

# How AI is Changing the Way To Understand the Earth and Us?

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GPU Tech Conference 2019 (S9495)

**Taegyun Jeon**  
Founder and CEO  
SI Analytics

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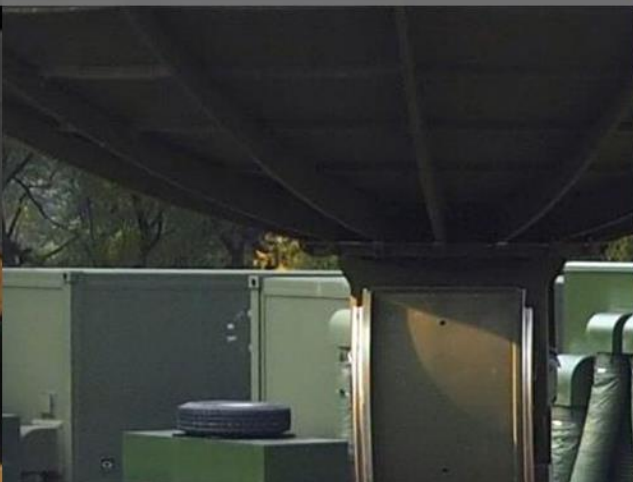
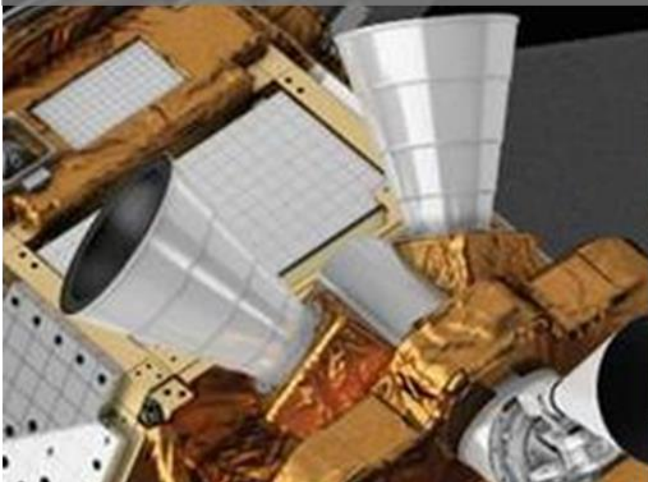
# Contents

- **Earth Observation with Artificial Intelligence**
- **Case #1: Object Detection and Classification with TensorRT**
- **Case #2: Road Extraction (DeepGlobe Challenge)**
- **Conclusions**

**01**

# Earth Observation



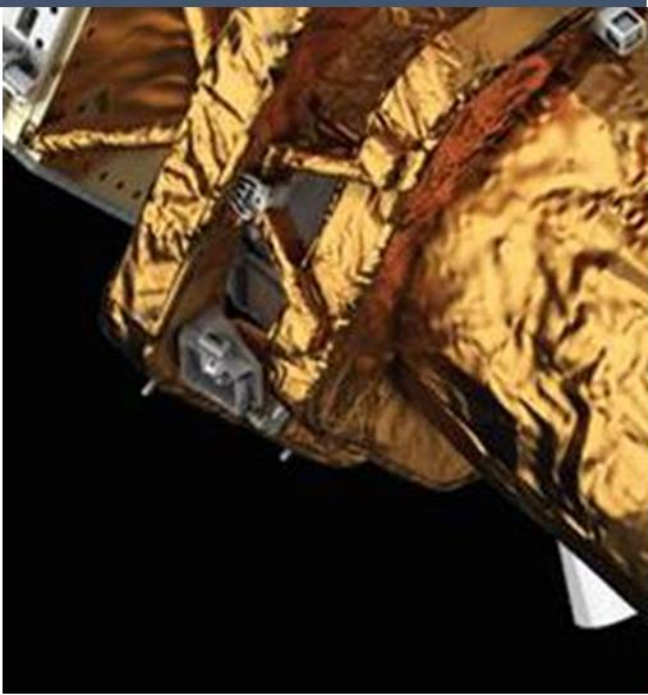


**Satellites**

**Ground Stations**

**Imaging Services**

**Analytics**





# Earth Observation

A satellite image of Earth showing the African continent, the Red Sea, and the Indian Ocean. The image is used as a background for the title and list.

- ✓ defense & Intelligence
- ✓ infrastructure monitoring
- ✓ forecasting weather
- ✓ biodiversity and wildlife trends
- ✓ land-use change
- ✓ natural disasters
- ✓ natural resources
- ✓ agriculture
- ✓ emerging diseases
- ✓ mitigating climate change
- ✓ maritime monitoring



**KITSAT-1 (1992)**  
GSD: 400m



**KITSAT-2 (1993)**  
GSD: 200m



**KITSAT-3 (1999)**  
GSD: 13m





KOMPSAT-3A  
(2015)  
GSD: 0.55m





This image of New York City, taken Nov. 4, 2015, by South Korea's Kompsat-3A satellite, is an example of the products that SI Imaging Services of Korea has begun selling on the market.





# Earth Observation with Artificial Intelligence

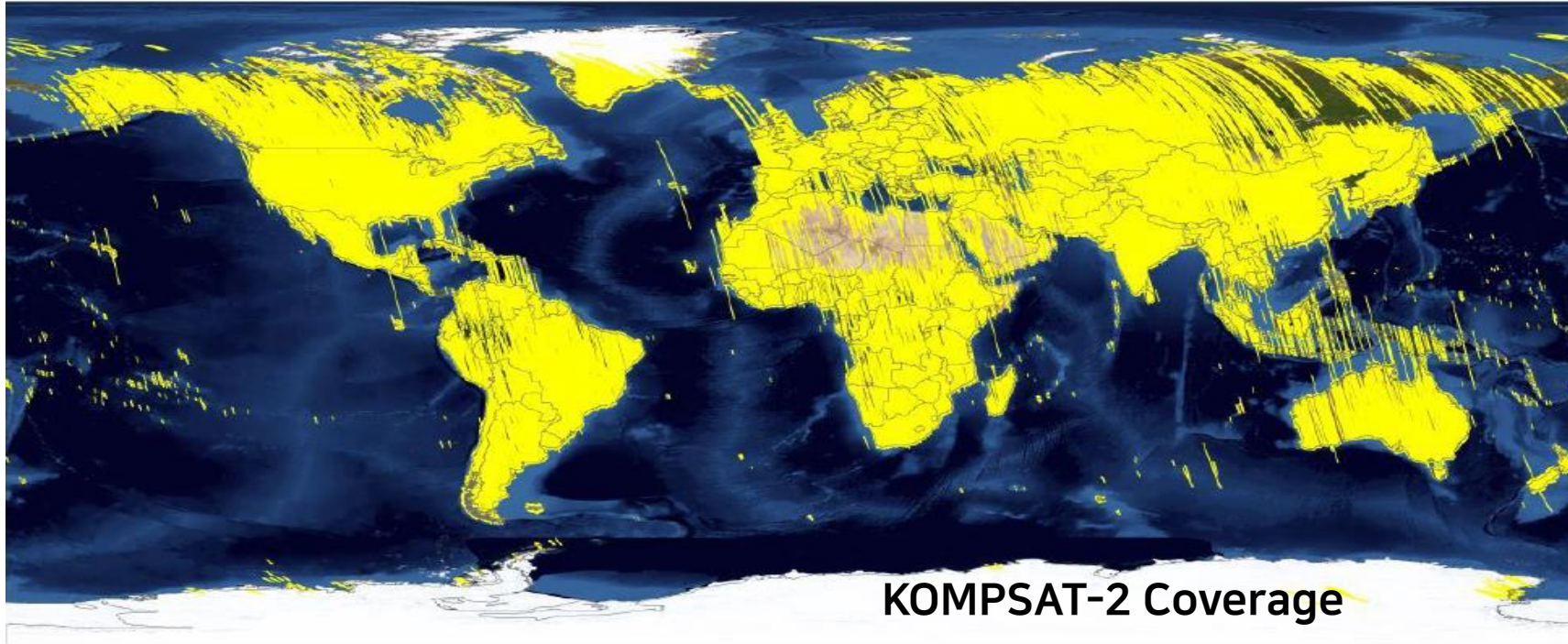
## Traditional EO

## EO with AI

<b>ORDERING</b>	On-demand data	On-demand <b>analysis</b>
	Reactive tasking based on single satellites  Data cost is driven by the data source (higher CAPEX system equates to higher data prices); lower-cost systems would imply lower data prices and services development	Reactive tasking based on <b>constellations</b>
<b>PROCESSING</b>	Owned data analysis	<b>Cloud approach</b> + Owned data analysis
	Manual/automated operations on desktop or internal network	<b>Deep Learning</b> based on Big Data
<b>DELIVERING</b>	Ad hoc services, ordering through reseller or web-portal tasking	<b>Service subscription</b> basis
	Reselling network, privileged distributors (government user focused)	<b>Platform deliveries (private sector focused)</b> and reselling network for governments



# Coverage



South Korea  
(100,210 km<sup>2</sup>)



England  
(243,610 km<sup>2</sup>)



USA  
(9,834,000 km<sup>2</sup>)

KOMPSAT Archive	KOMPSAT-2 (EO)	KOMPSAT-3 (EO)	KOMPSAT-3A (EO)	KOMPSAT-5 (SAR)
<b>Scenes</b> (Dec 15, 2016)	2,645,022	781,389	80,340	52,245
<b>Data volume</b> (TB)	743 TB	700 TB	59 TB	104 TB
<b>Coverage per day</b> (km <sup>2</sup> )	1,700,000	300,000	240,000	Up to 1,000,000



