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/

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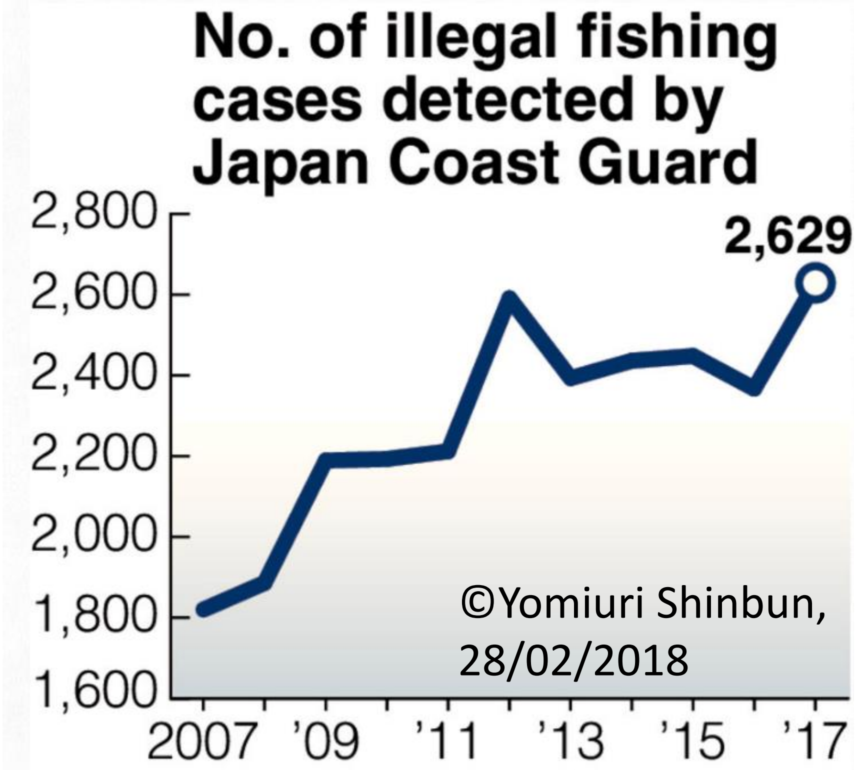
Motivation

Ship Classification is a key application in maritime surveillance

Helps in quick identification of ships involved in illegal activities

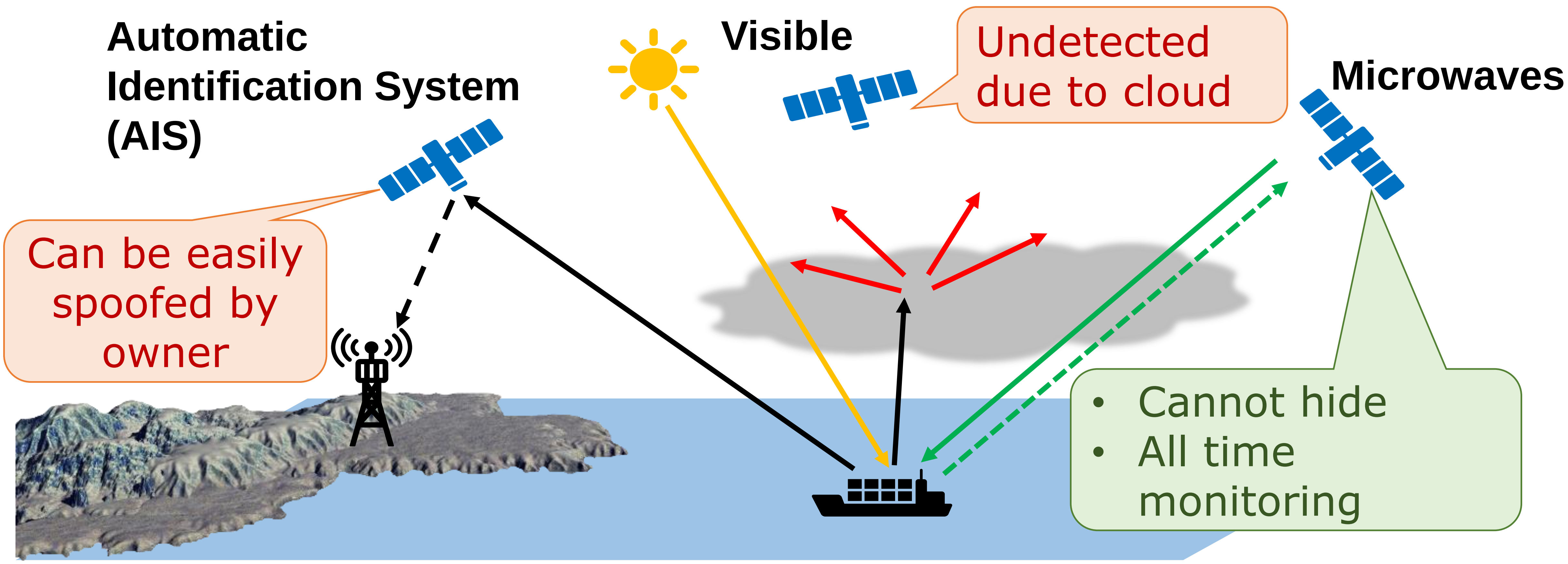


<u>$US23 billion</u> loss worldwide per year!

Ship Classification from Space

3 major sources of information : AIS, Visible and Microwaves

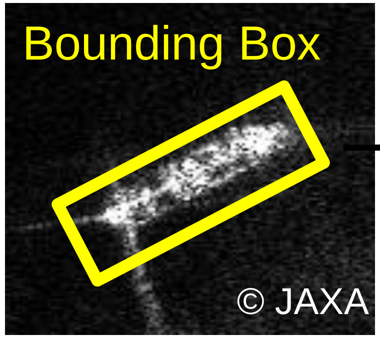
Microwaves can see ships undetected/spoofed by AIS and Visible



Microwave images are highly reliable for ship classification

Conventional Methods

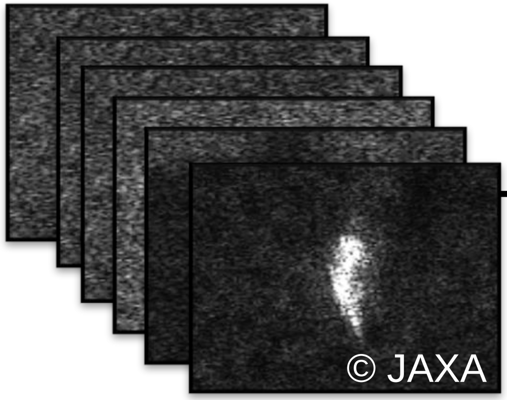
1. Hand-crafted feature (HCF)-based



Feature extractor* → Classifier (SVM) → Class

*Length, Area, Intensity, … etc.

2. Convolutional Neural Network (CNN)-based



CNN → Class

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

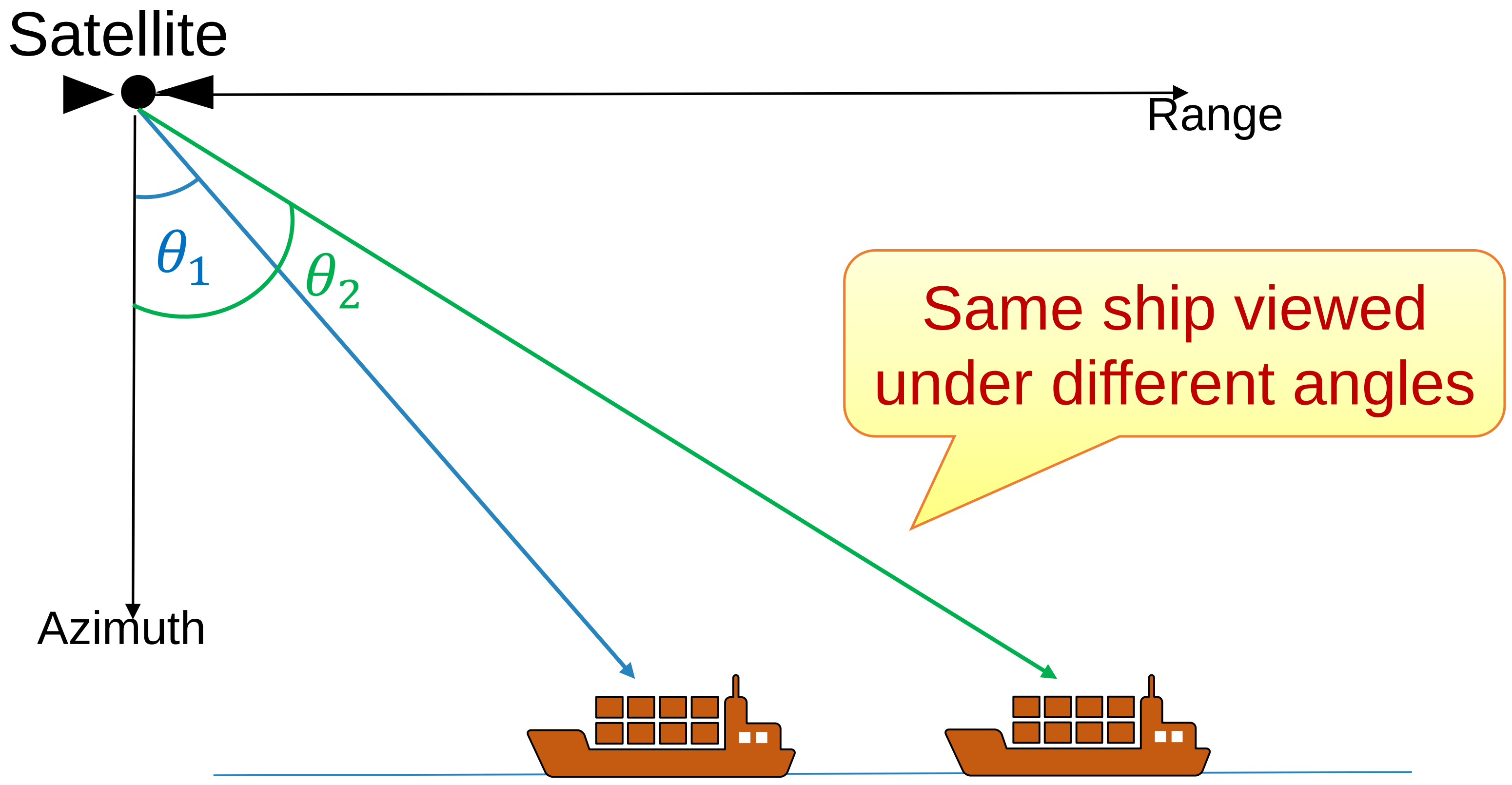
These methods classify a ship based on its appearance in image

Problem

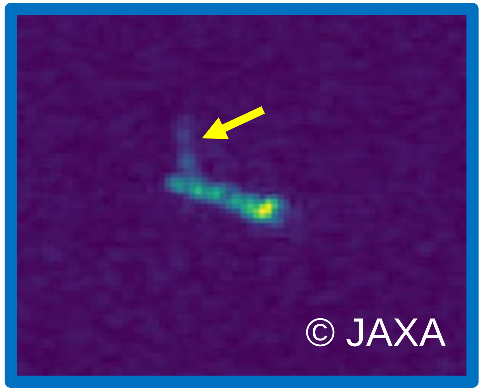
Appearance of a ship varies with satellite viewing angle

