SATELLITE IMAGE DISASTER RECOGNITION

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Computer Vision 2021

INTRO - IMAGE SEGMENTATION

Labels

0:
NO BUILDING

1:
BUILDING

GOAL

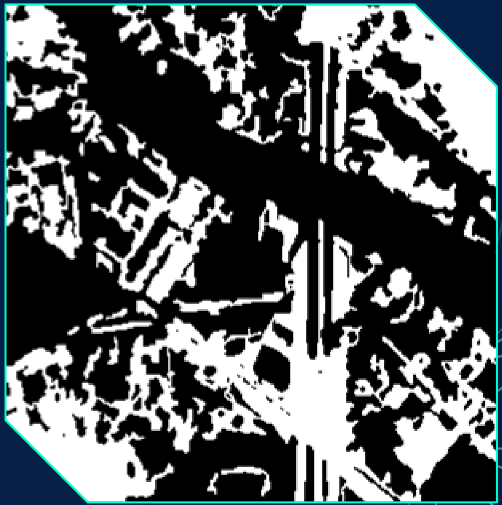
Extend a **binary segmentation** disaster detector to a **multiclass** case using **two** different **approaches**

FROM PAPER...

PRE-DISASTER

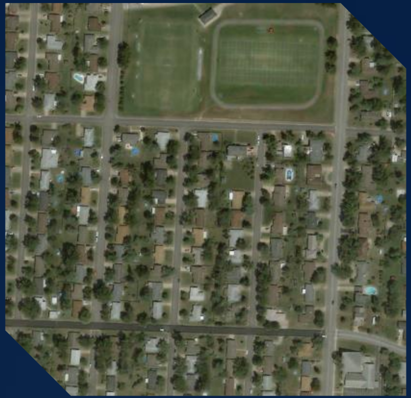
POST-DISASTER

BINARY DAMAGE MASK



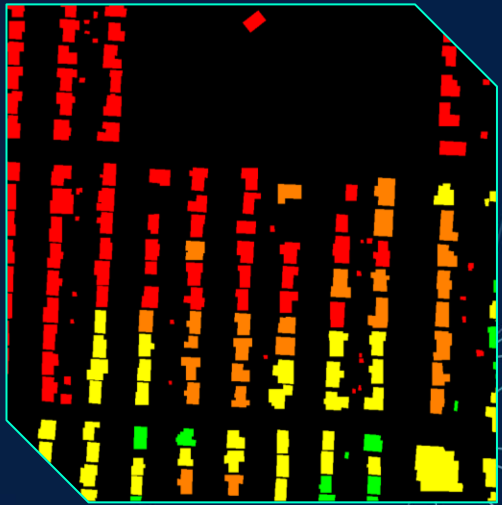
...TO OUR WORK

PRE-DISASTER



POST-DISASTER

MULTICLASS DAMAGE MASK

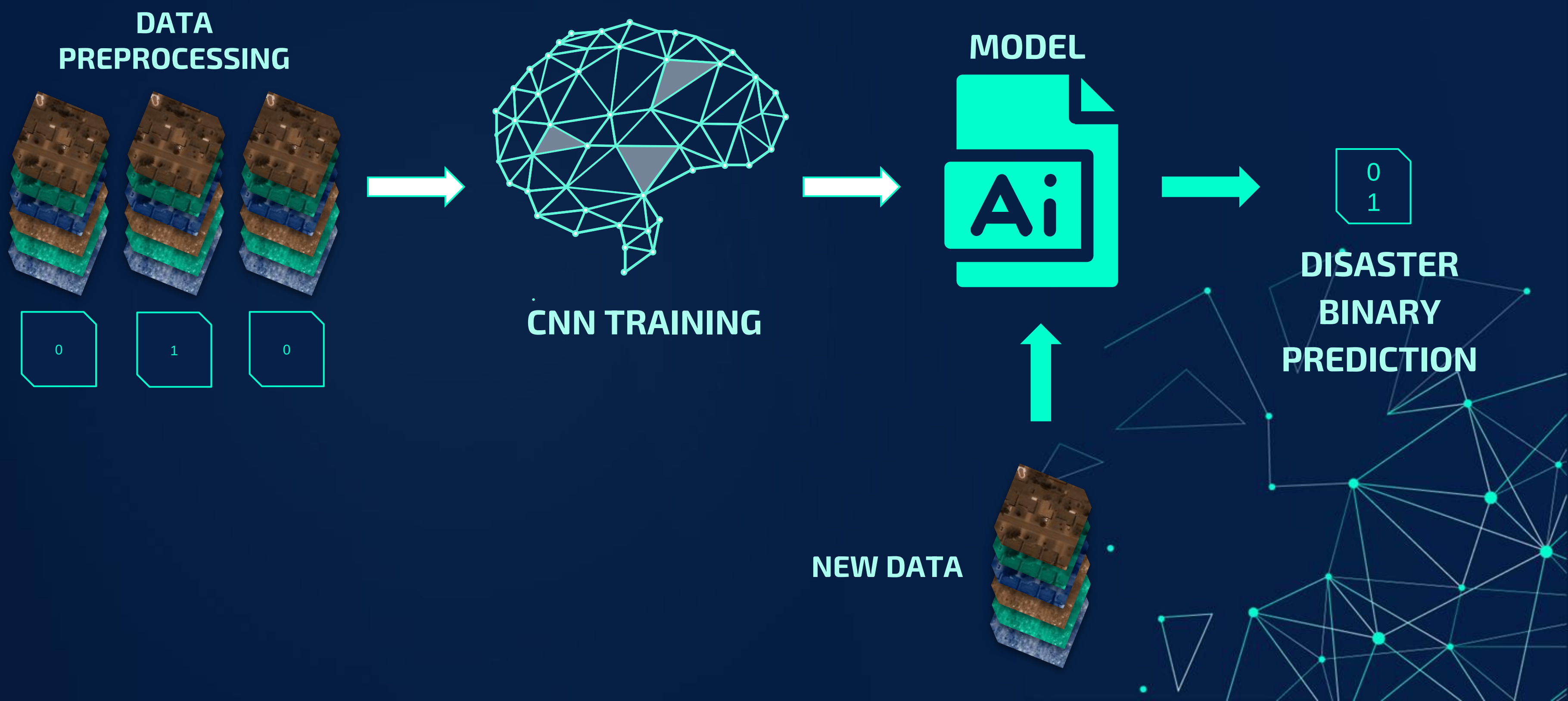


APPLICATIONS

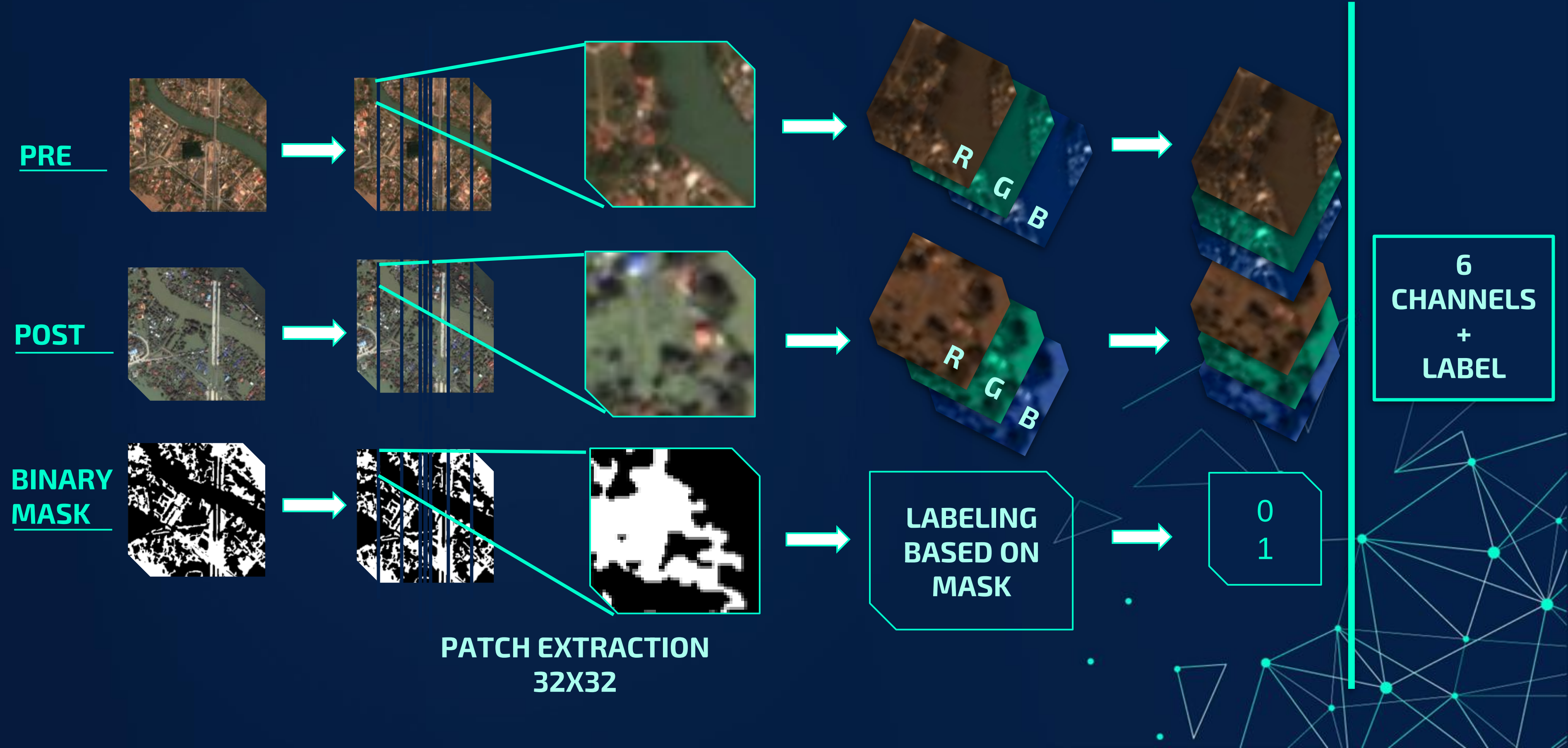
1

PAPER

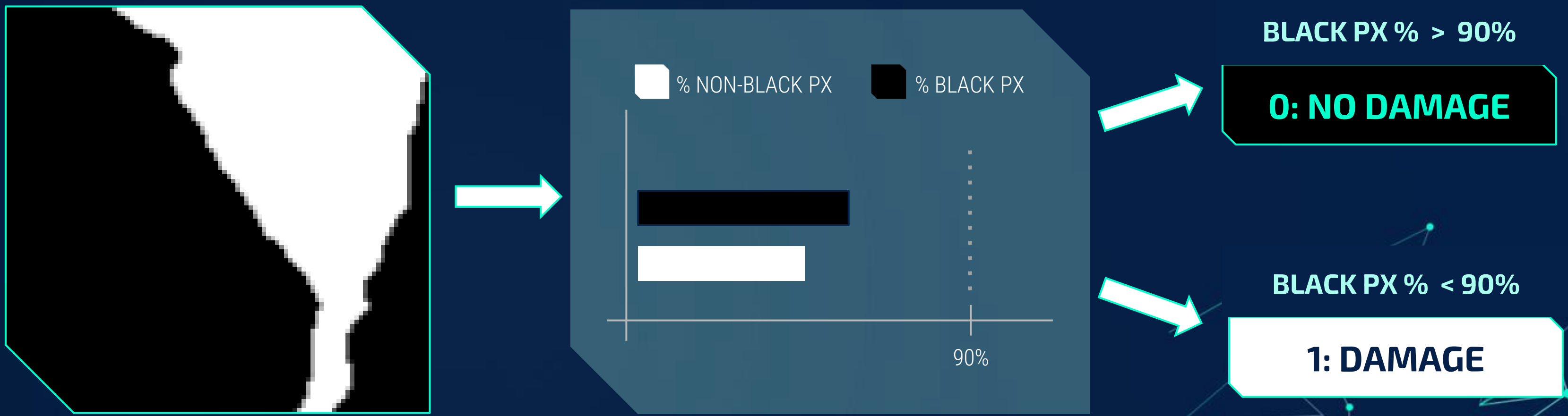
1 - WORKFLOW


DATA
PREPROCESSING