# Volume

0.7KB

150KB

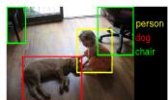
87MB

**MNIST**  
(28,28,1)

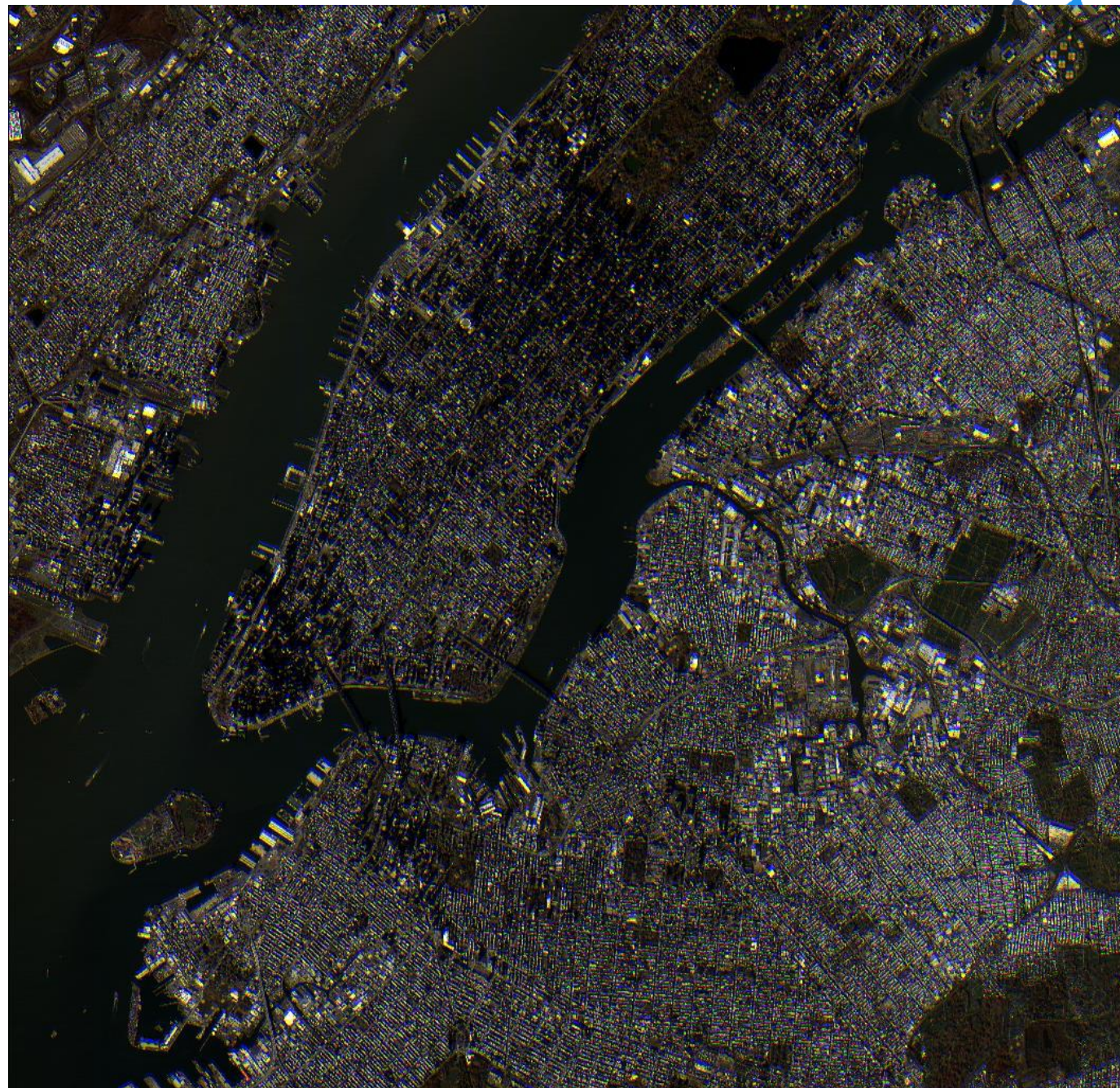
**ImageNet**  
(224,224,3)

**SpaceNet**  
(3K,3K,8)

2

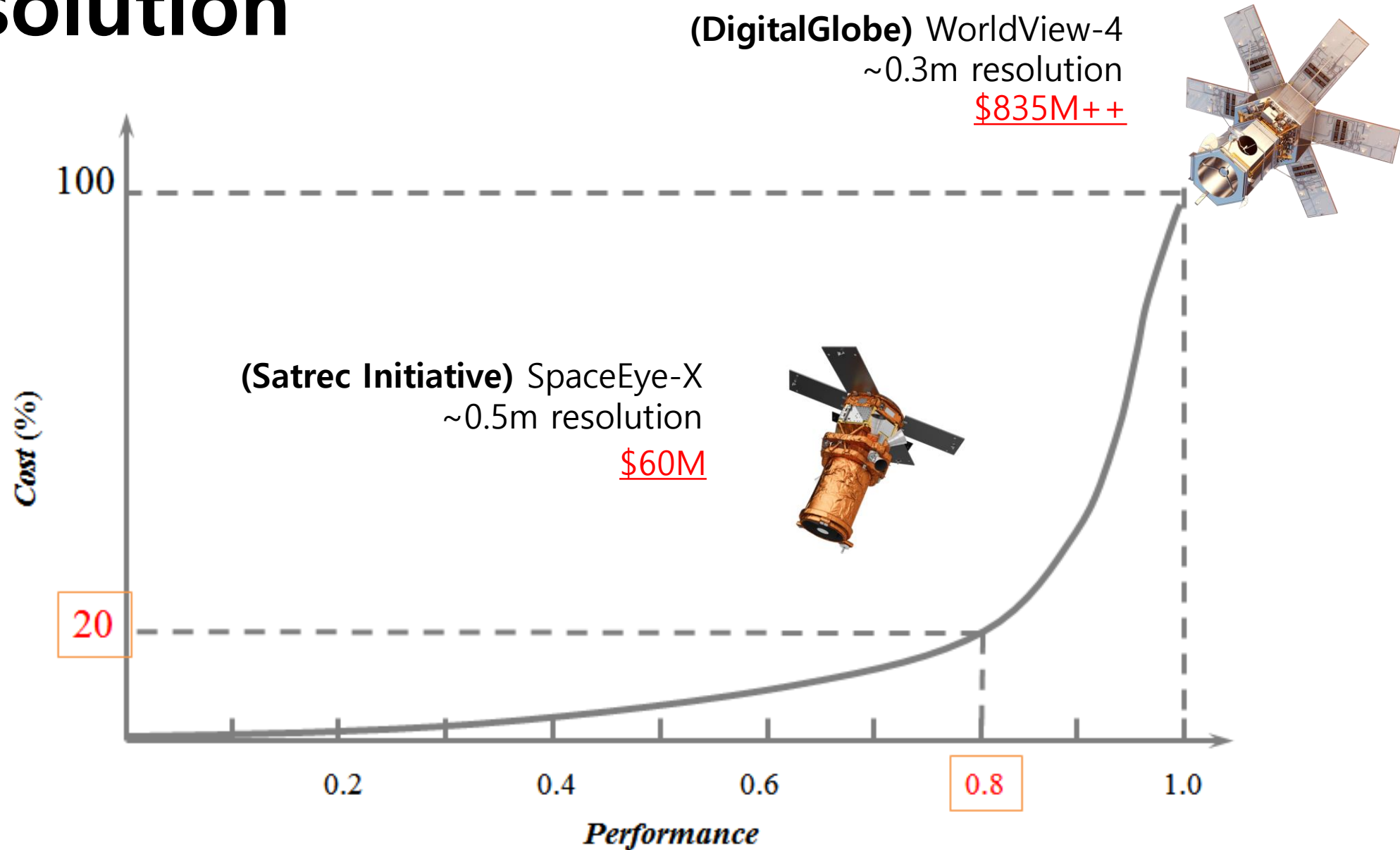


2.5GB  
**Satellite Scene**  
(25K, 25K, 4)





# Resolution





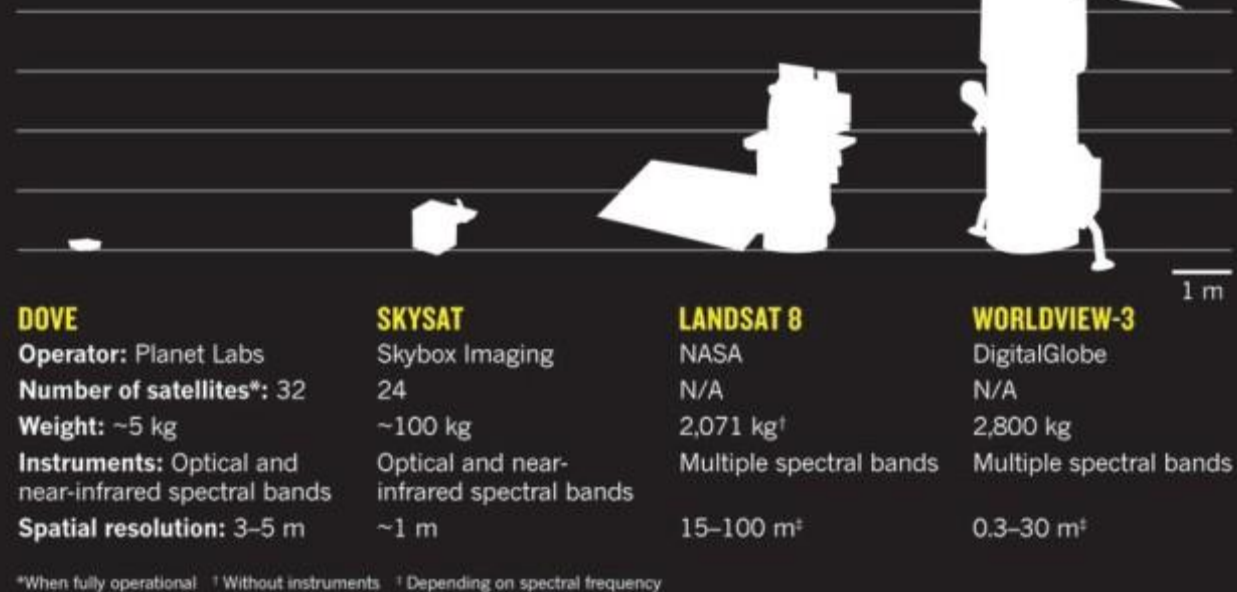
# Reusable rocket and Constellation space program

