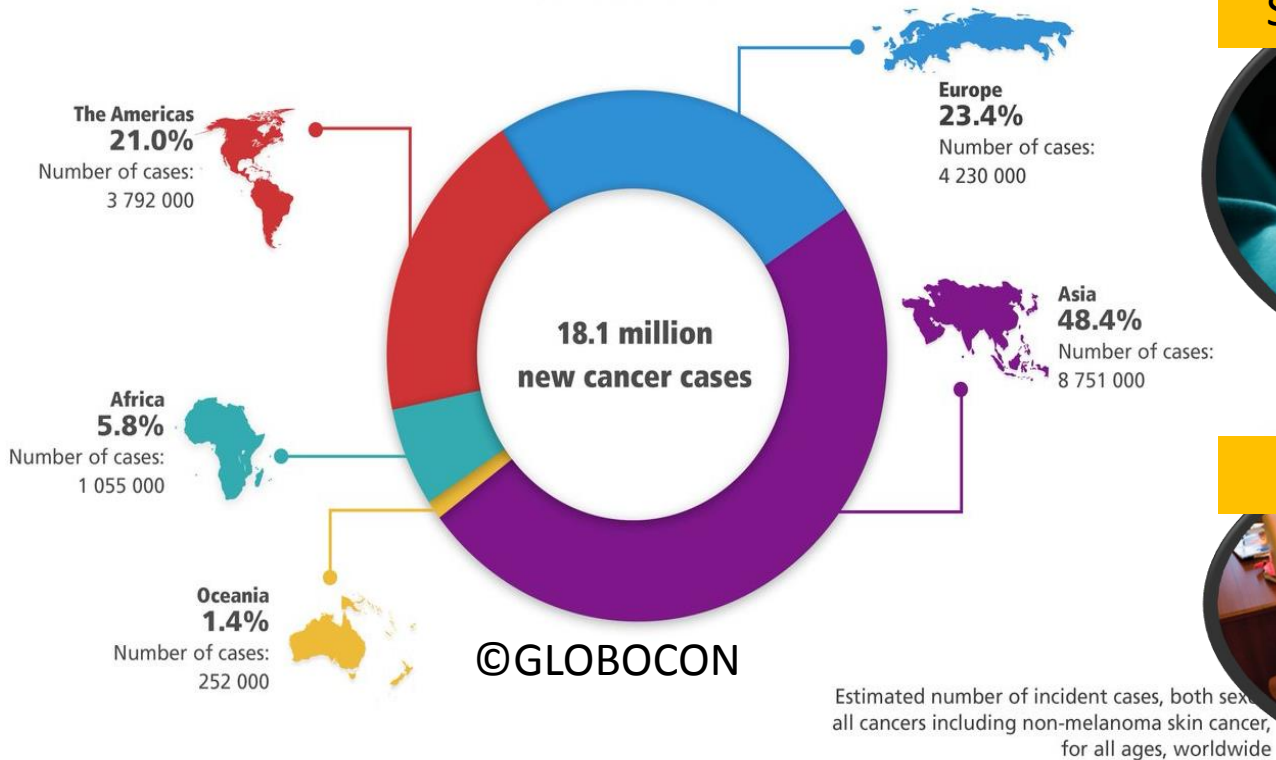
1. Ship Classification for Maritime Surveillance
2. Change Detection in Time-series of Images
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5. Case Study: Brain Tumor Segmentation with MRI