Labelled microwave images are very few to learn all possible variations

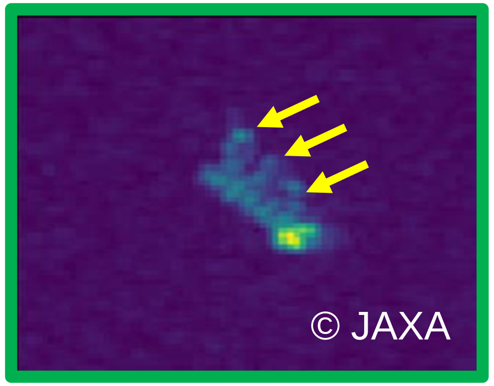
Example:



$\theta_1 = 30^\circ$



$\theta_2 = 40^\circ$

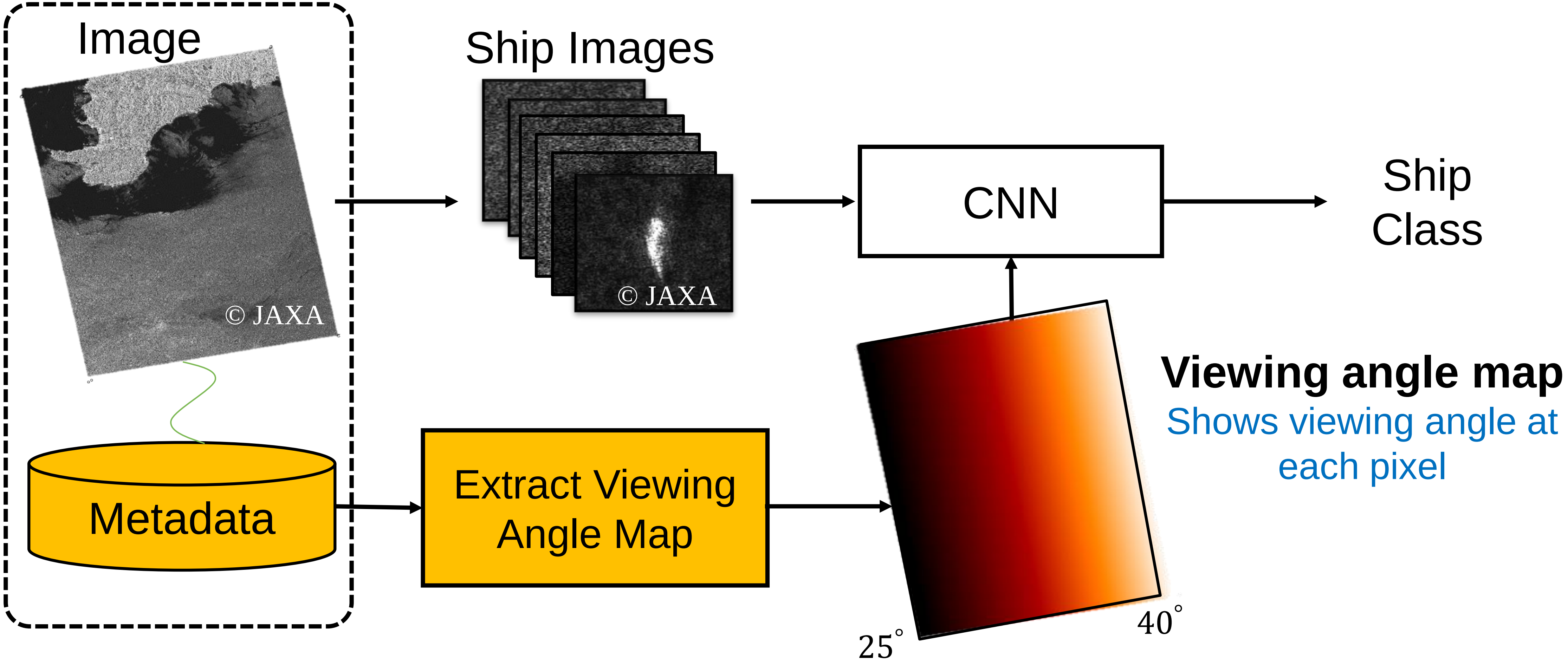


Only image information is insufficient for robust classification

Proposed Method

Use viewing angle as an additional information in a NN

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

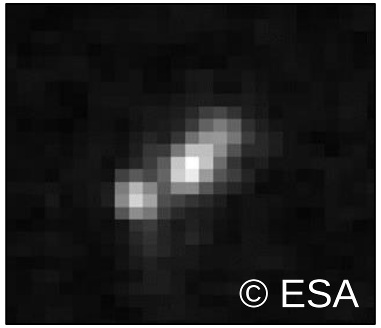


Sharma et al., CNN-based ship classification method incorporating SAR geometry information, SPIE RS 2018.

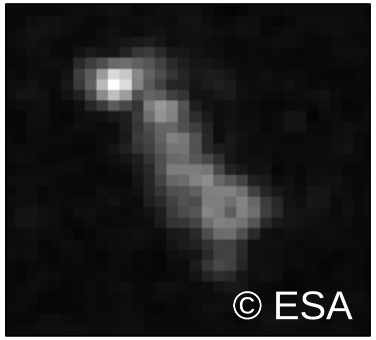
Experiments

Dataset: OpenSARShip*

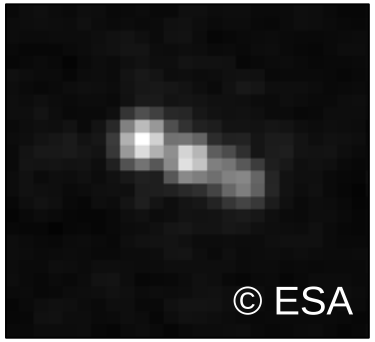
Container



Bulk-carrier



Tanker



*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).

Specifications

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

Conventional Methods

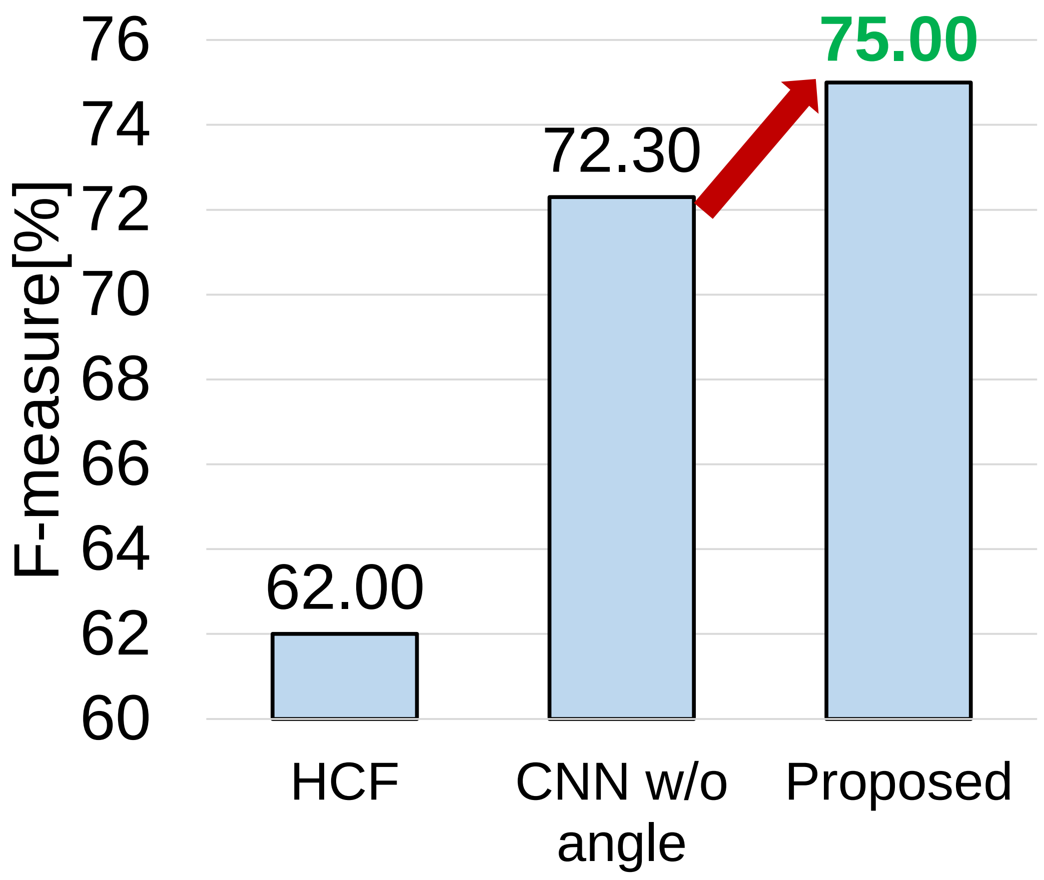
HCF	10 Features + SVM
CNN	w/o incident angle

Metrics

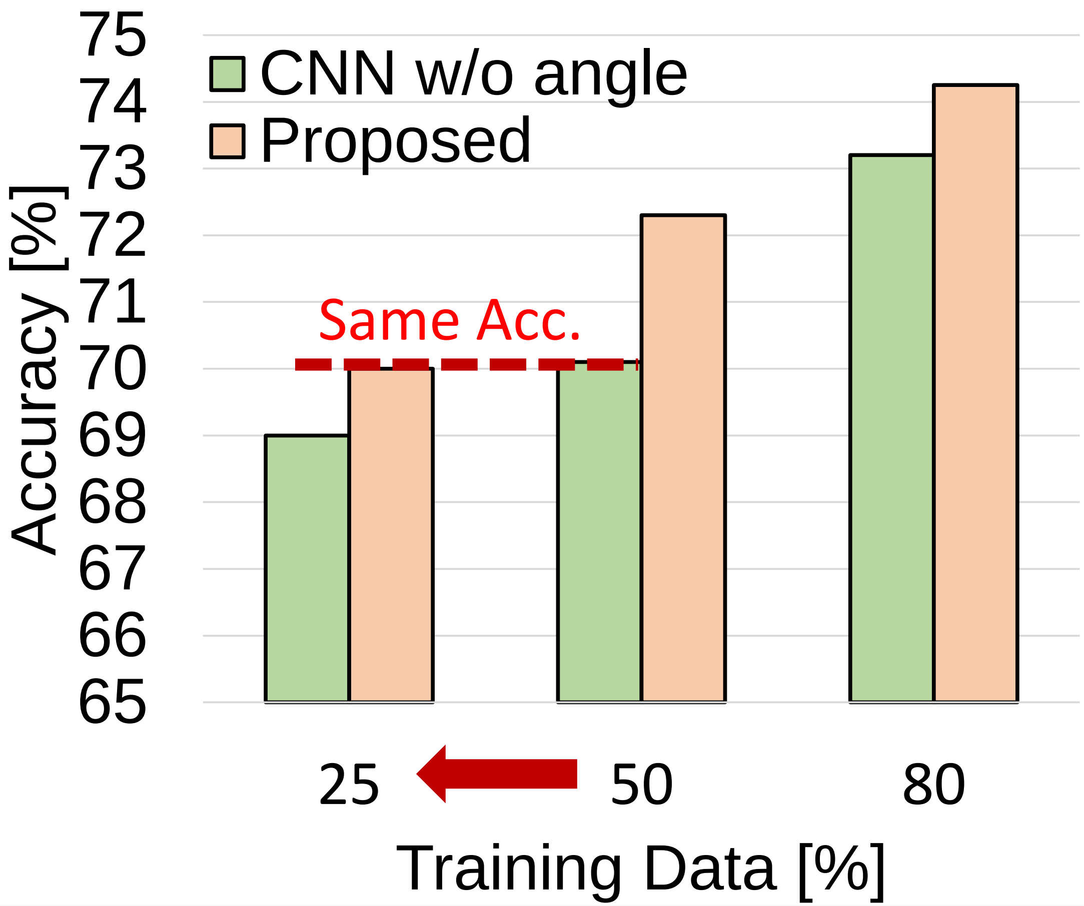
f-measure	Higher is better
#training data needed	Lower is better