0
1
0
CNN TRAINING
MODEL
Ai
0
1
DISASTER
BINARY
PREDICTION
NEW DATA

1 - DATA PREPROCESSING



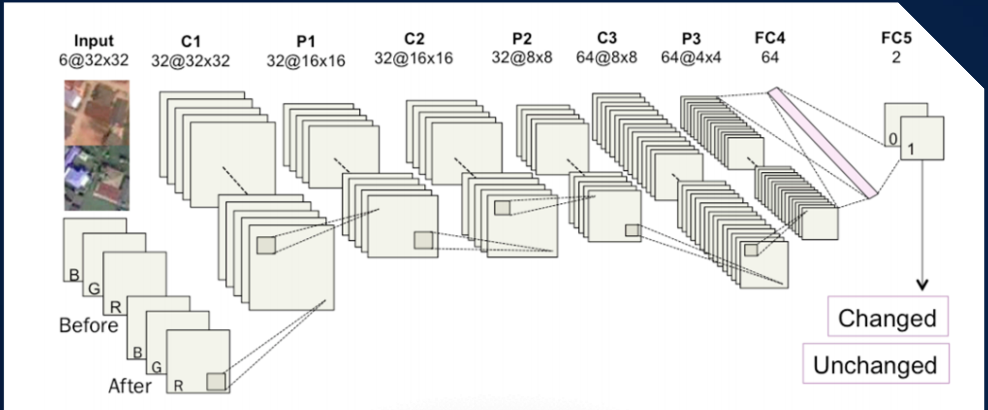
1 - LABELING CRITERIA



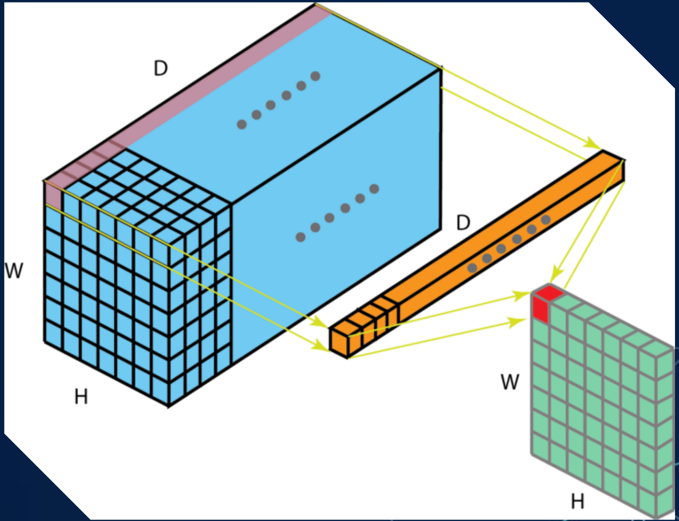
MASK PATCH

PIXELS %

1 - CNN ARCHITECTURE



The base architecture of CNN used



CNN

1x1 Convolution

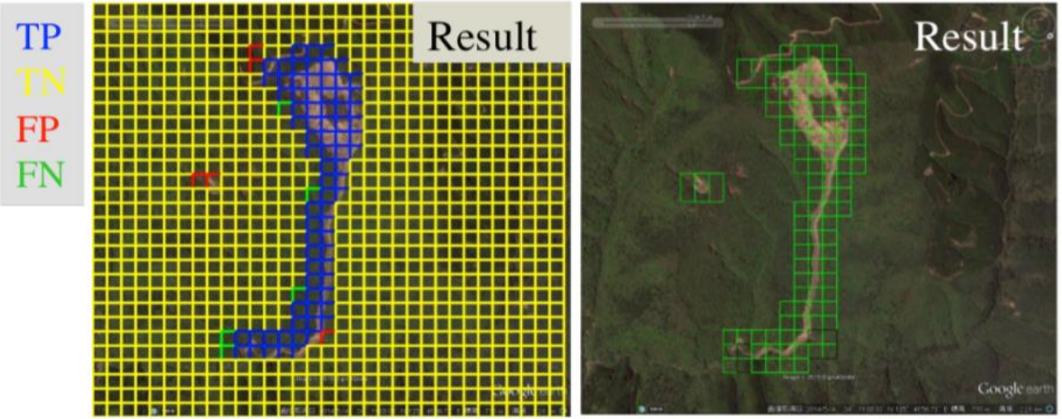
1 - RESULTS (LANDSLIDE)