Motivation

50,000+ new brain tumor cases are reported in India each year

20% are children, tumor kills more children than any other disease

2018 Global Cancer Incidence



Treatments

SURGERY



RADIATION



CHEMO

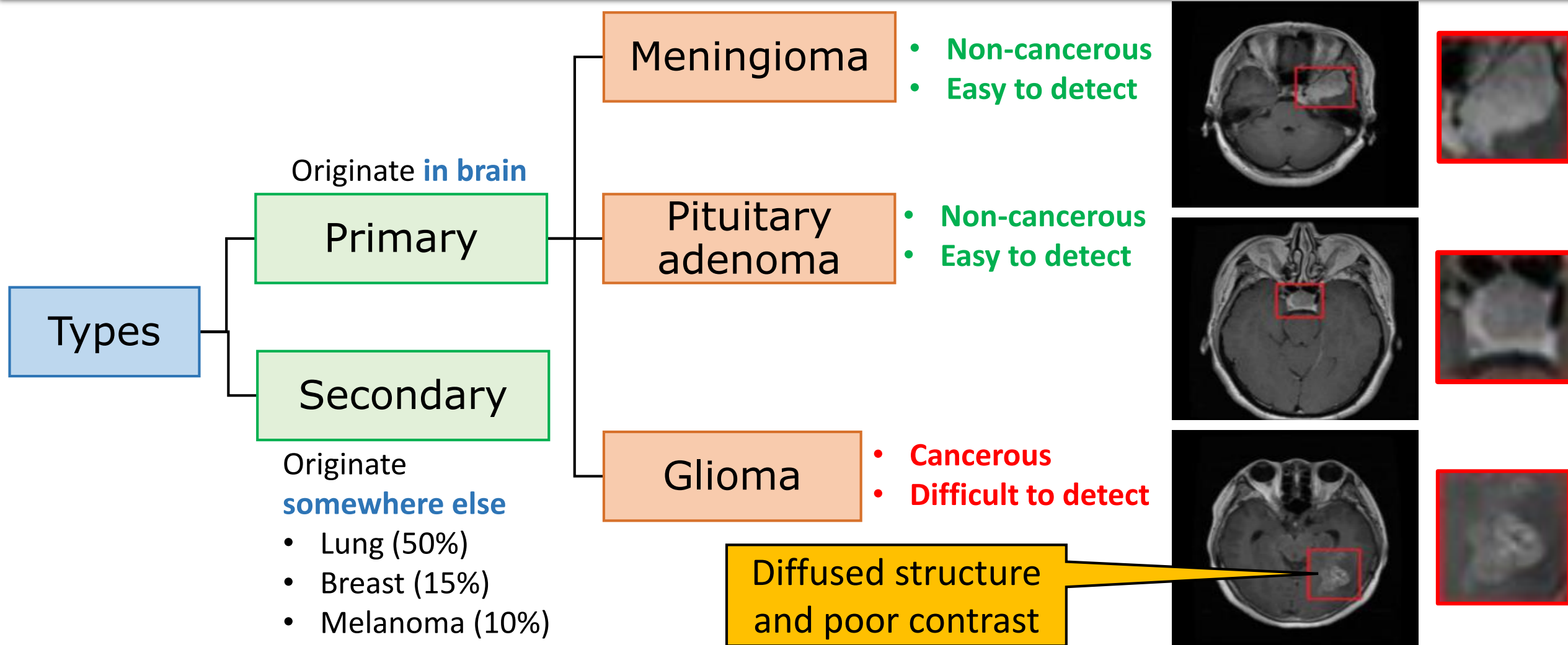


- Only 51% success
- Very painful
- Highly expensive

90% cases could be cured if detected early and correctly