Results

4.2% improvement in f-measure



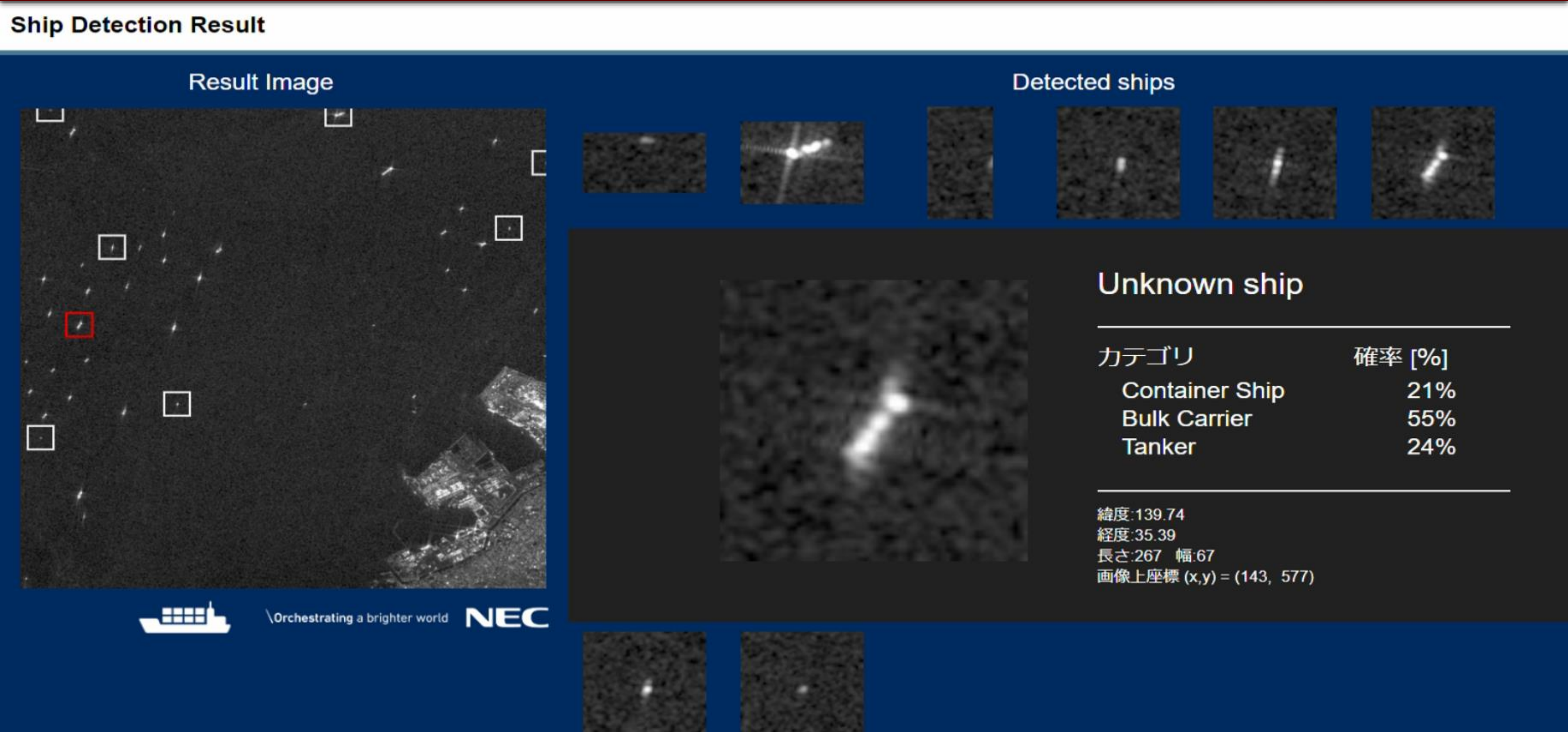
25% reduction in training data requirement



Proposed method outperforms the conventional methods

Demo Example

Presented at International Geosciences and Remote Sensing Symposium '19



Today I will present

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

Motivation

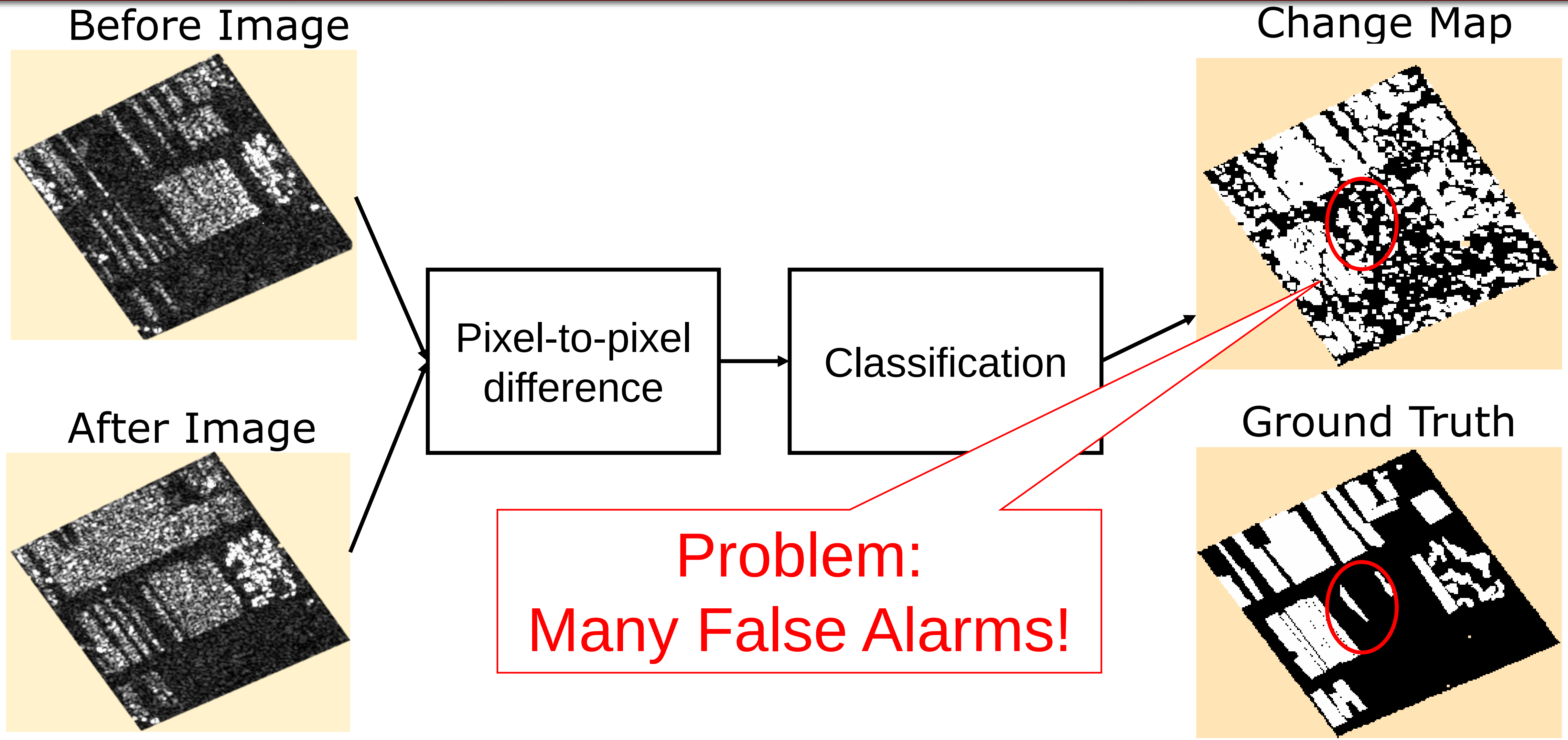
Change detection enables us to understand dynamics of Earth