- ✓ Low launch cost
- ✓ Low manufacturing cost
- ✓ Huge daily data



## THE SWARM COMETH

Small, light and cheap satellites could transform Earth observation. How they measure up to their larger brethren:



**100+**  
SATELLITE FLEET



**7+ PB**  
OF DATA, &  
7+TB ADDED DAILY



**GUI & API**  
AUTOMATED DATA PIPELINE  
& PLATFORM ACCESS



**02**

# Object Detection and Classification





# Detection and Classification

- **Aircraft Detection & Classification**

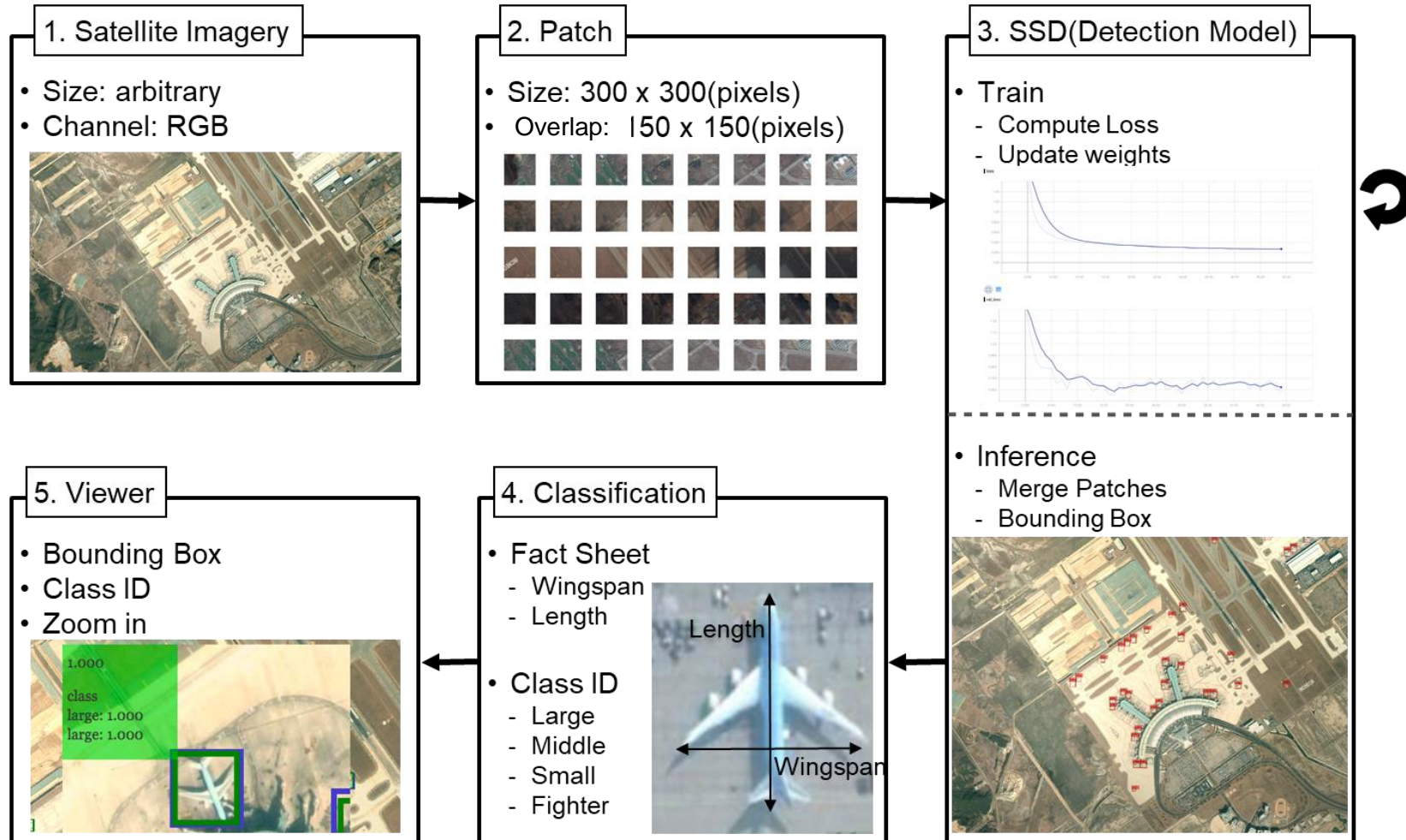
- **Task:** Detect and classify all aircraft on North Korea Airforce bases
- **Construct Own Dataset** for civil aircraft and military fighters
- **Compatibility:** Transfer Learning (GoogleEarth & KOMPSAT 2, 3, 3A)
- **Detection Accuracy:** 89%
- **Classification Accuracy:** 95.2%
- **Target Area:** All NK Airforce bases
- **Fill the gap for rare observation:** Combine synthetic data from GAN





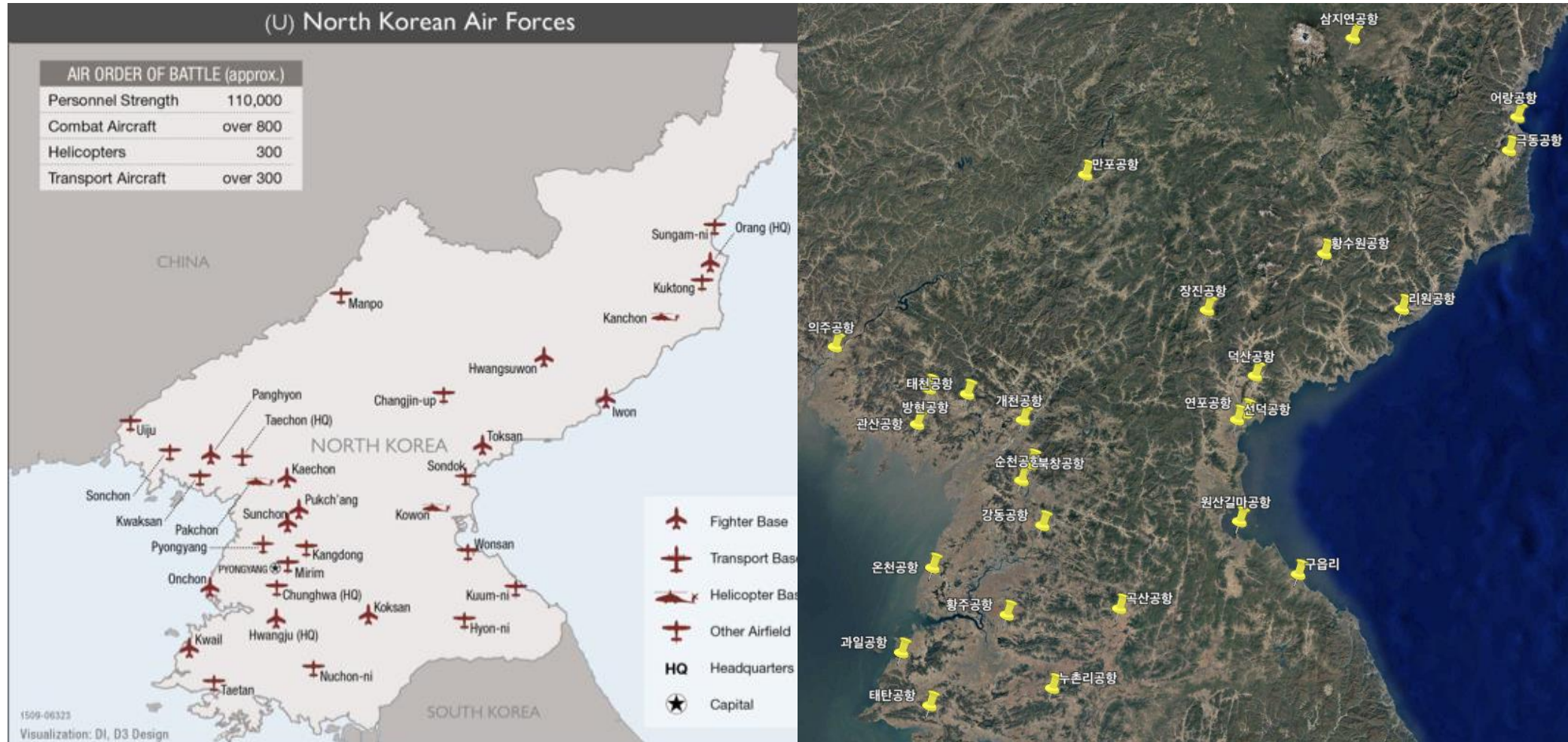
# Detection and Classification

- **Objective**: Detect aircraft and fighter, then classify the types of aircraft