Brain tumor and its types

Brain tumor is a lump created by abnormal growth of cells in brain



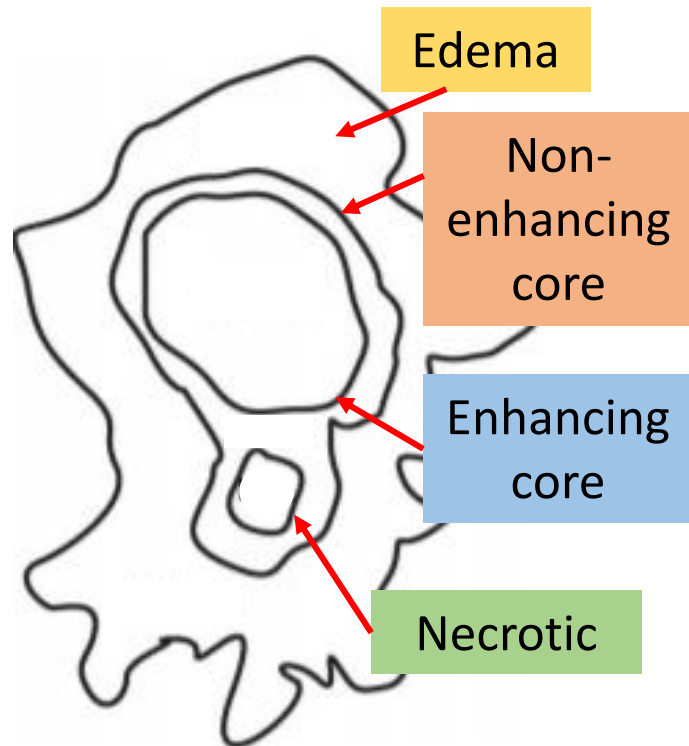
Accurate glioma segmentation is needed to detect brain cancer

Role of MRI images

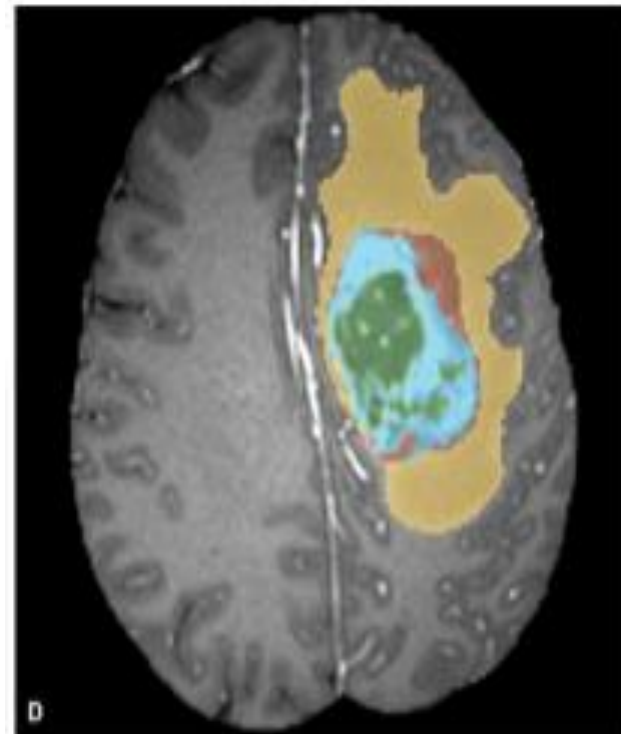
Provides unique information about different glioma segments