Dubai Coastal Expansion

Saudi Arabia Irrigation

Conventional Method

Based on pixel-to-pixel difference followed by classification

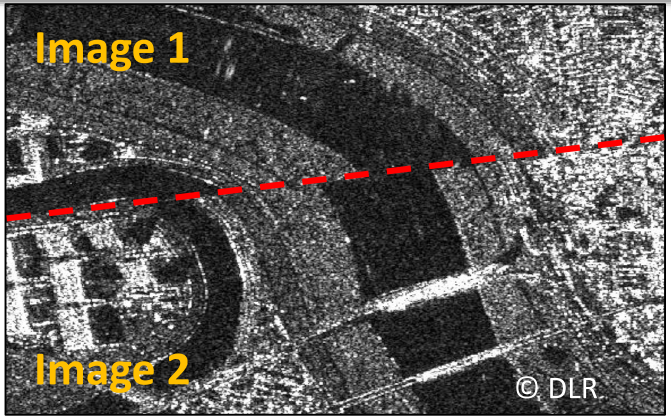


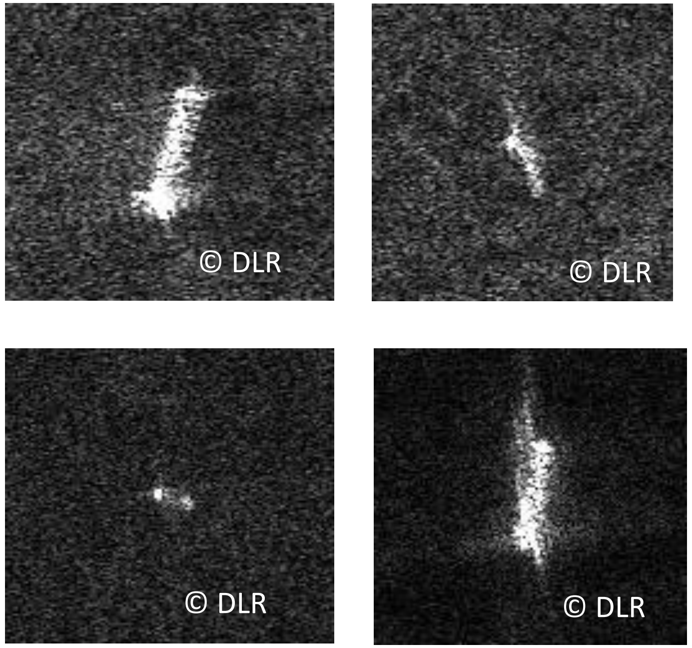
Problem

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

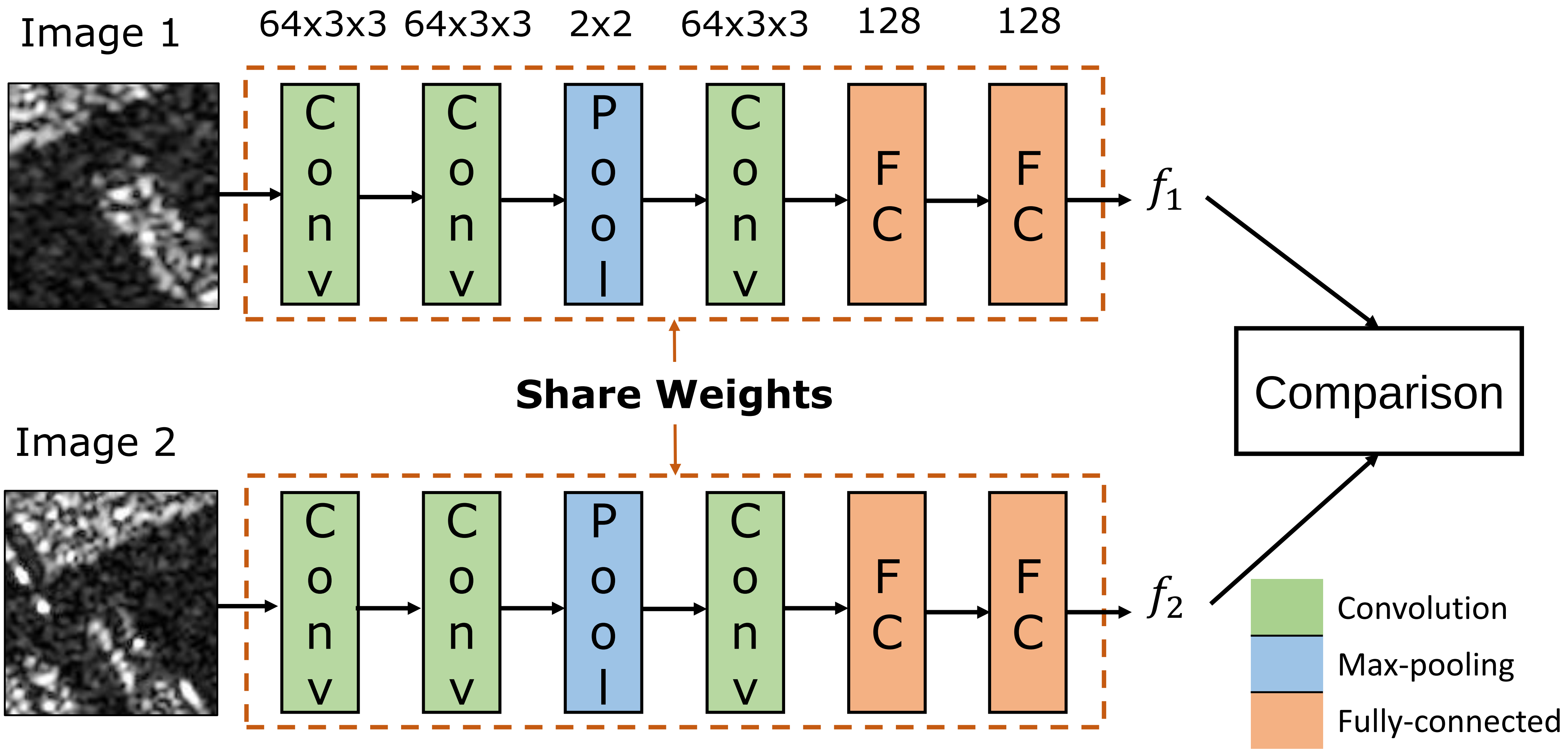




Solution

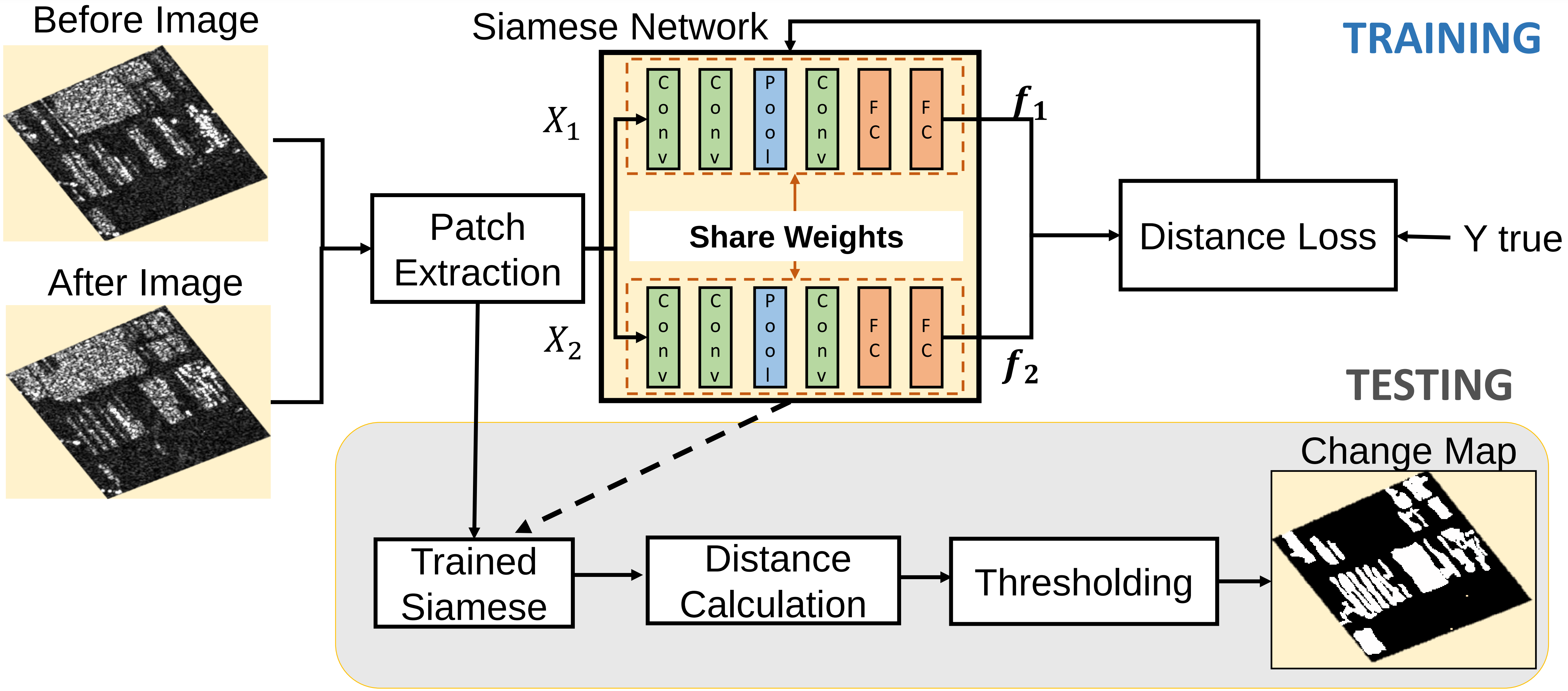
Feature-to-Feature difference method is robust to the conditions