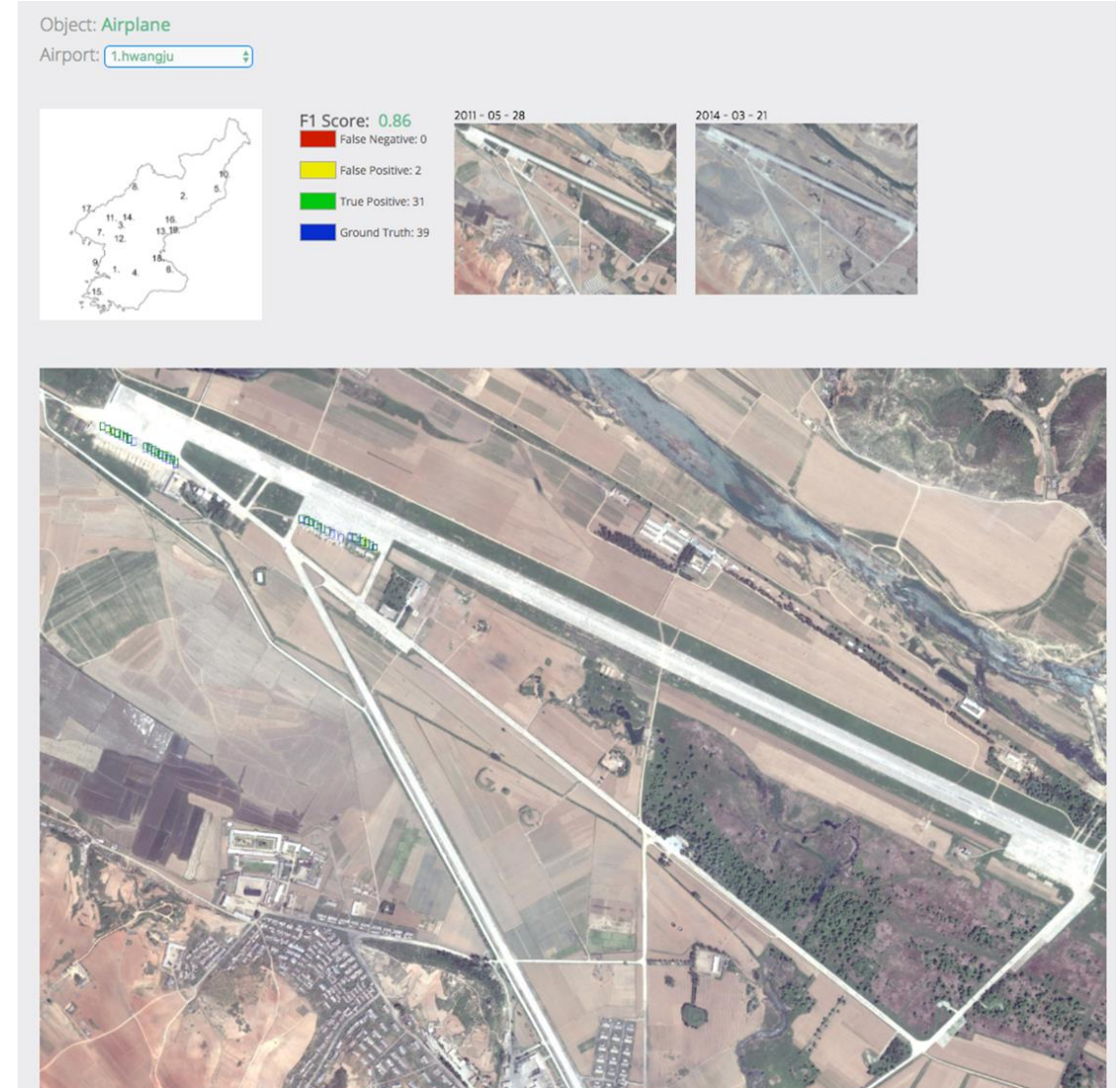
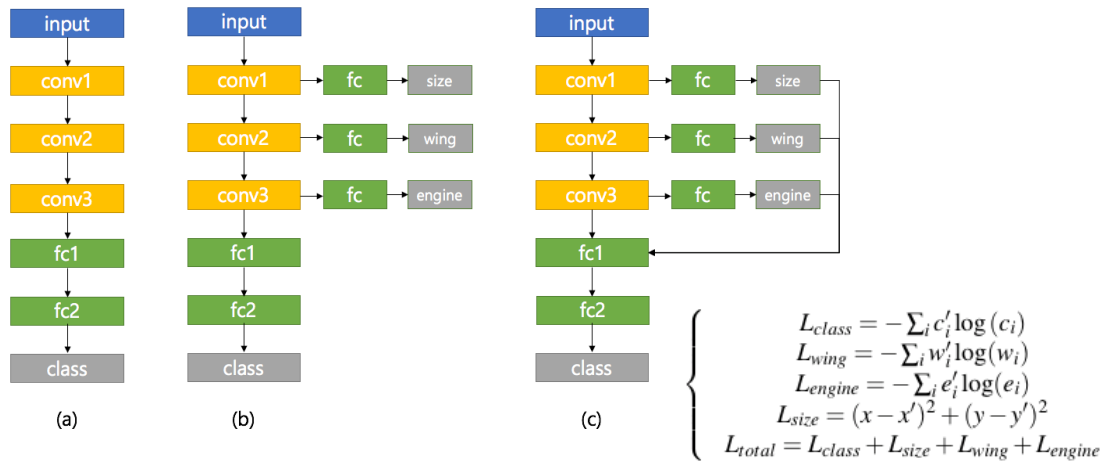
# North Korean Air Forces (25 regions)





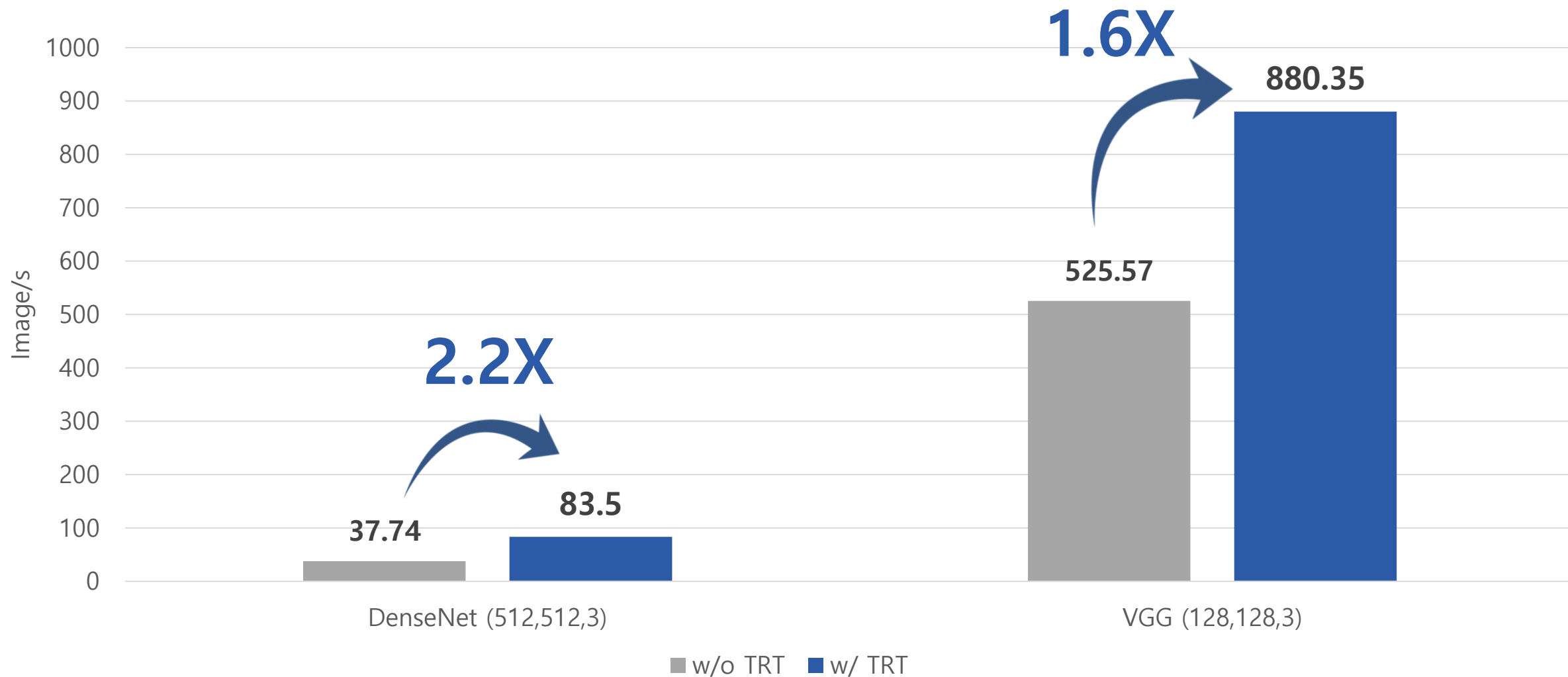
# Detection Results

- ROI: 25 Airports (North Korea)
- Detection results:  
Precision (0.84), Recall (0.79), F1 (0.82)
- Classification results:  
Top-1 (91.5%), Top-3 (95.4%)





# Classification with TensorRT



\* Experiments on DGX-Station

Probability (Detection)