MRI has high-resolution imaging quality and many modalities

Glioma
Segments



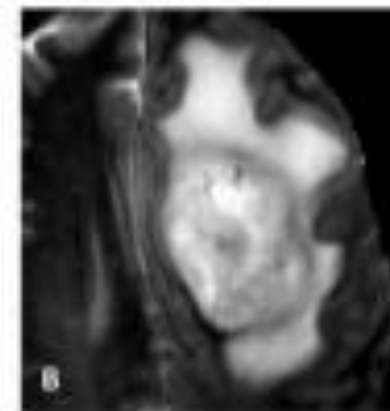
MRI showing
glioma segments



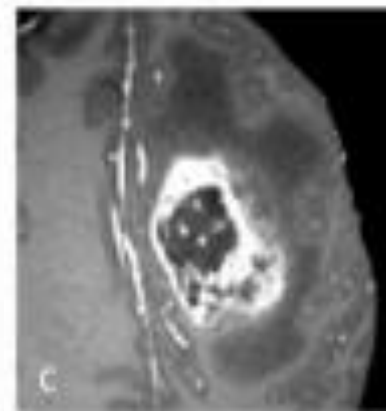
FLAIR



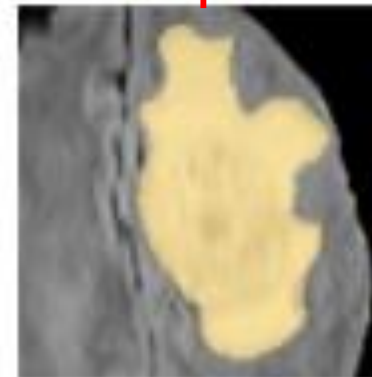
T2



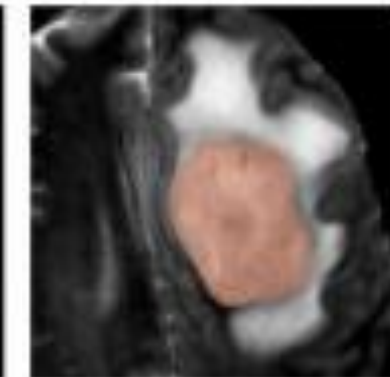
T1



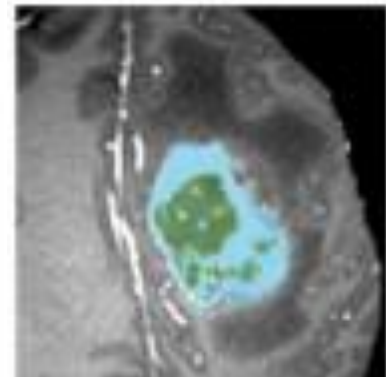
Complete



Core



Enhance



MRI images are highly suitable for glioma segmentation

Challenges in MRI-based Brain Tumor Segmentation

3 categories of challenges

1. MRI Artifacts	2. Glioma Features	3. Dataset
<ul style="list-style-type: none">• Noise• Intensity inhomogeneity• Non-standardized scale	<ul style="list-style-type: none">• Shape, size and location unpredictable• Tumor cells affect nearby healthy cells	<ul style="list-style-type: none">• Huge image size• Imbalanced dataset• Variation in expert labelling

Challenges in MRI-based Brain Tumor Segmentation

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Please Note: In this case study, I focus on presenting a feasible solution, and not on finding a research gap.

Challenges in MRI-based Brain Tumor Segmentation

3 categories of challenges

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MRI Pre-processing

MRI Pre-processing

Noise Removal



Intensity Homogeneity

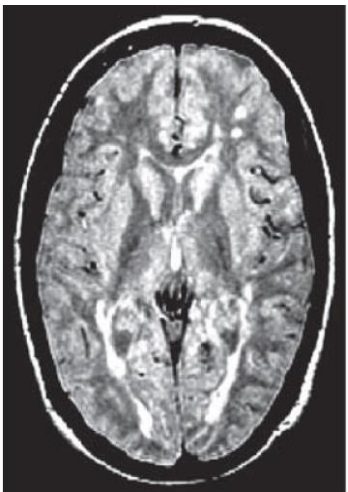


Intensity Standardization

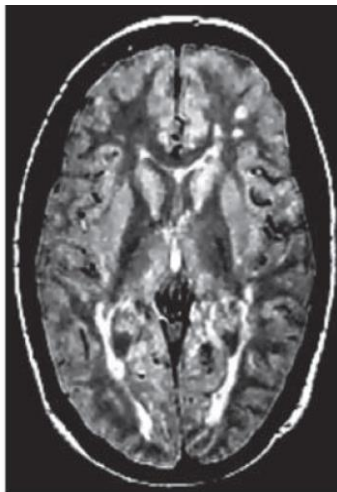
To **improve contrast** between brain tissues

To **remove intensity variations** caused by difference in magnetic field

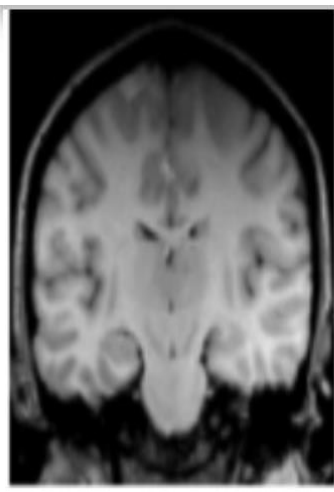
To **standardize intensity scales** varied due to different acquisition times