Siamese network has been widely used for feature comparison



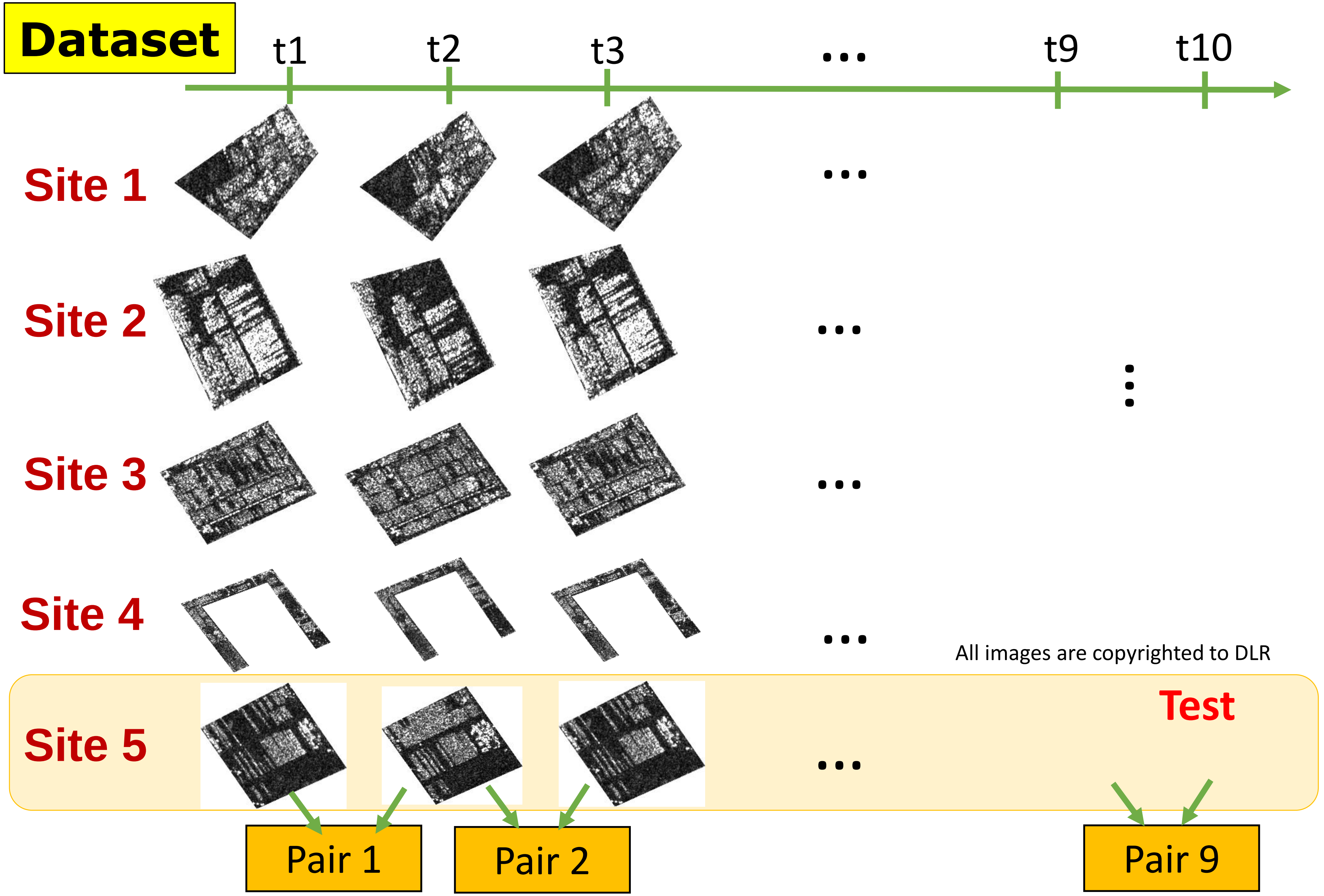
Proposed Method

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



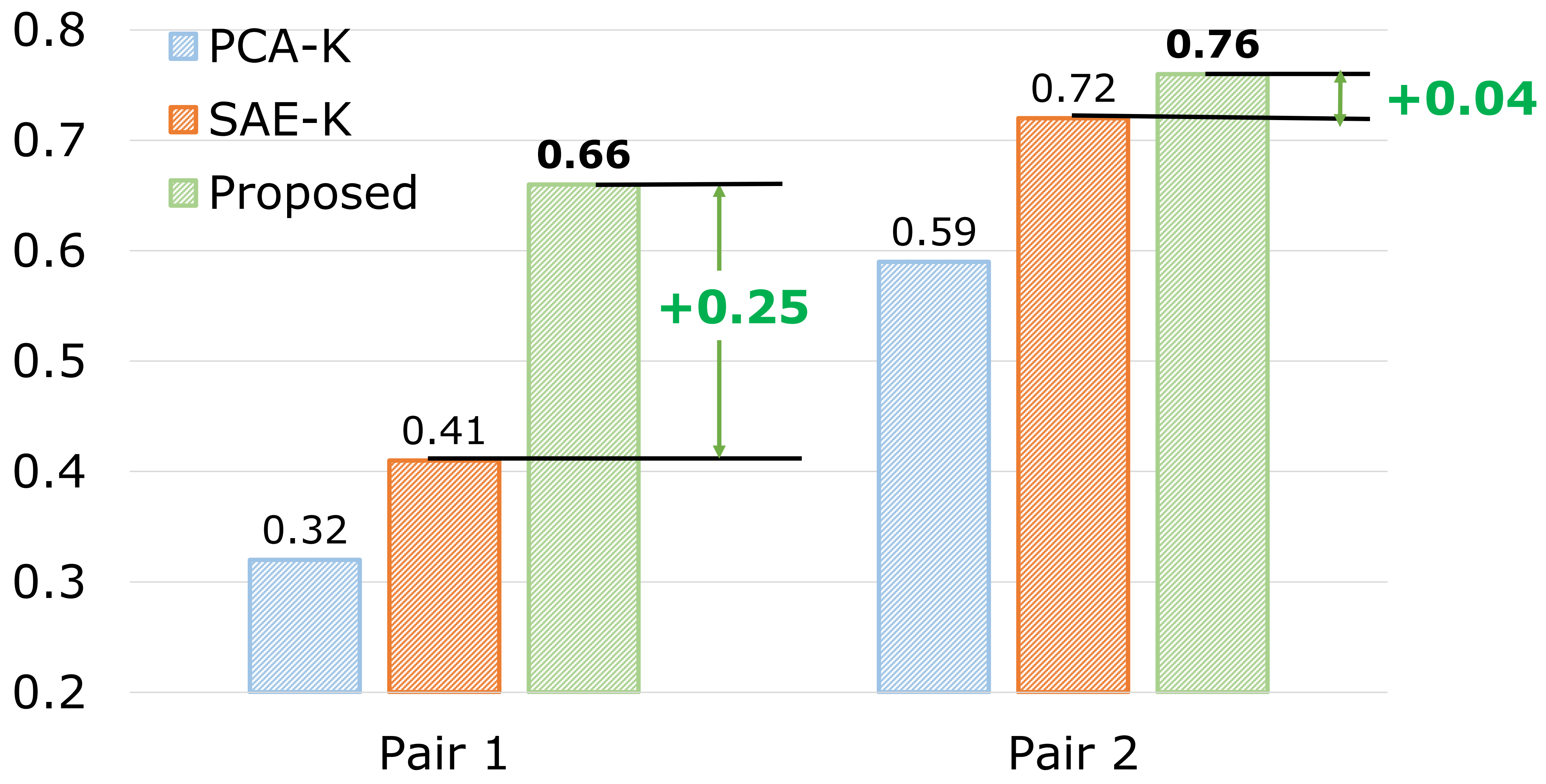
- **Specifications**
  - TerraSAR-X satellite
  - 1m resolution
- **Baselines:**
  - PCA-K [1]
  - SAE-K [2]
- **Evaluation Metrics**
  - f-measure
  - Change Maps

[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.