0.974

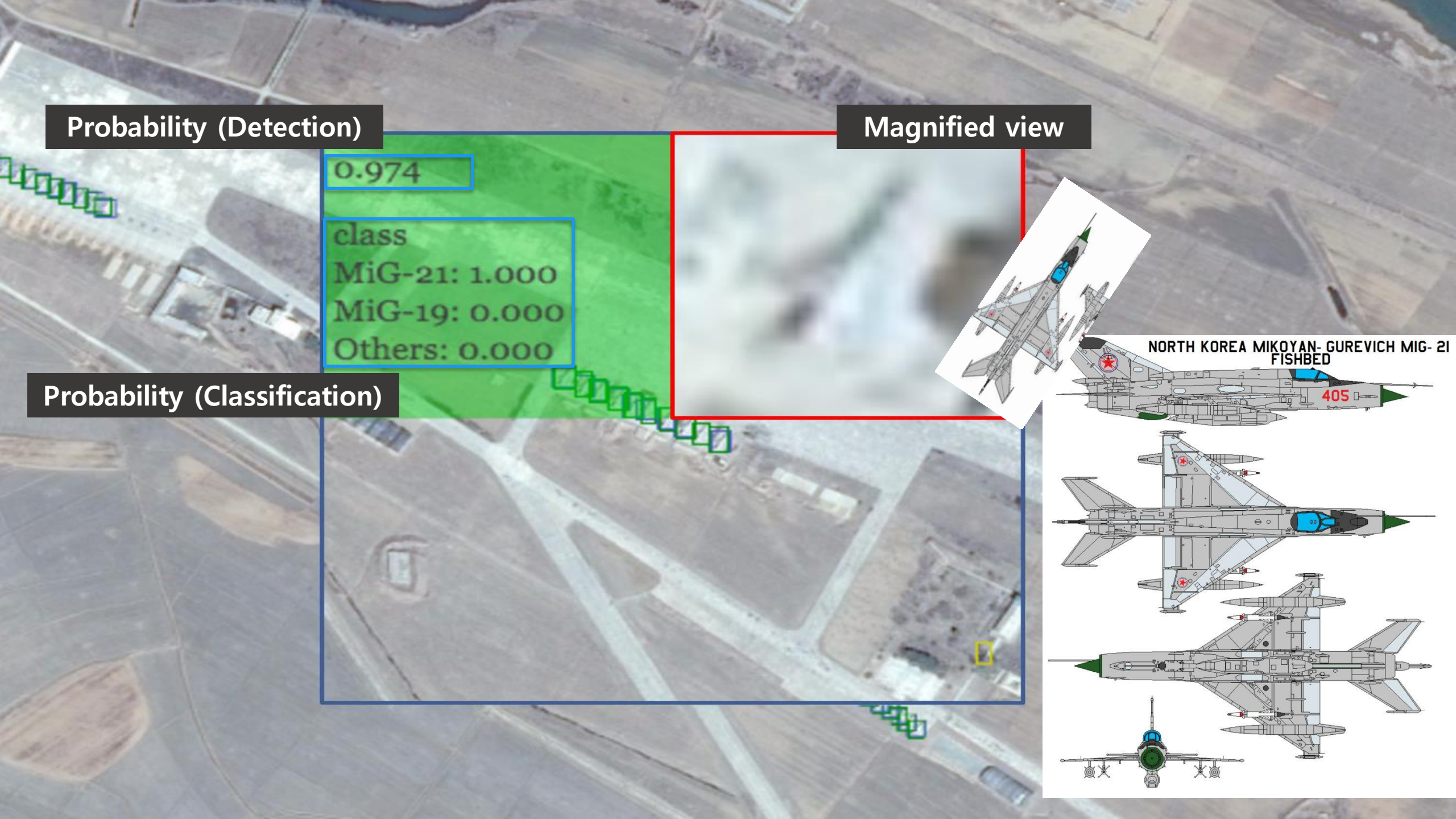
class  
MiG-21: 1.000  
MiG-19: 0.000  
Others: 0.000

Probability (Classification)

Magnified view

NORTH KOREA MIKOYAN-GUREVICH MIG-21  
FISHBED

405





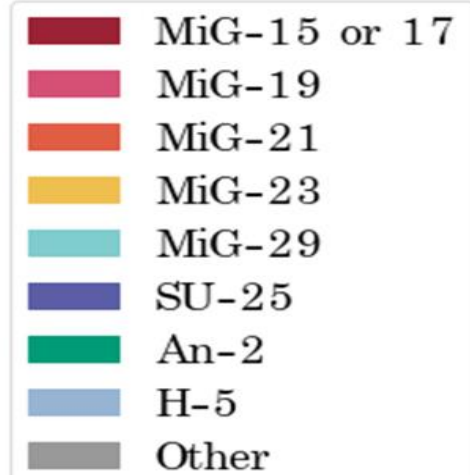




### Report for aircraft disposition (DPRK Air Force Bases)

The map displays the following aircraft counts at various bases in North Korea:

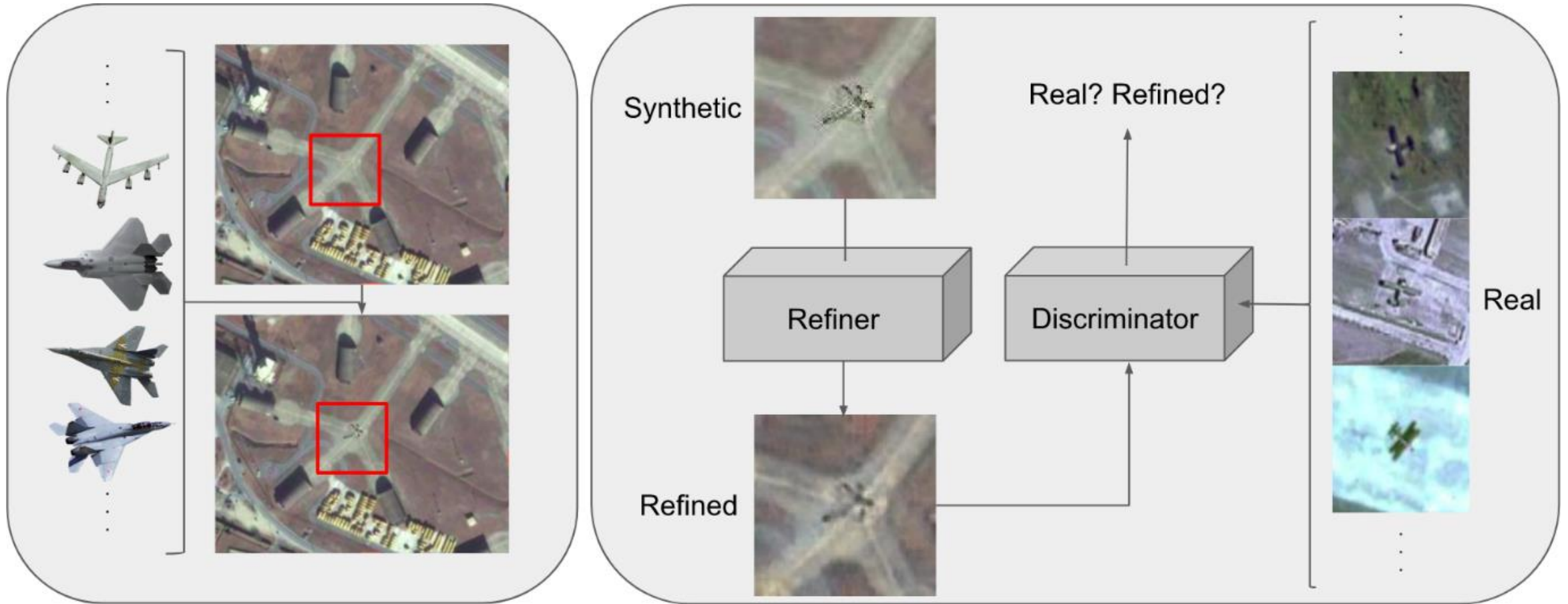
Base Name (Korean)	MiG-15 or 17	MiG-19	MiG-21	MiG-23	MiG-29	SU-25	An-2	H-5	Other
어랑 (Aerang)	50	0	0	0	0	0	0	0	0
극동 (Gukdong)	0	0	0	0	0	0	33	0	0
황수원 (Hwangsuwon)	3	0	11	0	0	0	0	0	0
리원 (Riwon)	25	0	0	0	0	0	0	0	0
장진 (Jangjin)	0	0	0	0	0	12	0	0	0
독산 (Doksan)	0	0	1	29	0	0	0	0	0
연포 (Yonpo)	0	0	0	0	0	33	0	0	0
선덕 (Sondeok)	0	0	0	0	0	47	0	0	0
원산 (Wonsan)	0	0	0	3	5	0	0	0	0
구읍리 (Gueupri)	13	0	8	0	0	0	0	0	0
곡산 (Goksan)	0	14	0	0	0	0	0	0	0
누춘리 (Nuchunri)	0	0	5	5	0	0	0	0	0
과일 (Gaeil)	33	0	0	0	0	0	0	0	0
태탄 (Taetan)	14	0	3	0	0	0	0	0	0
황주 (Hwangju)	0	0	23	43	0	0	0	0	0
온천 (Oncheon)	1	33	0	0	0	0	0	0	0
순천 (Sunchon)	0	0	0	0	0	27	0	0	0
북창 (Bukchang)	0	0	0	26	4	0	0	0	0
개천 (Gaechon)	1	36	0	0	0	0	0	0	0
태천 (Taechon)	0	0	0	0	0	0	50	0	0
파산 (Pasan)	0	0	0	0	0	0	55	0	0
방현 (Banghyeon)	2	0	0	0	0	0	67	0	0
의주 (Uiju)	0	0	0	0	0	0	0	14	0
만포 (Manpo)	0	0	0	0	0	0	1	44	0