Metrics

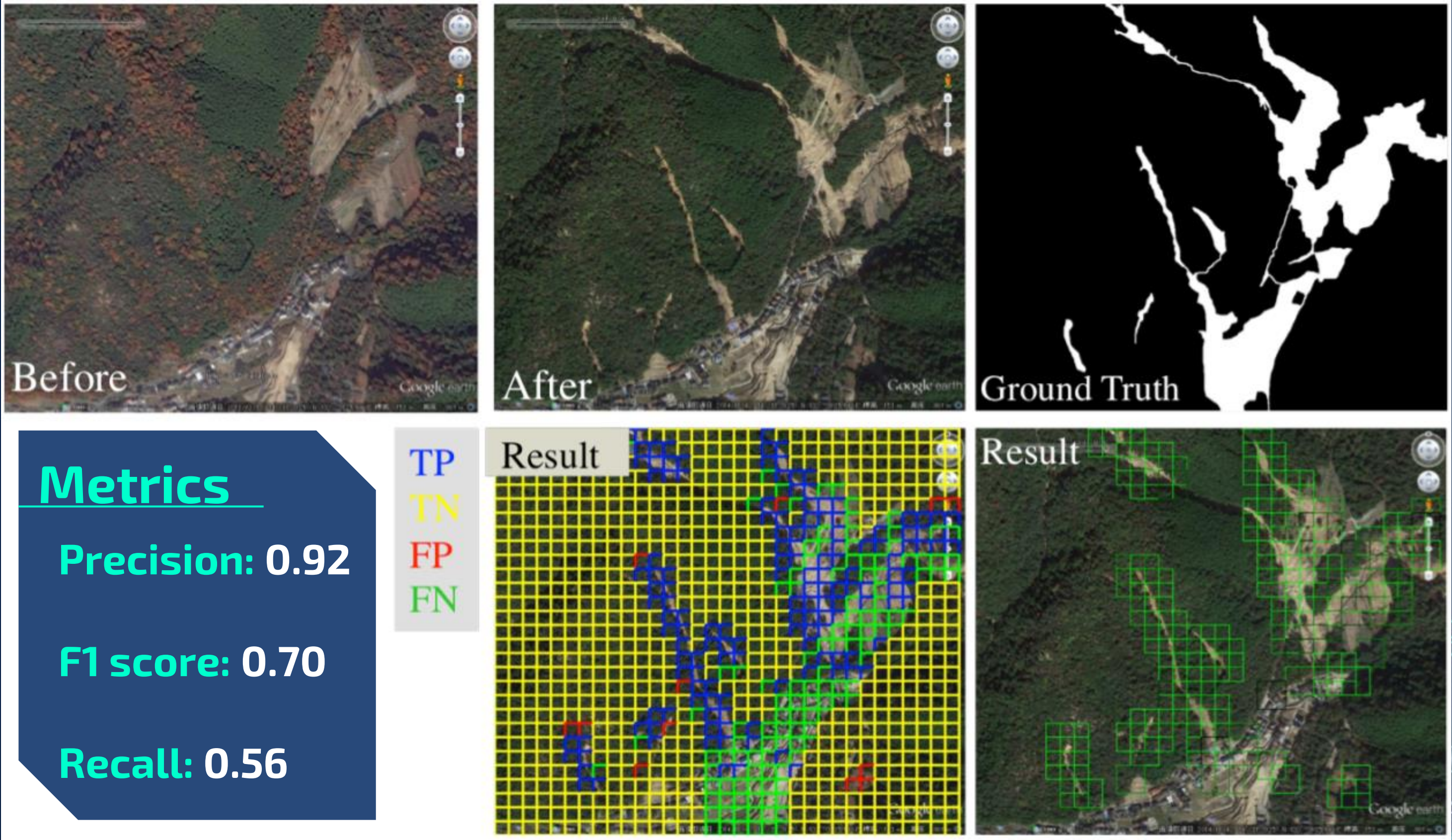
Precision: 0.93

F1 score: 0.93

Recall: 0.94



1 - RESULTS (LANDSLIDE)



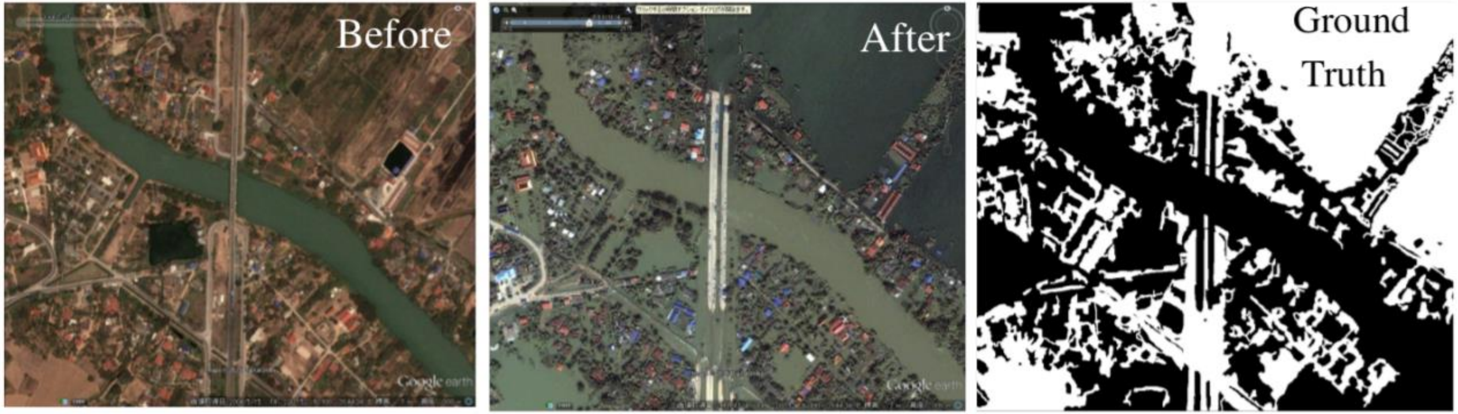
Metrics

Precision: 0.92

F1 score: 0.70

Recall: 0.56

1 - RESULTS (FLOODING)