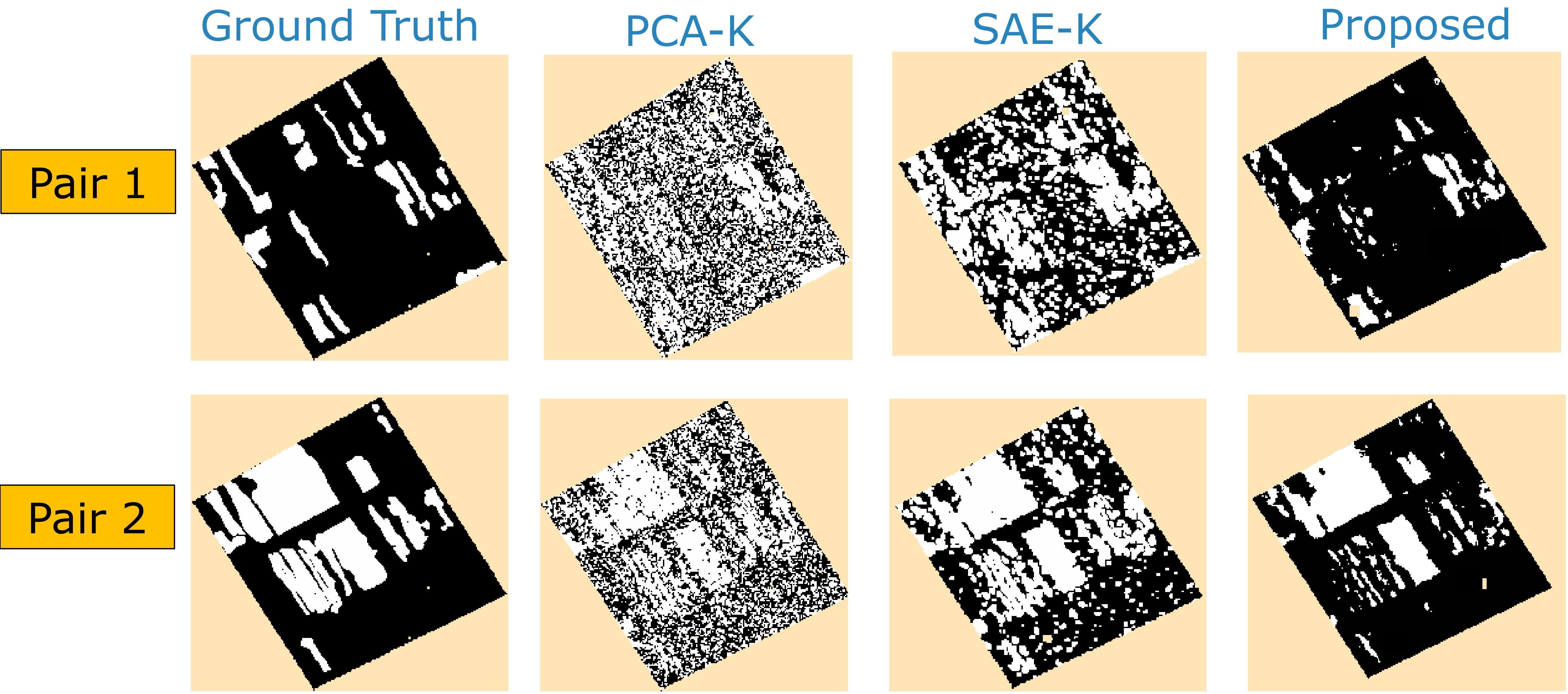
Result [1/2] : f-measure

Proposed method improves f-measure by 15% over baselines



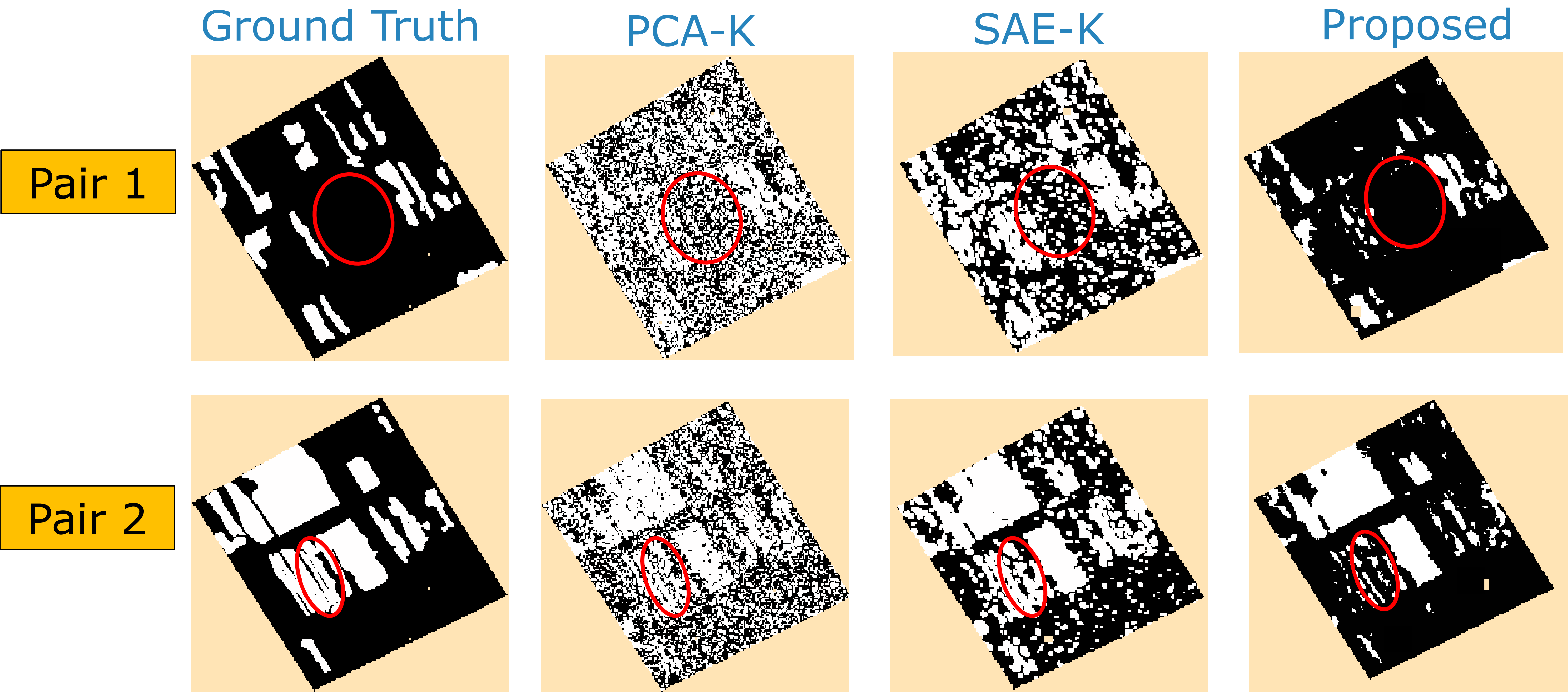
Result [2/2] : Change Maps

Proposed method produces visually better change maps



Result [2/2] : Change Maps

Proposed method produces visually better change maps



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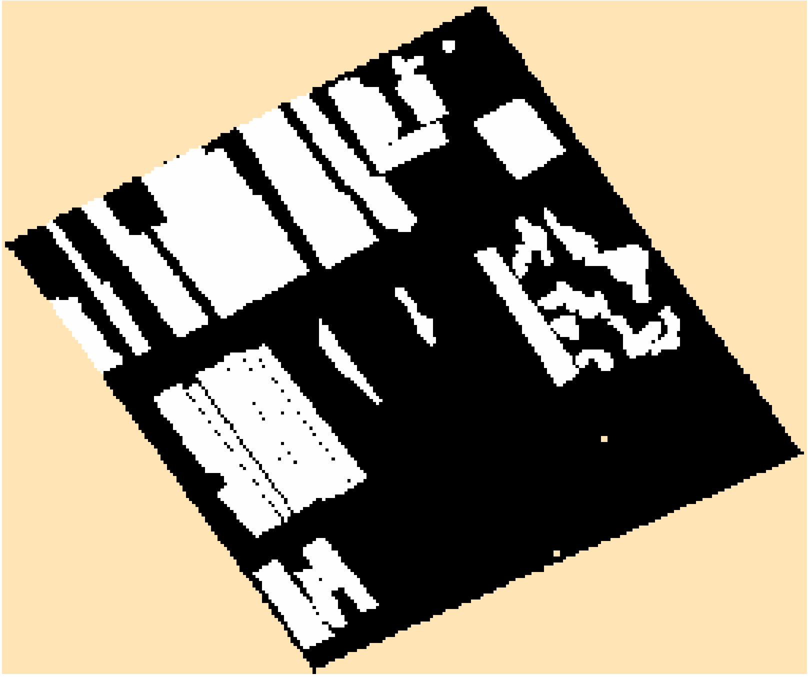
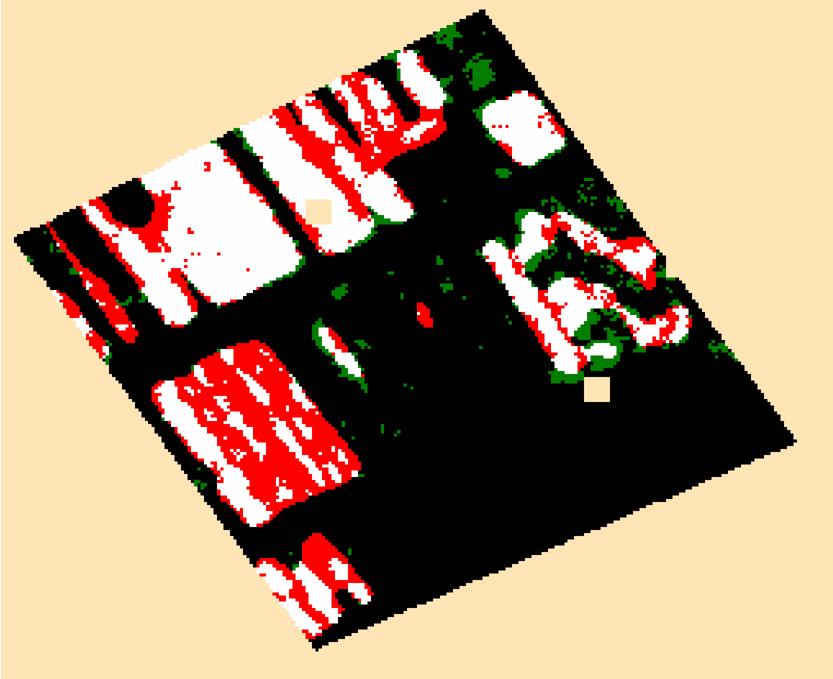
Current Work: Improving Proposed Network

False Negatives show that many foreground areas are undetected

Ground Truth



Colorized Change Map



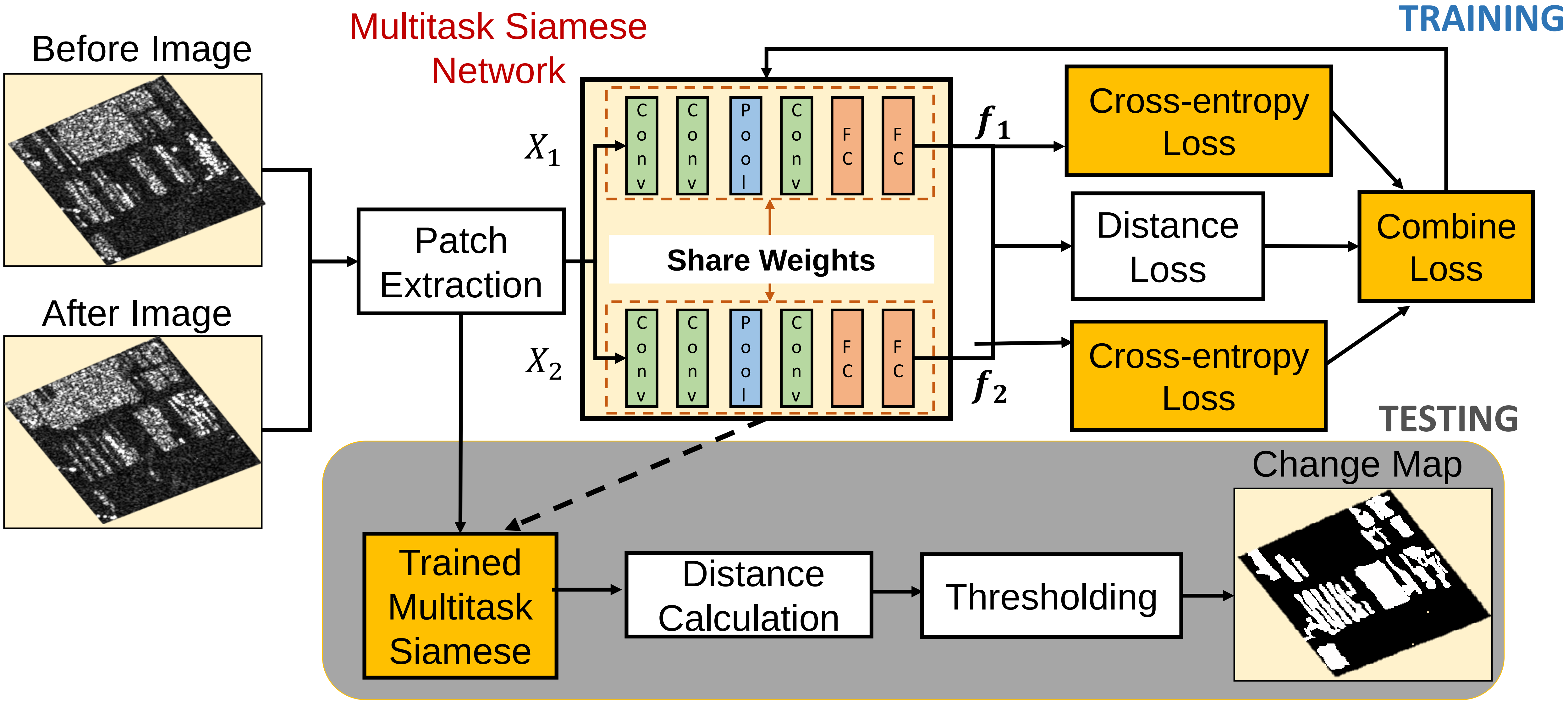
Legend: TP, TN, FP, FN

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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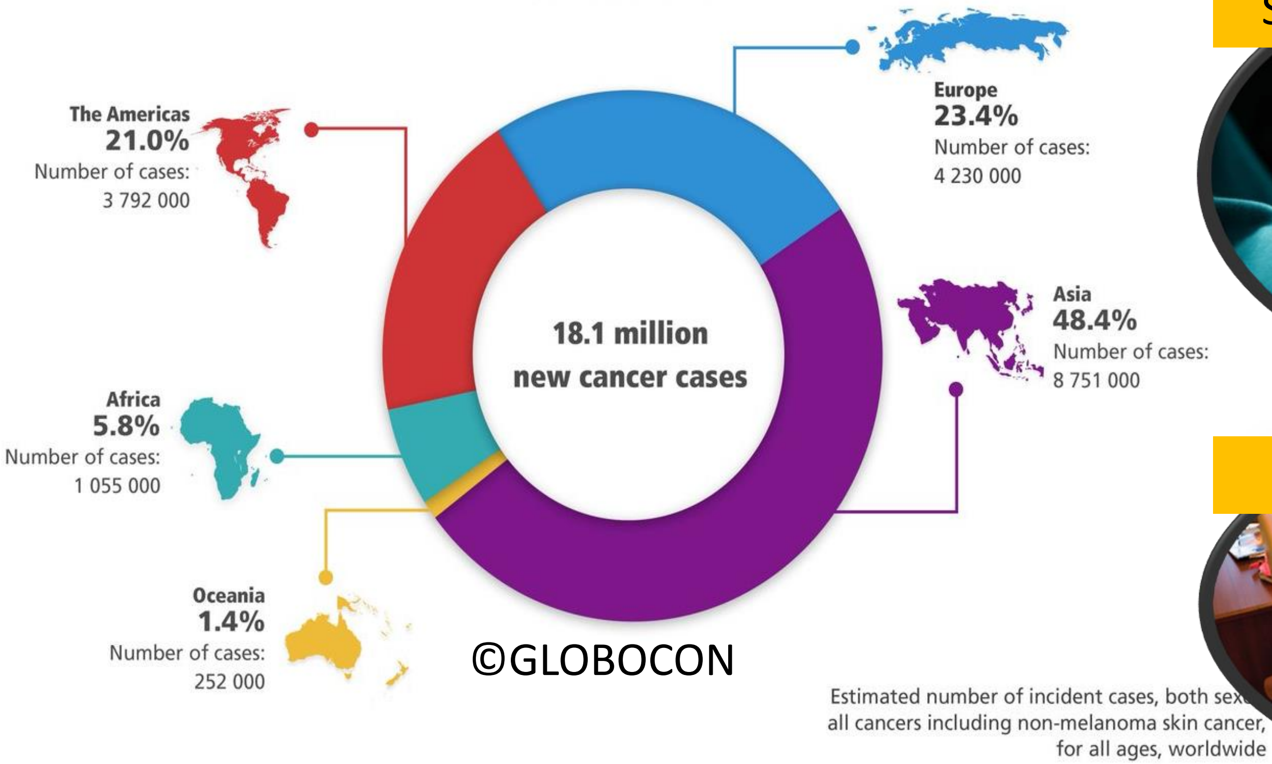
Motivation