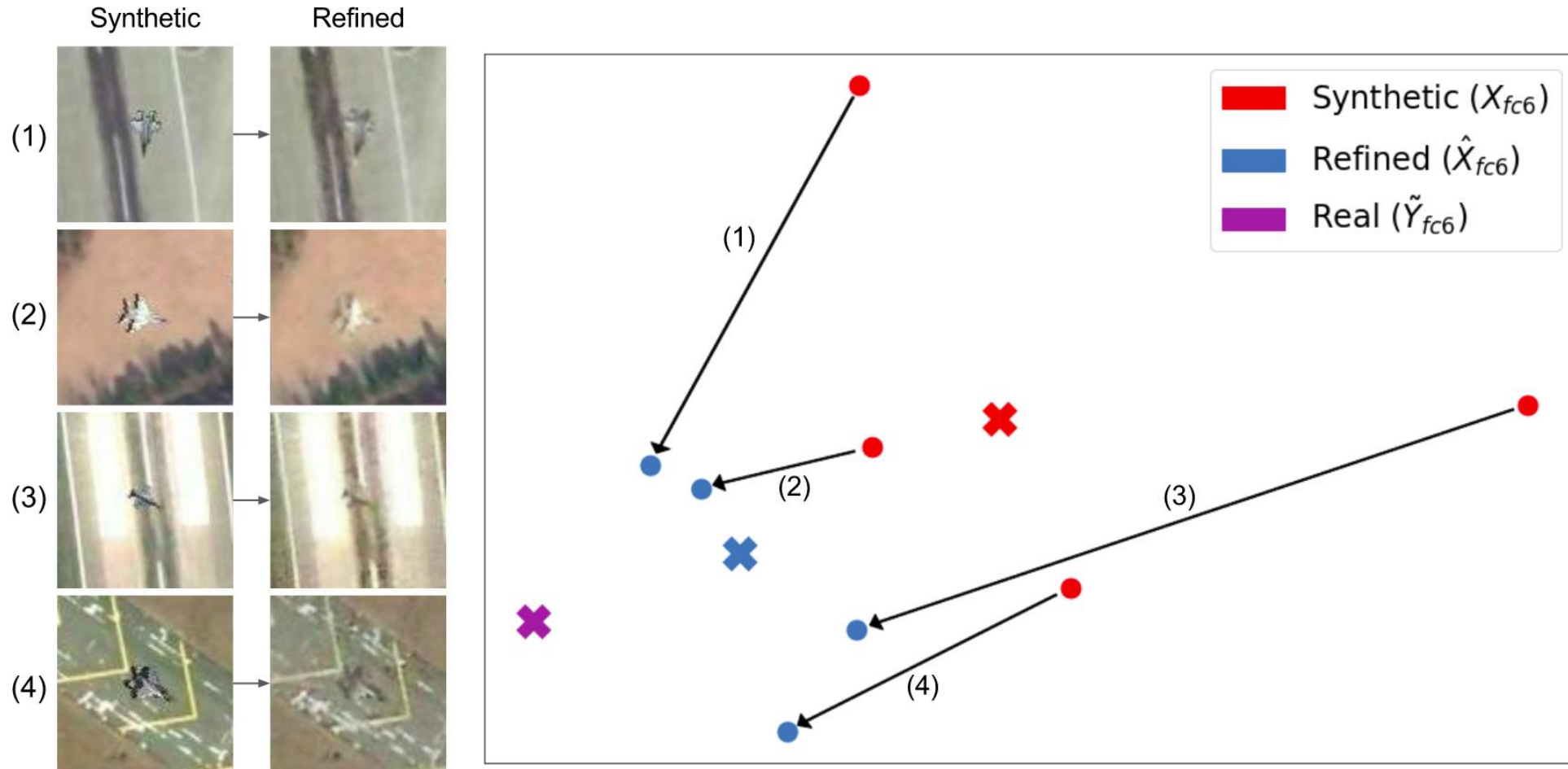
# Synthetic Data Generator and Refiner

J. Seo, S. Jeon and T. Jeon, "Domain Adaptive Generation of Aircraft on Satellite Imagery via Simulated and Unsupervised Learning", *MLAIP Workshop @ ACML (2017)*



Adversarial Learning to refine the synthetic images from reference images

# Synthetic Data Generator and Refiner



Qualitative and Quantitative Evaluation



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# Summary

- **Task:** Detect and classify all aircraft on North Korea Airforce bases
- **Construct Own Dataset** for civil aircraft and military fighters
- **Compatibility:** Transfer Learning between [GoogleEarth](#) and [KOMPSAT 2, 3, 3A](#)
- **TensorRT:** Speed-up to [2.2X \(DenseNet\)](#) and [1.6X \(VGG\)](#).
- **Fill the gap for rare observation:** [Combine synthetic data from GAN](#)

**03**

# Road Extraction





# Road Extraction

- Automatic Mapping from Image to Road

- Usages

- Automated Map Update
- Urban Planning
- City Monitoring
- Road Navigation
- Operation of Unmanned Vehicles
- Attention of Safety Road





# DeepGlobe Challenge (CVPR 2018)



DEEPGLOBE - CVPR18

Home

Challenge

Leaderboard

Workshop

Committee

Resources

facebook

## Challenge Tracks



### Road Extraction

In disaster zones, especially in developing countries, maps and accessibility information are crucial for crisis response. We would like to pose the challenge of automatically extracting roads and street networks from satellite images. This will be a binary segmentation problem to detect all the road pixels in each area. The evaluation will be based on the accuracy of



### Building Detection

Modeling population dynamics is of great importance for disaster response and recovery, and detection of buildings and urban areas are key to achieve so. We would like to pose the challenge of automatically detecting buildings from satellite images. This problem is formulated as a binary segmentation problem to localize all building polygons in



### Land Cover Classification

Automatic categorization and segmentation of land cover is of great importance for sustainable development, autonomous agriculture, and urban planning. We would like to introduce the challenge of automatic classification of land cover types. This problem is defined as a multi-class segmentation task to detect areas of urban, agriculture,



DigitalGlobe

UBER





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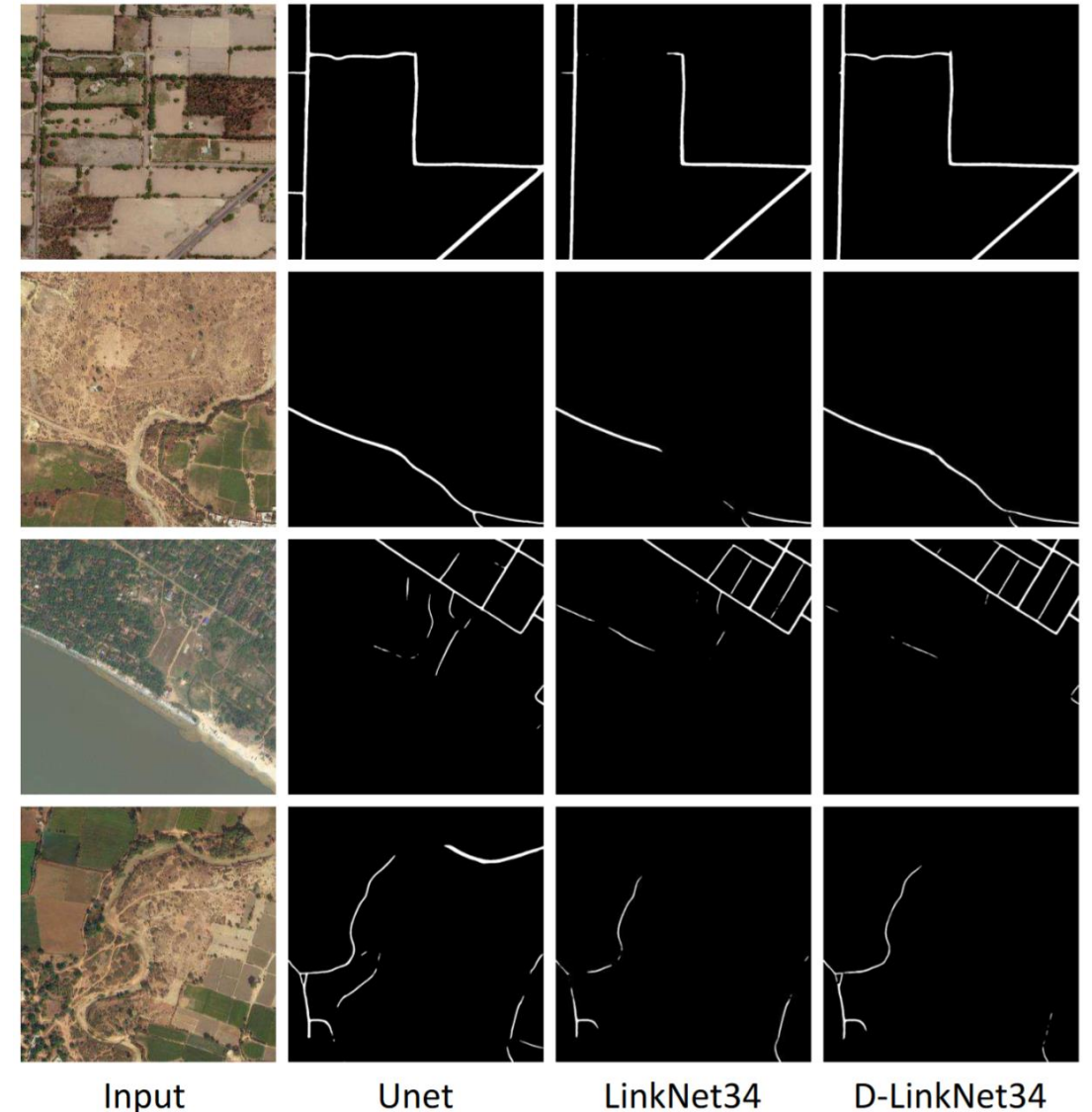
# Challenges of Road Extraction

- Wide-area Processing
- Noisy Labeling & Ambiguity
- Extraction of Road Network Topology
- Model Efficiency
- Intrinsic Noise of Road Image