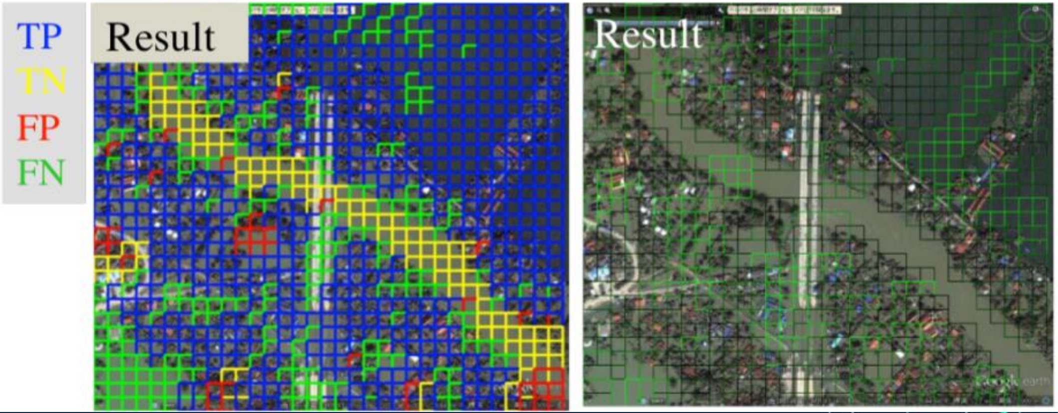


Metrics

Precision: 0.94

F1 score: 0.83

Recall: 0.76



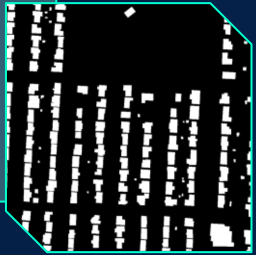
2

DATA

2 - DATASET TYPES

BINARY

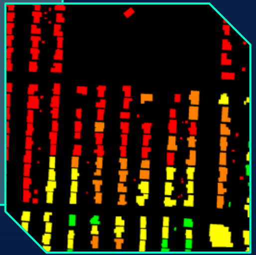
Disaster,
No Disaster



DATASETS

MULTICLASS

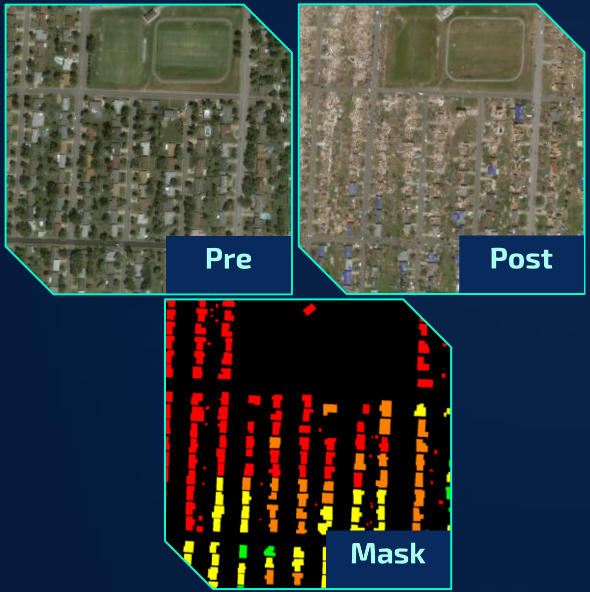
No Damage,
Light Damage,
High Damage



2 - *xView* MULTICLASS DATASET

9168 samples:

- Pre
- Post
- Mask



6 disaster types:

- wildfire
- flooding
- tornado/hurricane
- volcano
- earthquake
- tsunami

5 labels:

1. No Building
2. No Damage
3. Light Damage
4. Medium Damage
5. Destroyed

2 - *xView* MULTICLASS DATASET

Features

Image identifiers	• Sample_id • Image_id • Event_name • Event_type • Folder • Image_fname • Mask_fname
Pixel-level info	• non_damaged_pixels • light_damaged_pixels • medium_damaged_pixels • destroyed_pixels
Building-level info	• non_damaged_buildings • Light_damaged_buildings • medium_damaged_buildings • destroyed_buildings

3

EXPERIMENTS

3 - CHALLENGES

SMALL BETWEEN CLASS VARIATION

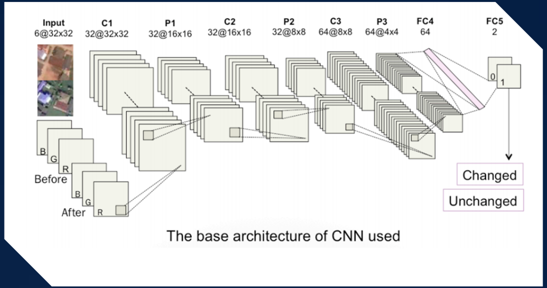
MULTIPLE AND UNBALANCED CLASSES

DIFFERENT ENVIRONMENTS

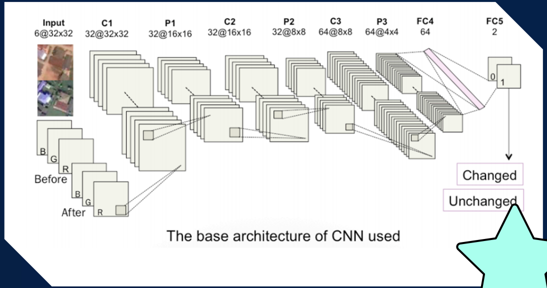
3.1
APPROACH #1

3.1 - WHAT'S NEW?