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



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Treatments

SURGERY

RADIATION

CHEMO

- **Only 51% success**
- **Very painful**
- **Highly expensive**

90% cases could been cured if detected early and correctly

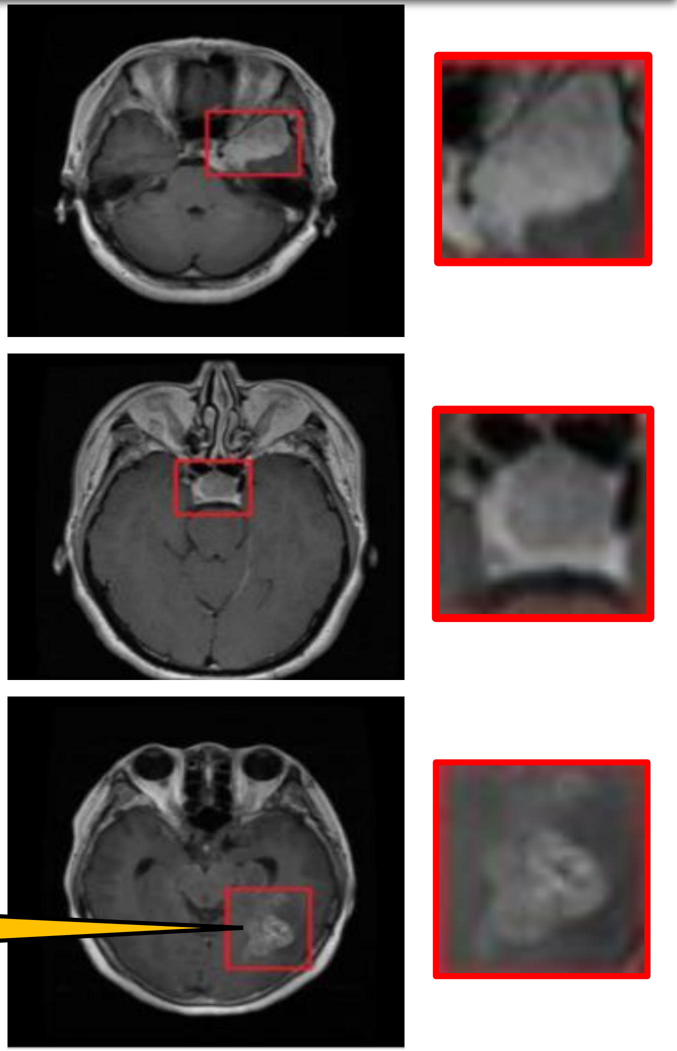
Brain tumor and its types

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

Types

- Primary
  - Originate **in brain**
  - Meningioma
    - Non-cancerous
    - Easy to detect
  - Pituitary adenoma
    - Non-cancerous
    - Easy to detect
  - Glioma
    - Cancerous
    - Difficult to detect
- Secondary
  - Originate **somewhere else**
    - Lung (50%)
    - Breast (15%)
    - Melanoma (10%)

Diffused structure and poor contrast



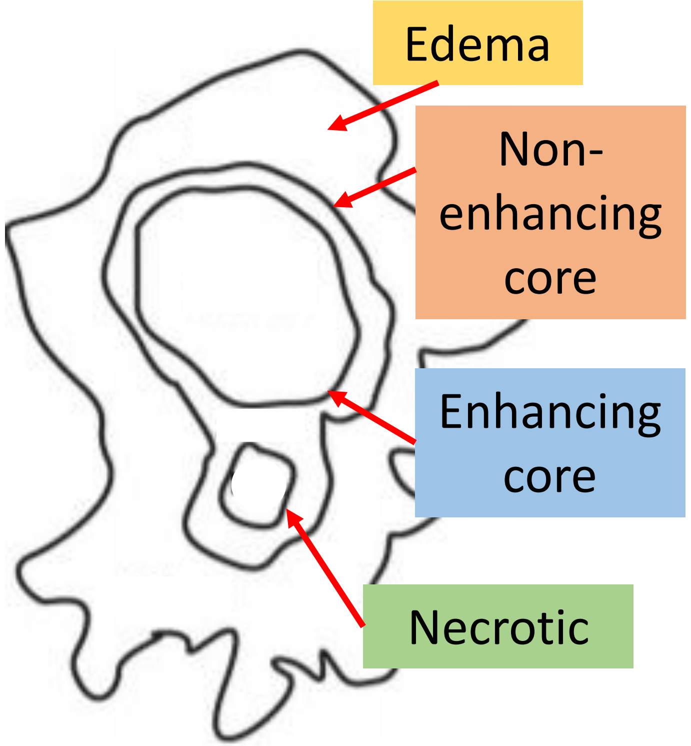
Accurate glioma segmentation is needed to detect brain cancer

Role of MRI images

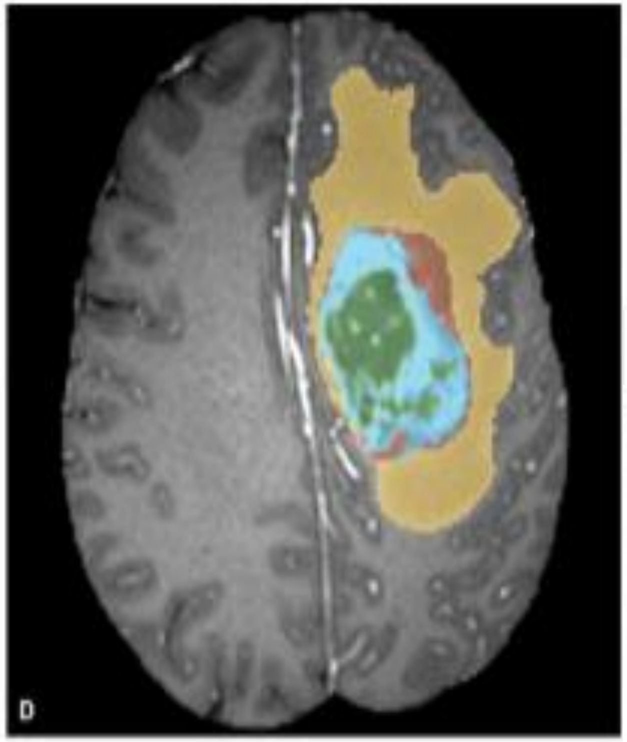
Provides unique information about different glioma segments

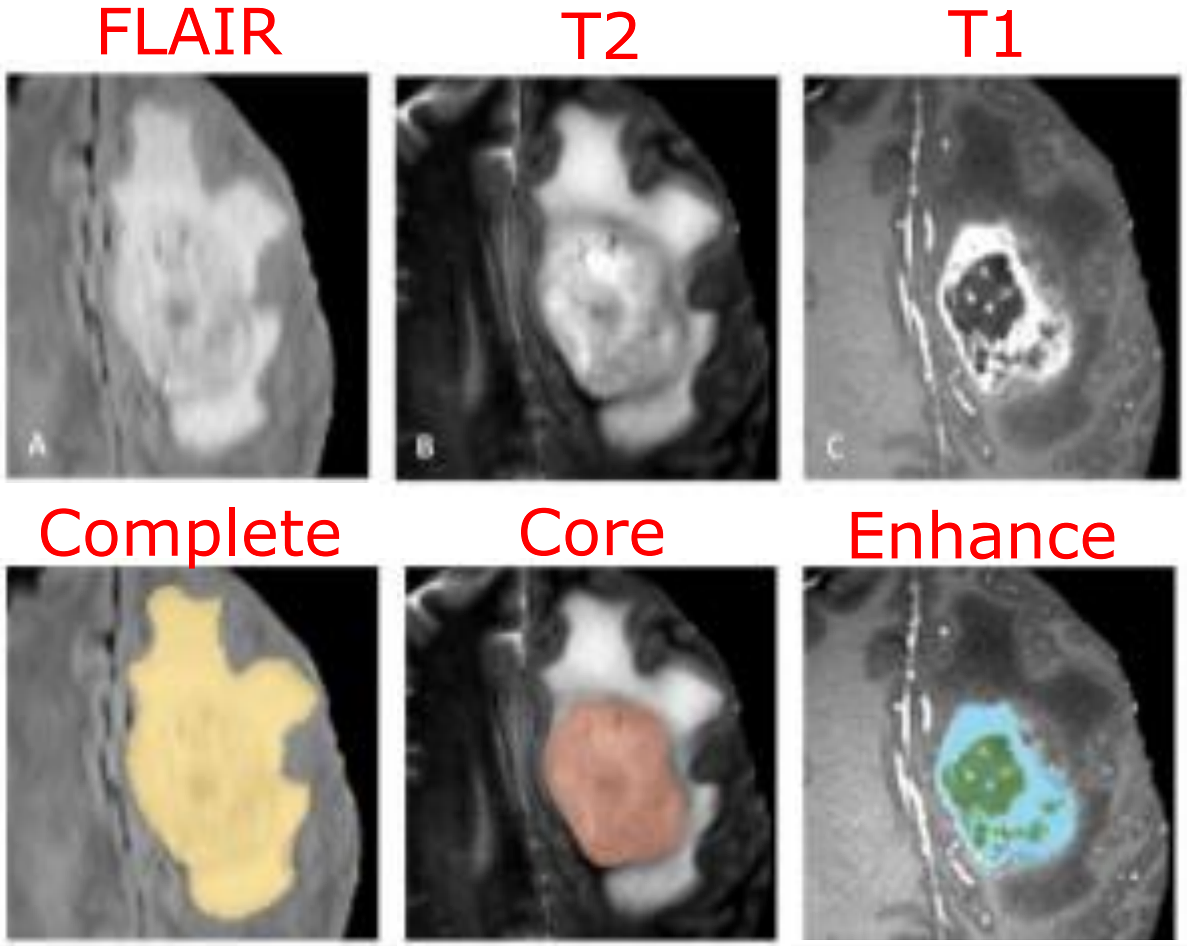
MRI has high-resolution imaging quality and many modalities

Glioma Segments



MRI showing glioma segments





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
• Noise • Intensity inhomogeneity • Non-standardized scale	• Shape, size and location unpredictable • Tumor cells affect nearby healthy cells	• 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

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MRI Pre-processing

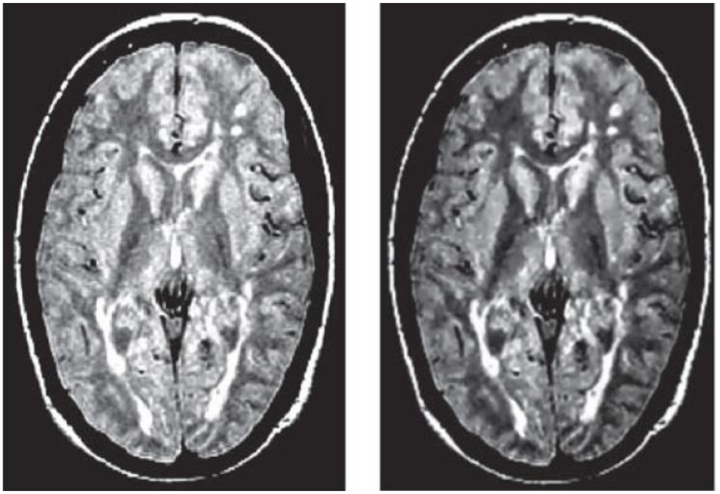
MRI Pre-processing

Noise Removal → **Intensity Homogeneity** → **Intensity Standardization**

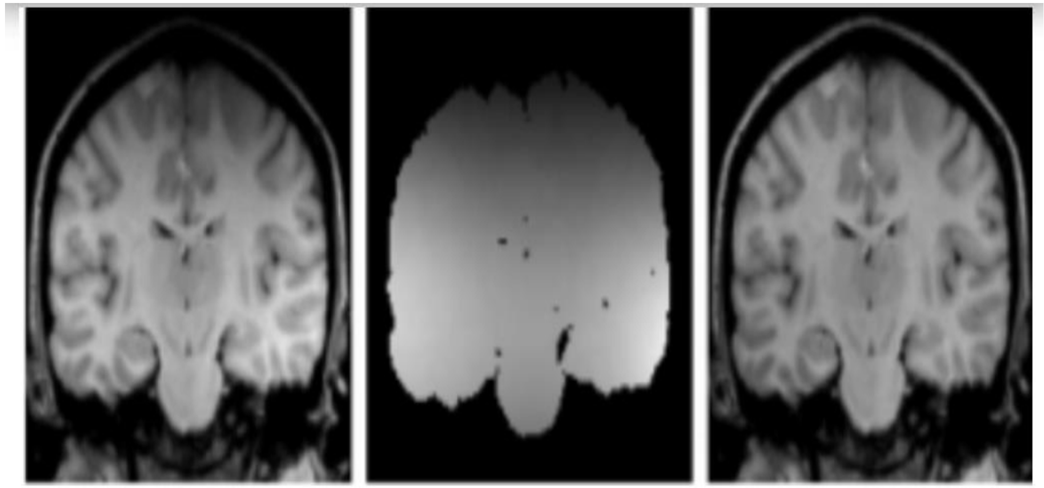
To improve contrast between brain tissues