# D-LinkNet: 1<sup>st</sup> Winner of the 2018 Challenge

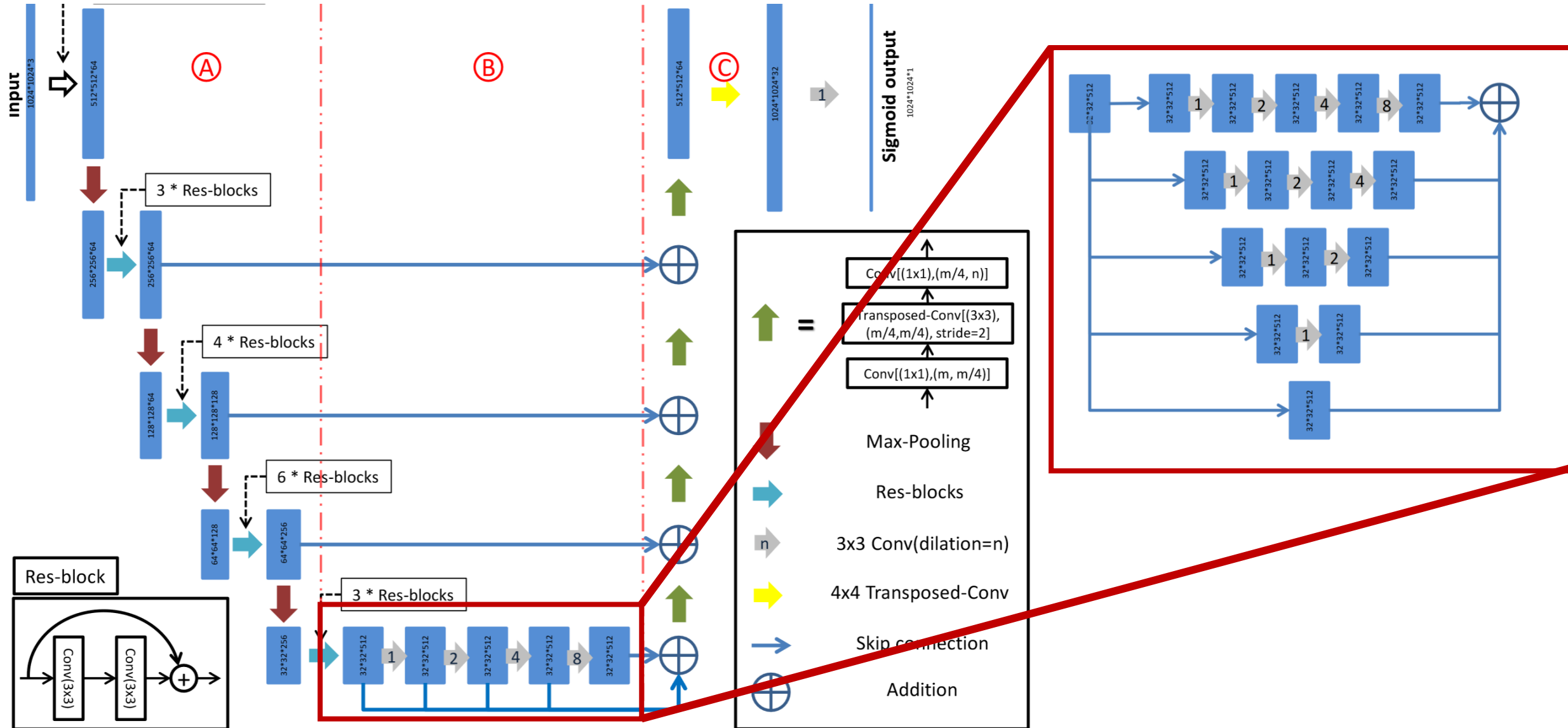


Model	IoU on validation set
Unet (7 pooling layers, no-pretrain)	0.6294
LinkNet34 (pretrained encoder)	0.6300
Ensemble of Unet and LinkNet34	0.6394
D-LinkNet (pretrained encoder)	0.6412

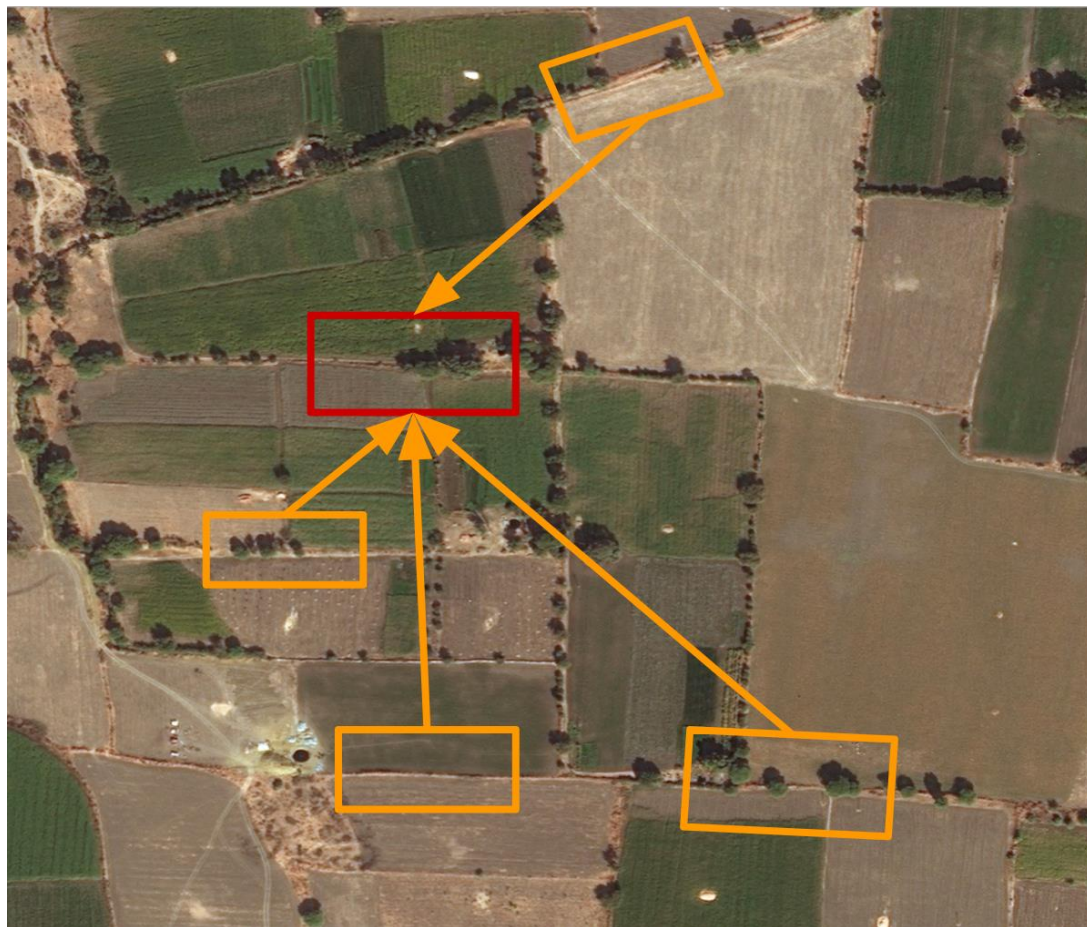




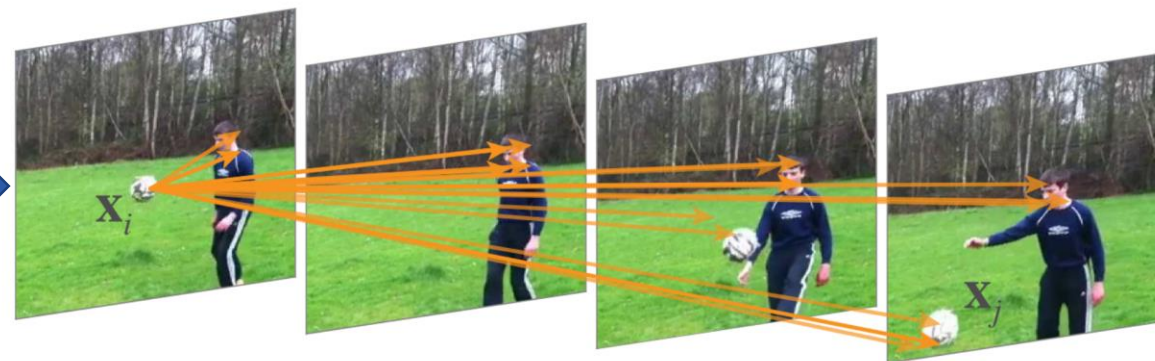
# D-LinkNet: 1<sup>st</sup> Winner of the 2018 Challenge



# Our Motivation



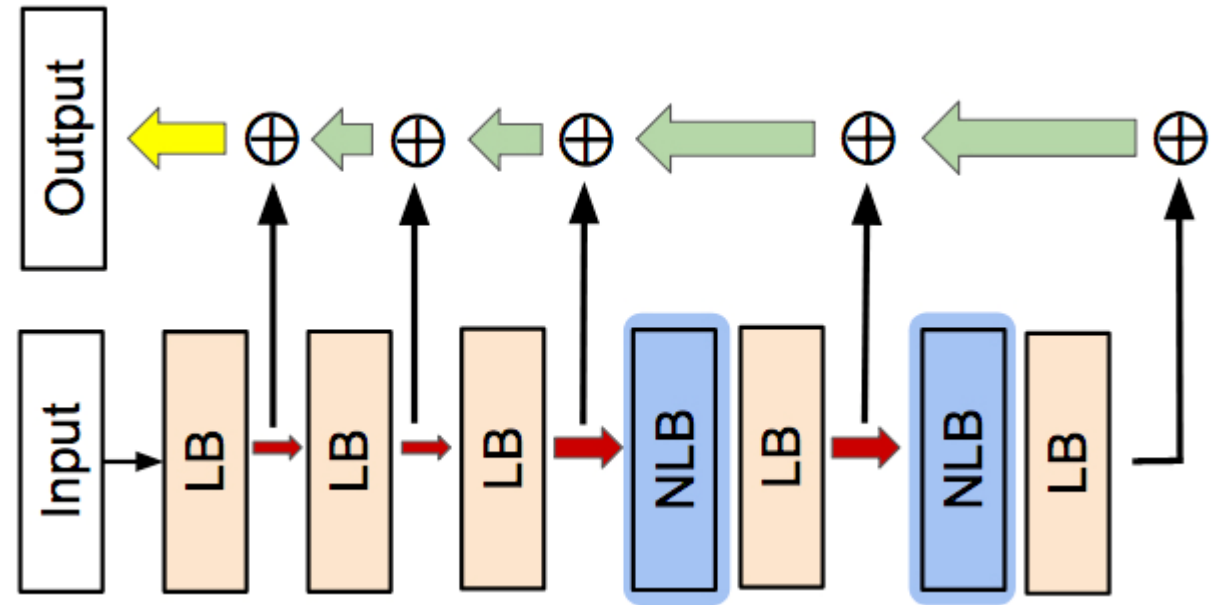
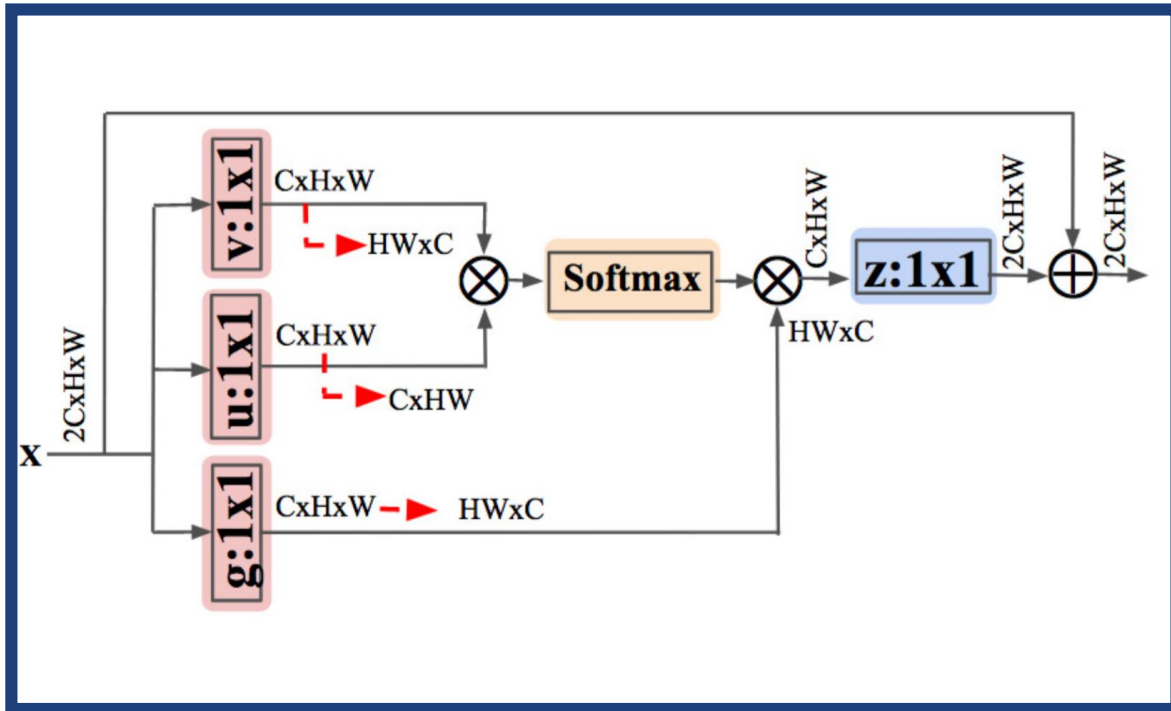
## Non-Local Operations