MODEL



ORIGINAL PAPER CNN



IMPROVED CNN

CLASSIFICATION

BINARY

0
1

MULTICLASS

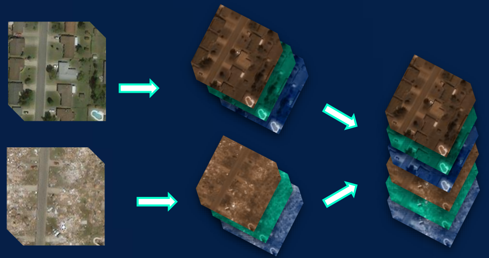
0
1
2

3.1 - DATA SELECTION

IMAGES SELECTION

- LESS GENERALIZATION
- MORE BALANCING
- WORST RESULTS

BASED ON PIXELS CLASS

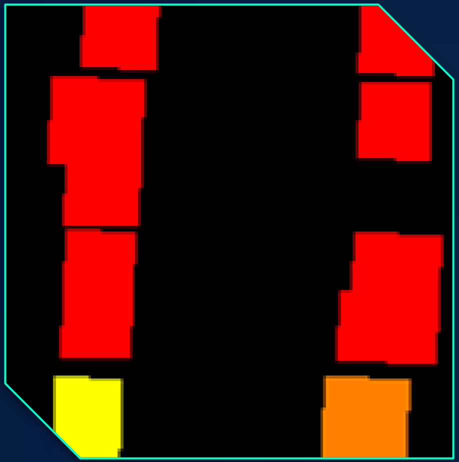


PATCH GENERATION FROM IMAGES

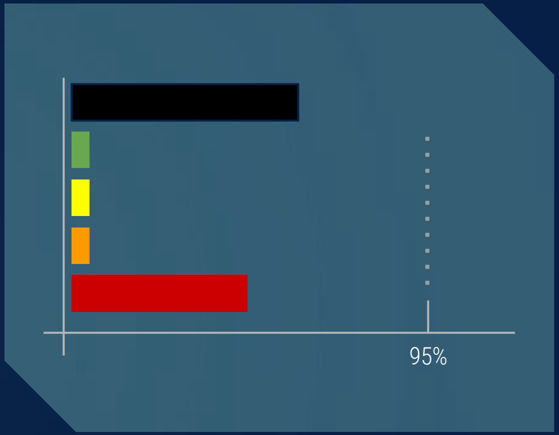
- MORE GENERALIZATION
- LESS BALANCING
- BETTER RESULTS

BASED ON EVENTS

3.1 - LABELING CRITERIA



MASK PATCH 32X32



PIXELS %

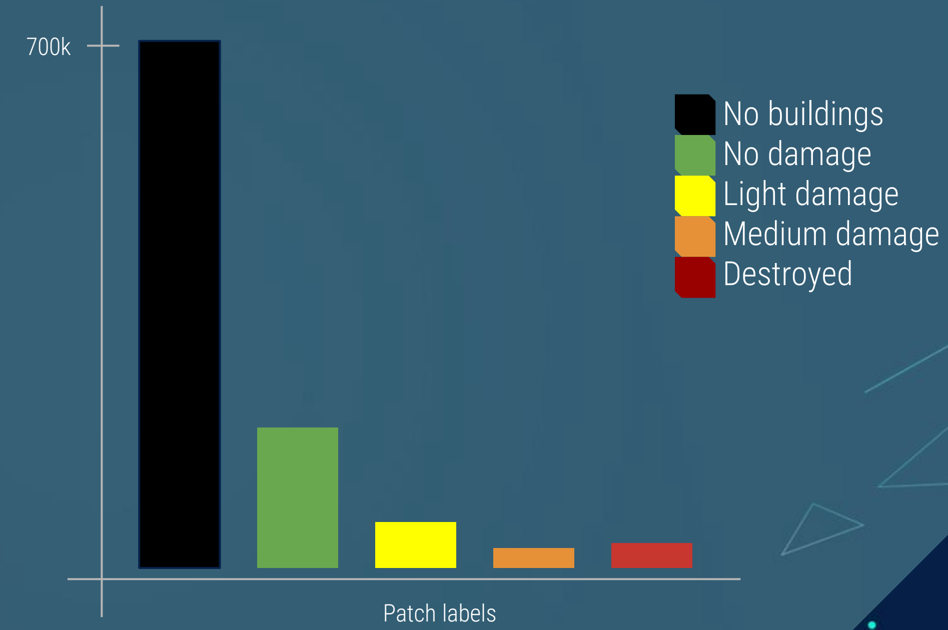
BLACK PX % > 95%

0: NO DAMAGE

BLACK PX % < 95%

CLASS WITH
MAX PIXELS %

3.1 - PATCH DISTRIBUTION



3.1 - TUNED PARAMETERS

AUGMENTATION ✗

UNDERSAMPLING ✗

CNN STRUCTURE ✓

CLASS WEIGHTS ✓

3.1 - NEW CNN STRUCTURE

Original structure

Additional structure

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 32, 32, 32)	224
max_pooling2d_6 (MaxPooling2	(None, 16, 16, 32)	0
conv2d_7 (Conv2D)	(None, 16, 16, 32)	1056
max_pooling2d_7 (MaxPooling2	(None, 8, 8, 32)	0
conv2d_8 (Conv2D)	(None, 8, 8, 32)	1056
max_pooling2d_8 (MaxPooling2	(None, 4, 4, 32)	0
conv2d_9 (Conv2D)	(None, 4, 4, 32)	1056
max_pooling2d_9 (MaxPooling2	(None, 2, 2, 32)	0
conv2d_10 (Conv2D)	(None, 2, 2, 32)	1056
max_pooling2d_10 (MaxPooling	(None, 1, 1, 32)	0
conv2d_11 (Conv2D)	(None, 1, 1, 64)	2112
max_pooling2d_11 (MaxPooling	(None, 1, 1, 64)	0
flatten_1 (Flatten)	(None, 64)	0
dense_2 (Dense)	(None, 64)	4160
dropout_1 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 5)	325