Original Image



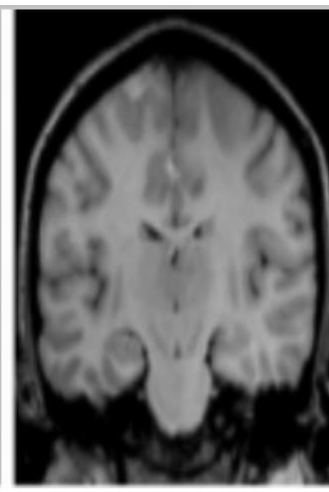
Noise Suppressed



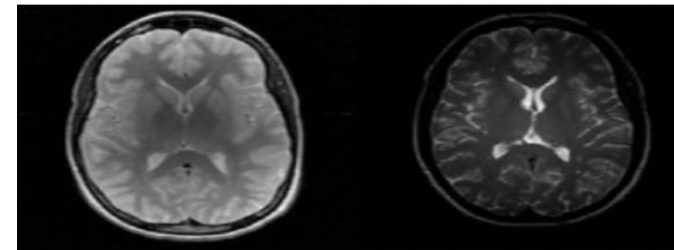
Original Image



Inhomogeneity field



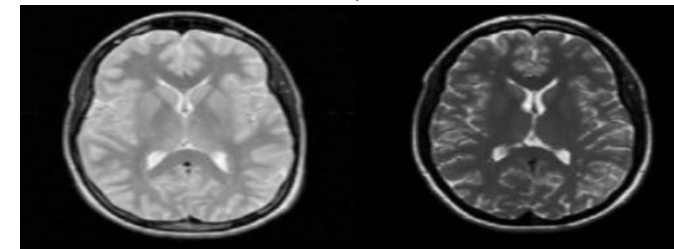
Corrected Image



T2



T2



Challenges in MRI-based Brain Tumor Segmentation

3 categories of challenges

1. MRI Artifacts	2. Glioma Features	3. Dataset
<ul style="list-style-type: none">• Noise• Intensity inhomogeneity• Non-standardized scale	<ul style="list-style-type: none">• Shape, size and location unpredictable• Tumor cells affect nearby healthy cells	<ul style="list-style-type: none">• Huge image size• Imbalanced dataset• Variation in expert labelling