To remove intensity variations caused by difference in magnetic field

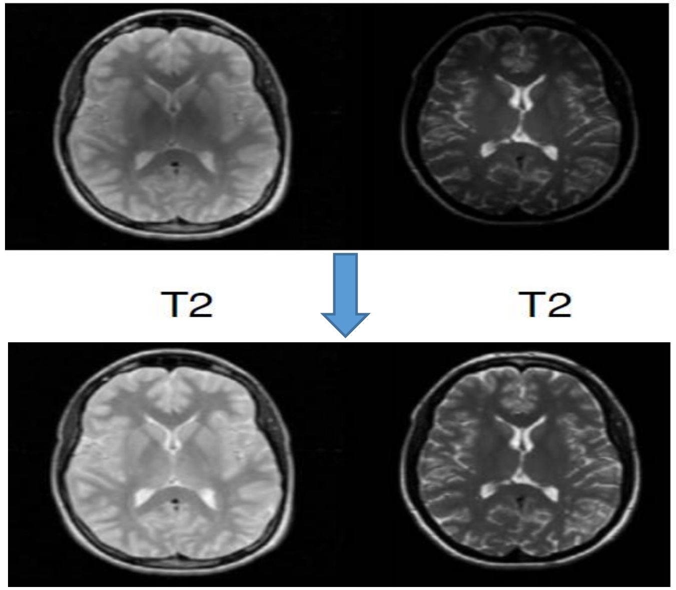
To standardize intensity scales varied due to different acquisition times



Original Image | **Noise Suppressed**



Original Image | **Inhomogeneity field** | **Corrected Image**



Challenges in MRI-based Brain Tumor Segmentation

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MRI Pre-processing

Convolutional Neural Network

Challenges in MRI-based Brain Tumor Segmentation

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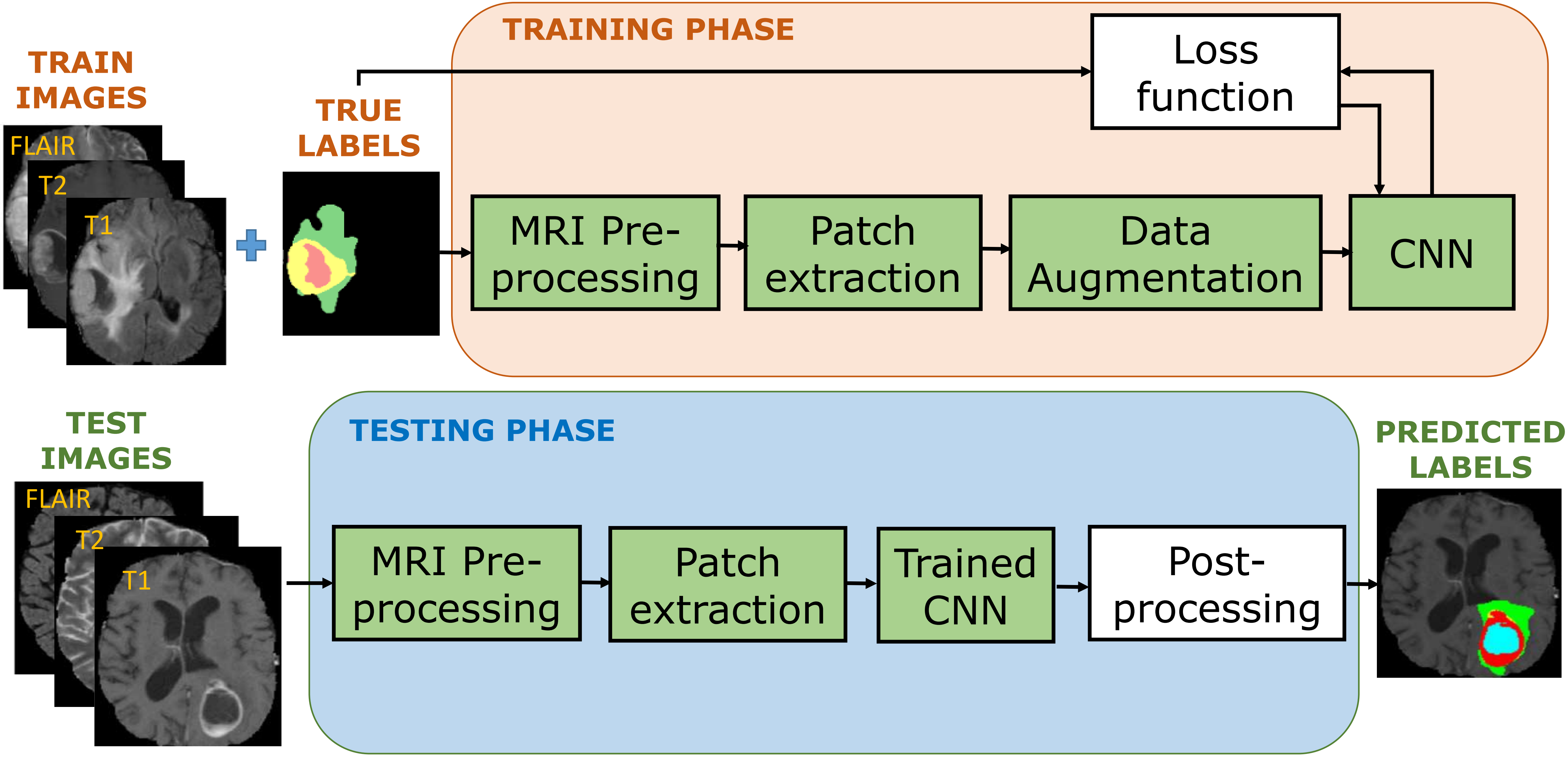
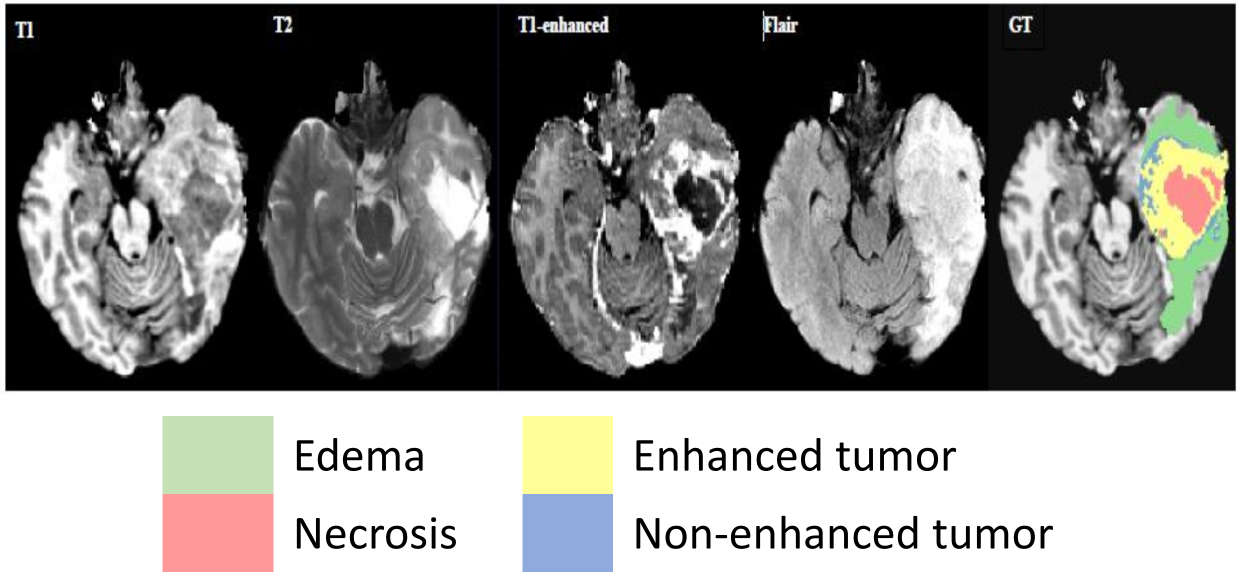
• Noise • Intensity inhomogeneity • Non-standardized scale	• Shape, size and location unpredictable • Tumor cells affect nearby healthy cells	• Huge image size • Imbalanced dataset • Variation in expert labelling
↓ MRI Pre-processing	↓ Convolutional Neural Network	↓ Patch Extraction Data Augmentation

Proposed Solution

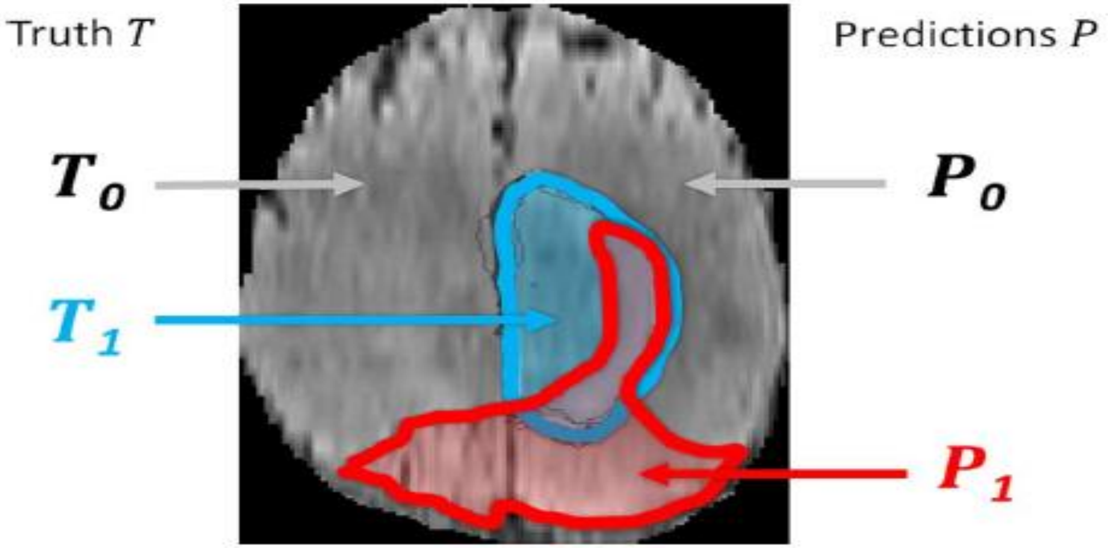


Experimental Set-up for Evaluation

- **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 $= \dfrac{2(P_1 \cap T_1)}{P_1 + T_1}$
  - Sensitivity $= \dfrac{P_1 \cap T_1}{T_1}$
  - Specificity $= \dfrac{P_0 \cap T_0}{T_0}$



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!