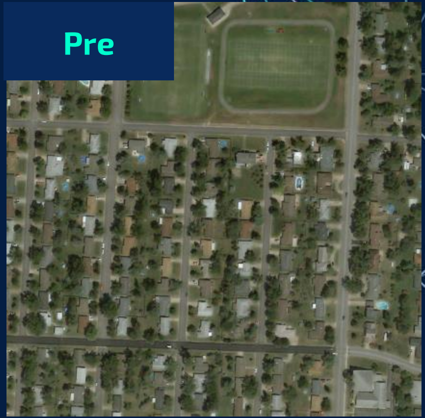
Metrics

Training: Accuracy: 0.861 - F1: 0.860

Test: Accuracy: 0.857 - F1: 0.853

CASE #1
FEW BUILDINGS

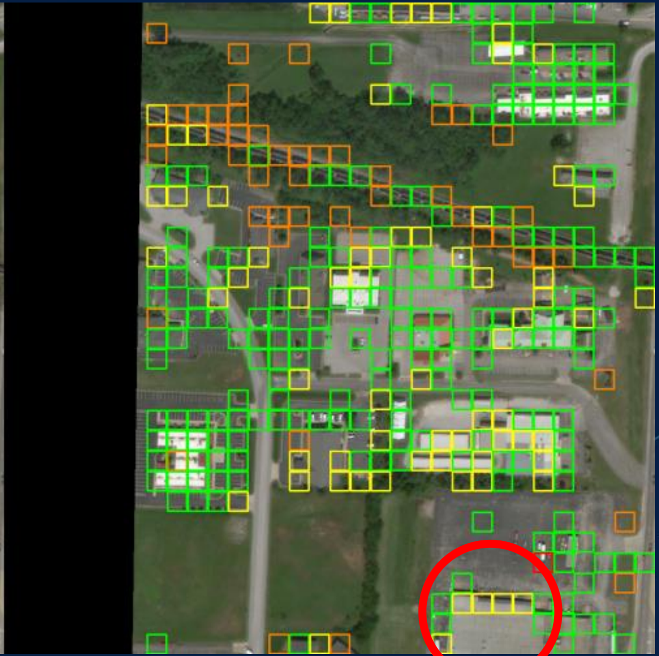
RESULTS



CASE #2
MANY BUILDINGS

3.1 - RESULTS CASE #1

True Mask



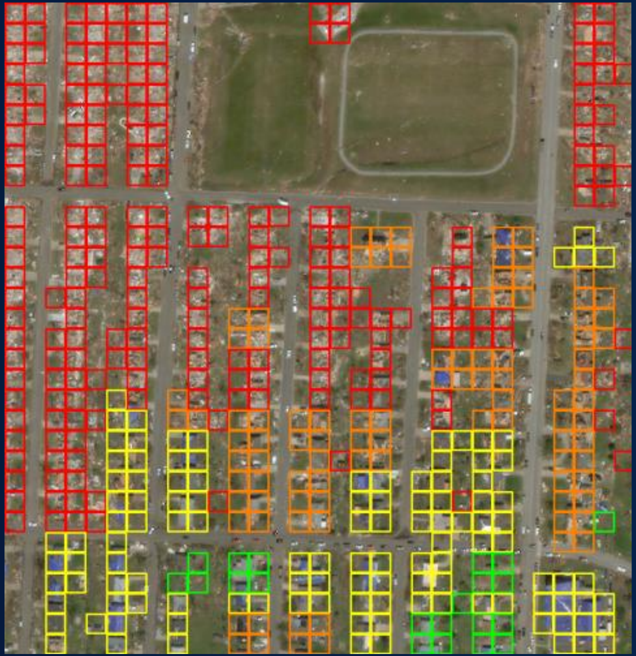
Pred Mask

Metrics

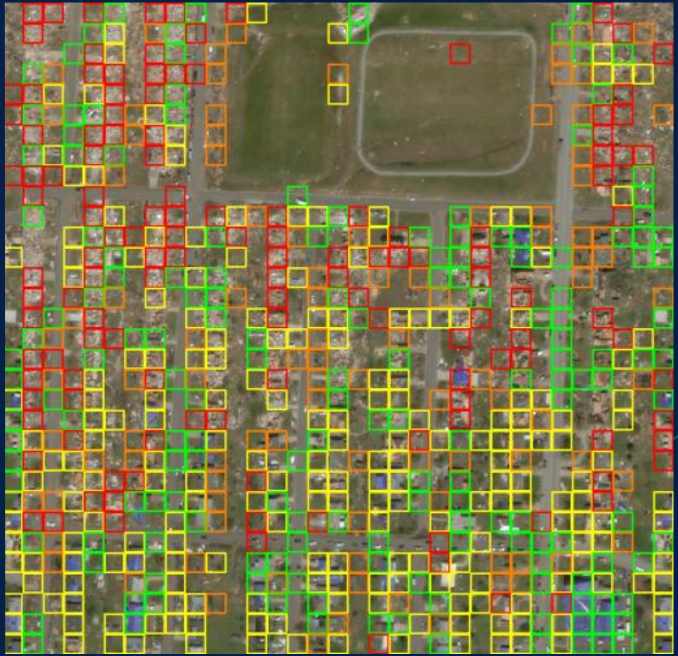
Accuracy: 0.75

F1 score: 0.70

3.1 - RESULTS CASE #2



True Mask



Pred Mask

Metrics

Accuracy: 0.50

F1 score: 0.59

3.1 - FUN FACT

PRE-POST

POST-POST

Metrics (pre-post)

Accuracy: 0.83

F1 score: 0.82

Metrics (post-post)

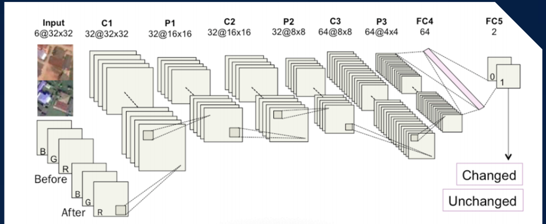
Accuracy: 0.75

F1 score: 0.70

3.2
APPROACH #2

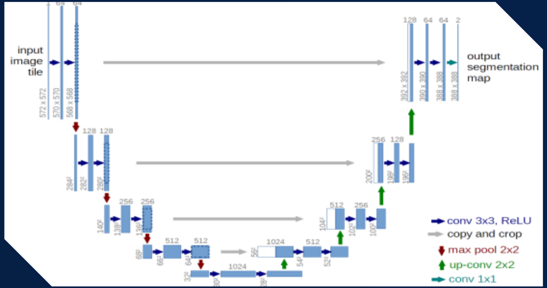
3.2 - WHAT'S NEW?