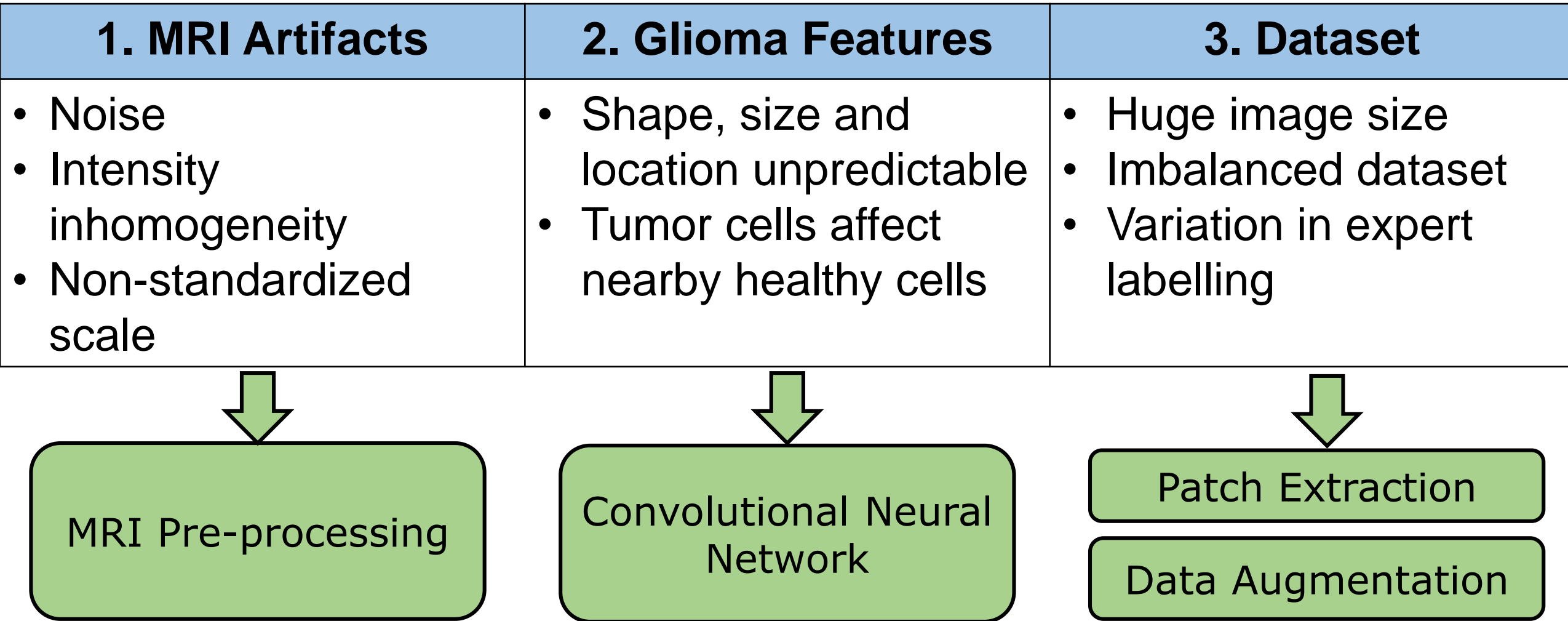
MRI Pre-processing



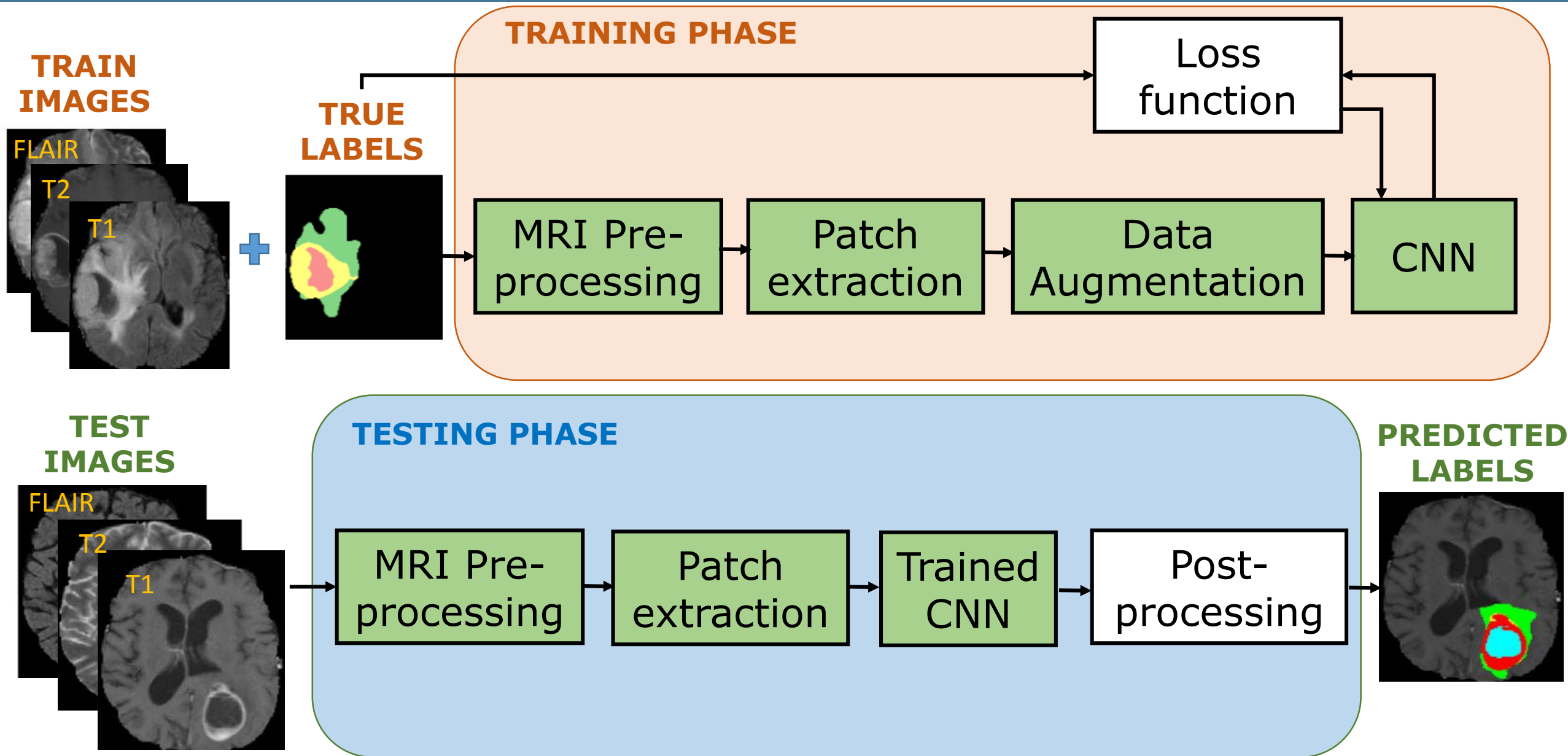
Convolutional Neural
Network

Challenges in MRI-based Brain Tumor Segmentation

3 categories of challenges



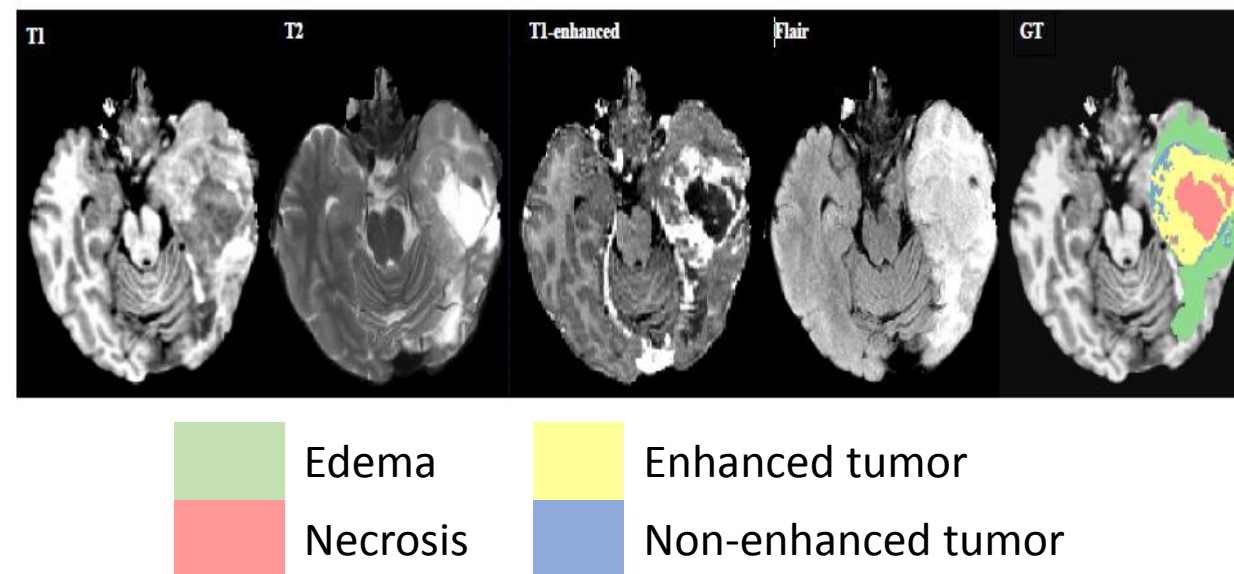
Proposed Solution



Experimental Set-up for Evaluation

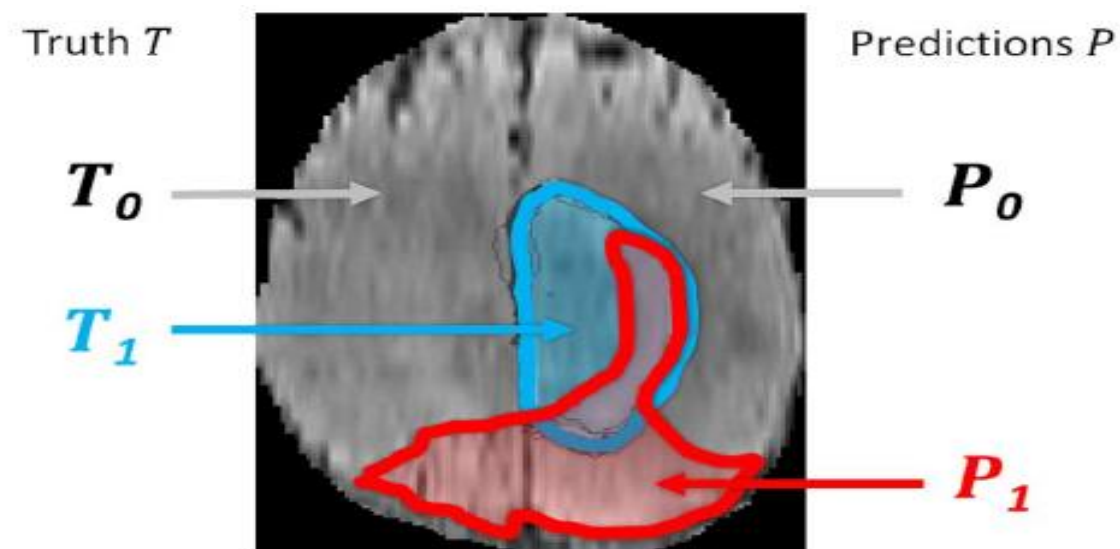
▪ Dataset- BraTS 2013-2018

- Benchmark dataset
- A challenge in MICCAI conference
- For each brain there exists 4 modalities
 - T1, T2, T1-enhanced, FLAIR
- Ground truth for 5 segmentation labels
 - namely non-tumor
 - necrosis
 - edema
 - non-enhancing tumor
 - enhancing tumor



▪ Evaluation Metric

- Dice Coefficient = $\frac{2(P_1 \cap T_1)}{P_1 + T_1}$