# Non-Local LinkNet (NL-LinkNet)

## Non-Local Block (NLB)



Overall Architecture

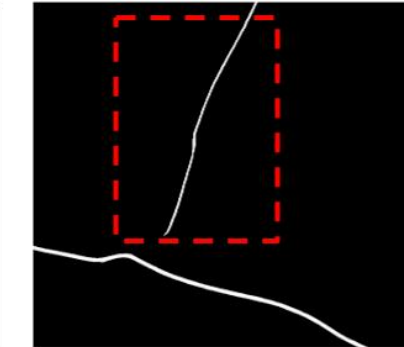
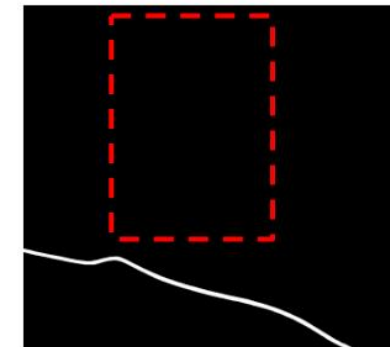
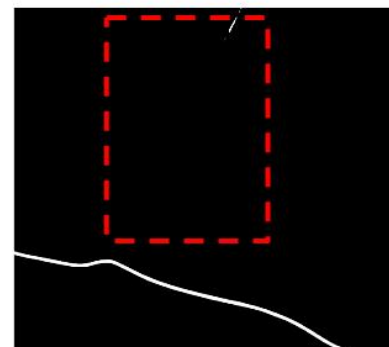
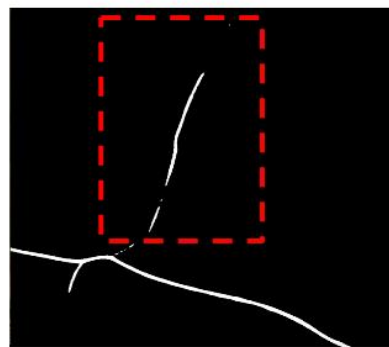
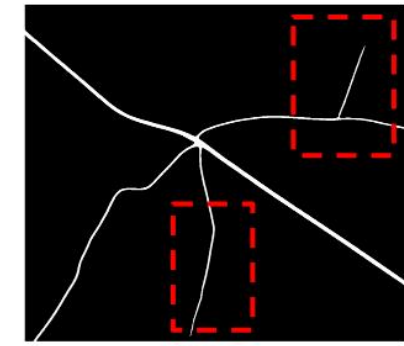
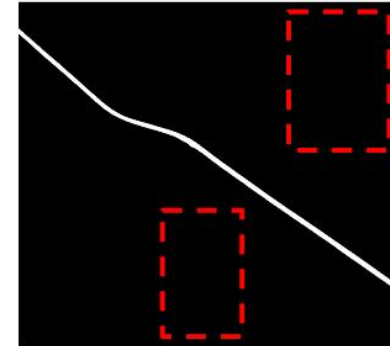
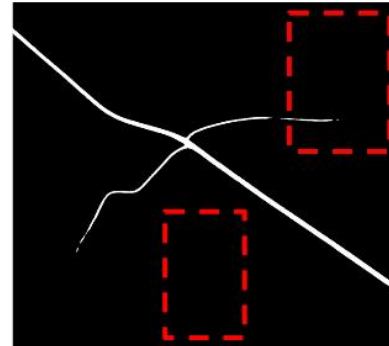
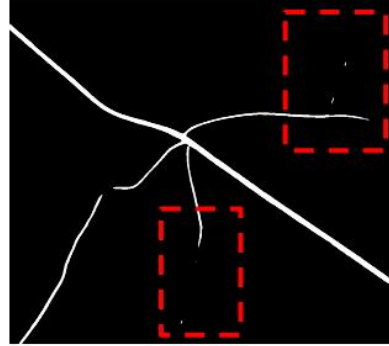
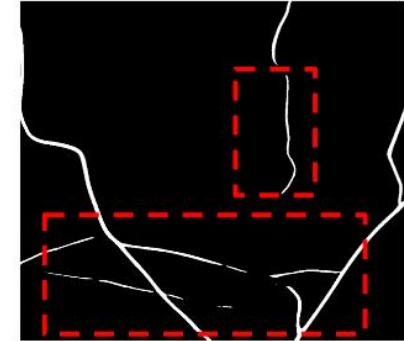
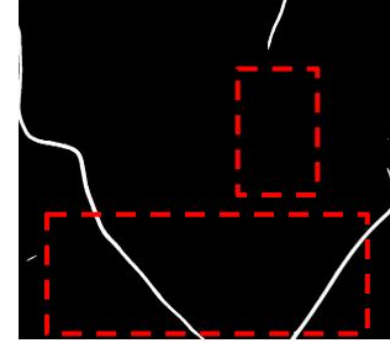
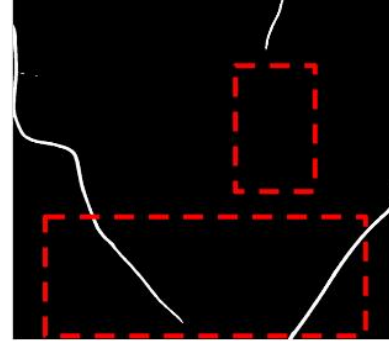
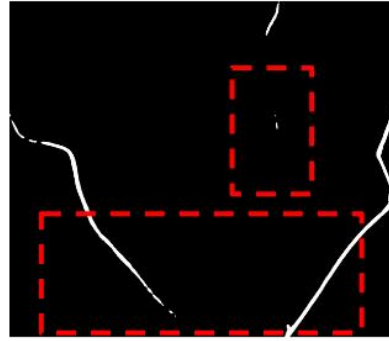
# Quantitative Comparison

TABLE I  
BENCHMARKS FOR DEEPGLOBE ROAD EXTRACTION CHALLENGE

BenchMarks	mIOUs	Remarks
EosResUNet [23]	55.96	4th place 3rd place from [15]
StackedUNet [24]	60.60	
ResInceptSkipNet [25]	61.30	
U-Net [12]	62.94	
LinkNet [13]	63.00	
FCN [10]	64.00	2nd place
D-LinkNet [15]	64.12	1st place
NL34-LinkNet	64.59	Ours
<b>NL34-LinkNet+MS</b>	<b>65.00</b>	<b>Ours</b>



# Visual Comparison



(a) Input

(b) U-Net

(c) LinkNet

(d) D-LinkNet

(e) NL-LinkNet

# Model Efficiency



TABLE II  
PERFORMANCES OF NON-LOCAL BLOCKS ADDED INTO DIFFERENT STAGES

Models	NLB3	NLB4	DB	mIOUs	Params
Baseline	X	X	X	63.07	21.657M
D-LinkNet	X	X	O	64.12	31.096M
NL3-LinkNet	O	X	X	64.15	<b>21.690M</b>
NL4-LinkNet	X	O	X	64.40	21.789M
NL34-LinkNet	O	O	X	<b>64.59</b>	21.822M



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# Summary

- Core Idea: Non-local Operations
- Non-Local Block is better than traditional convolutional ops.

**04**

# Conclusions





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# Conclusions

- **Object Detection and Classification:** Use case for Defense
- **TensorRT:** Speed-up to 2.2X (DenseNet) and 1.6X (VGG).
- **Fill the gap for rare observation:** Combine synthetic data from GAN
- **Non-Local Block:** Extraction of Road Network Topology



**Thank you for attention!**

**SI Analytics Co., Ltd.** (Satrec Initiative Group)  
441Expo-ro, Yuseong-gu, Daejeon, 34051, Korea

tgjeon@si-analytics.ai  
www.si-analytics.ai