- Sensitivity = $\frac{P_1 \cap T_1}{T_1}$
- Specificity = $\frac{P_0 \cap T_0}{T_0}$



Future Directions

- Incorporating blood reports and prescription data
- Glioma grading – grade 1,2,3,4
- 3D CNN's for handling voxels

References

- **Course on fundamentals of medical image analysis**
 - CAP5516- Medical Image Computing, Prof. Ulas Bagci, UCF
- **Survey research papers**
 - Litjens, Geert, et al. "A survey on deep learning in medical image analysis." *Medical image analysis* 42 (2017): 60-88.
 - Lundervold et al., "An overview of deep learning in medical imaging focusing on MRI" (2019), <https://arxiv.org/abs/1811.10052>
- **Brain tumor segmentation papers**
 - Akkus, Zeynettin, et al. "Deep learning for brain MRI segmentation: state of the art and future directions." *Journal of digital imaging* 30.4 (2017): 449-459.
 - Havaei, Mohammad, et al. "Brain tumor segmentation with deep neural networks." *Medical image analysis* 35 (2017): 18-31.
 - Pereira, Sérgio, et al. "Brain tumor segmentation using convolutional neural networks in MRI images." *IEEE transactions on medical imaging* 35.5 (2016): 1240-1251.
 - Menze, Bjoern H., et al. "The multimodal brain tumor image segmentation benchmark (BRATS)." *IEEE transactions on medical imaging* 34.10 (2014): 1993-2024.
- **Cancer statistics**
 - Global Cancer Observatory <https://gco.iarc.fr/today/home>
 - <http://cancerindia.org.in/globocan-2018-india-factsheet/>

Thank You!