MODEL



The base architecture of CNN used

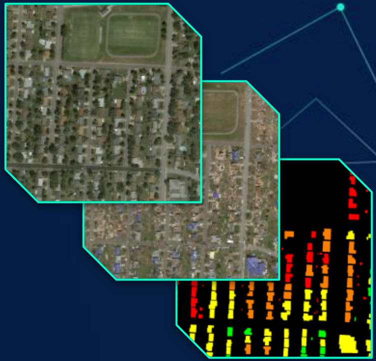
CNN



UNET MODEL

INPUT DATA

PATCHES
32x32px



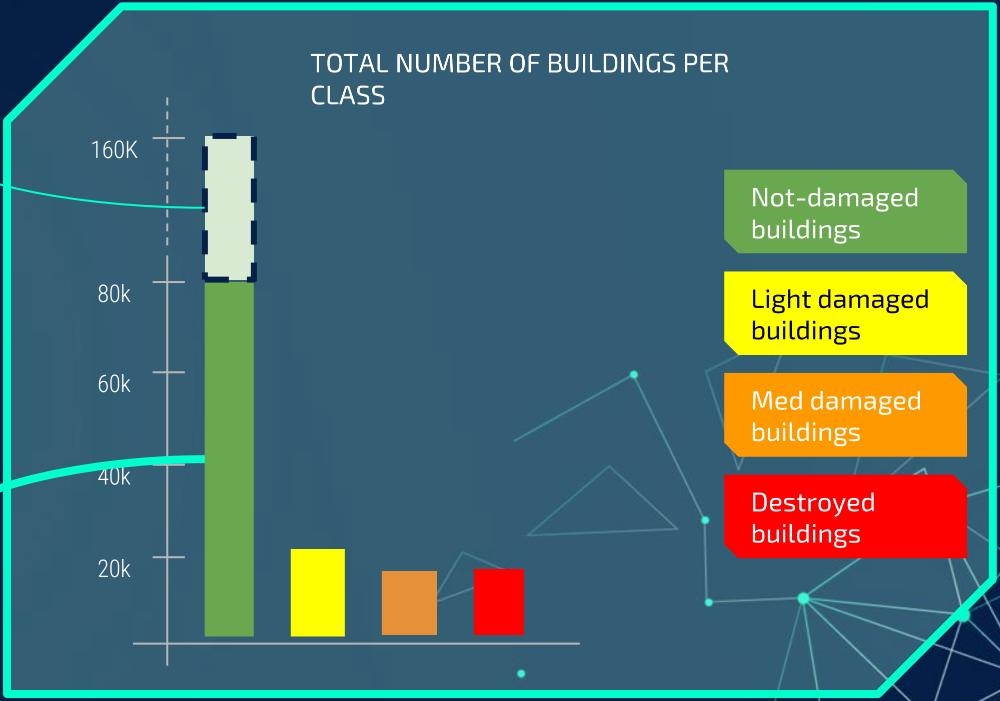
IMAGES 1024x1024px

3.2 - DATA SELECTION

5928 with 0 damaged buildings

9168 samples

3240 with at least one



3.2 - DATA SELECTION

STRATIFIED RANDOM SAMPLING

- MORE GENERALIZATION
- WORST CLASS BALANCING
- WORST RESULTS

BASED ON EVENT TYPE ✗

- LESS GENERALIZATION
- BEST CLASS BALANCING
- BETTER RESULTS

✓ **BASED ON CLASS DISTRIBUTION**

3.2 - TUNED PARAMETERS

TRAIN IMAGE RESOLUTION ✗

TRANSFER LEARNING ✗

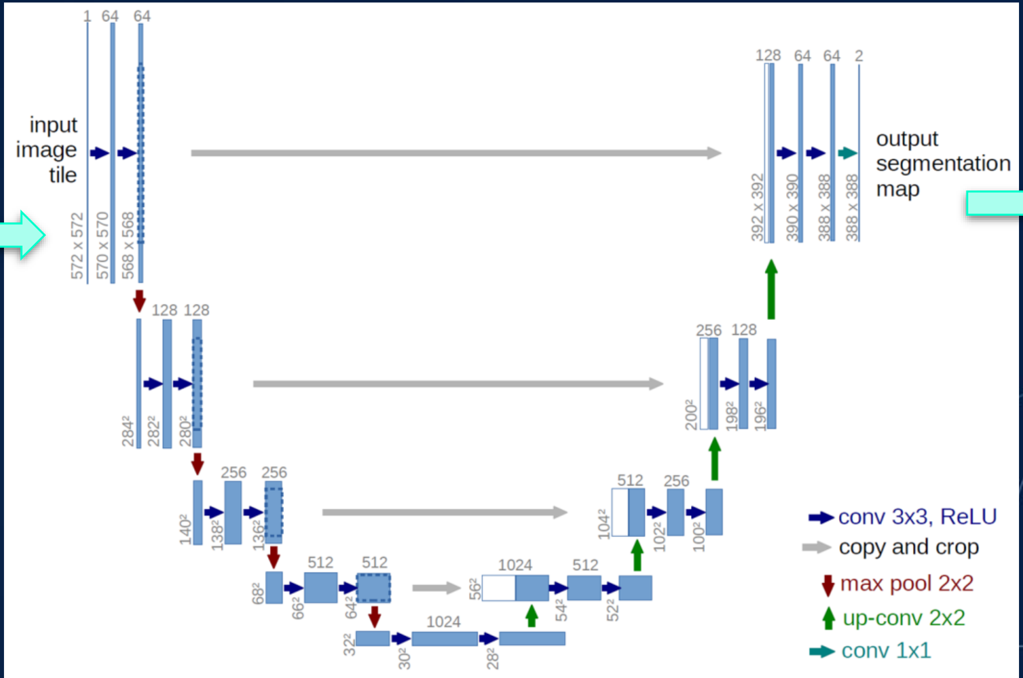
UNDERSAMPLING ✓

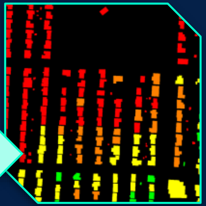
CLASS WEIGHTS ✓

3.2 - UNET ARCHITECTURE

Pre

Post



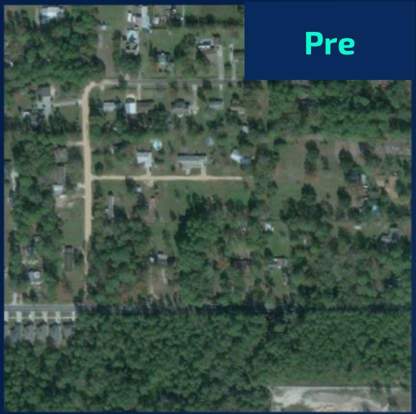


Metrics

Training:
Accuracy: 0.925
F1: 0.921

Test:
Accuracy: 0.925
F1: 0.920

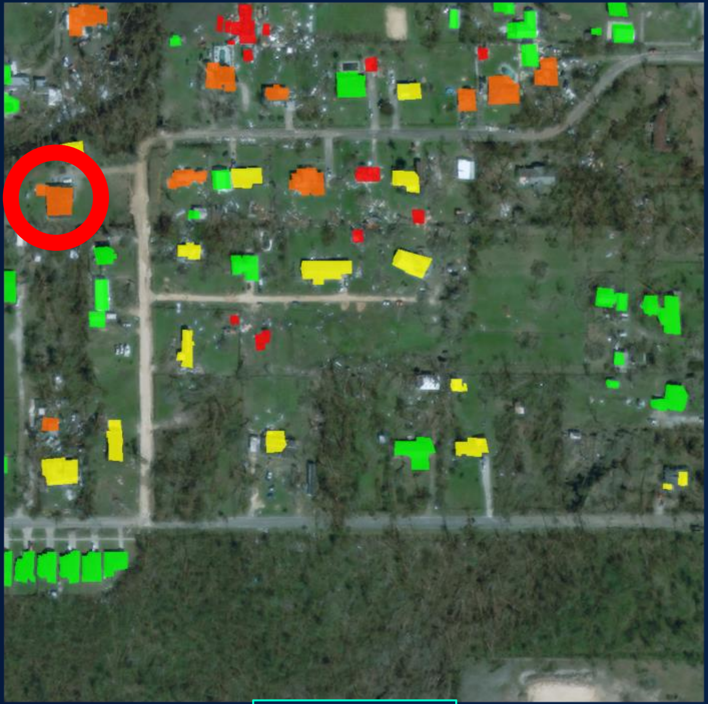
CASE #1
FEW BUILDINGS



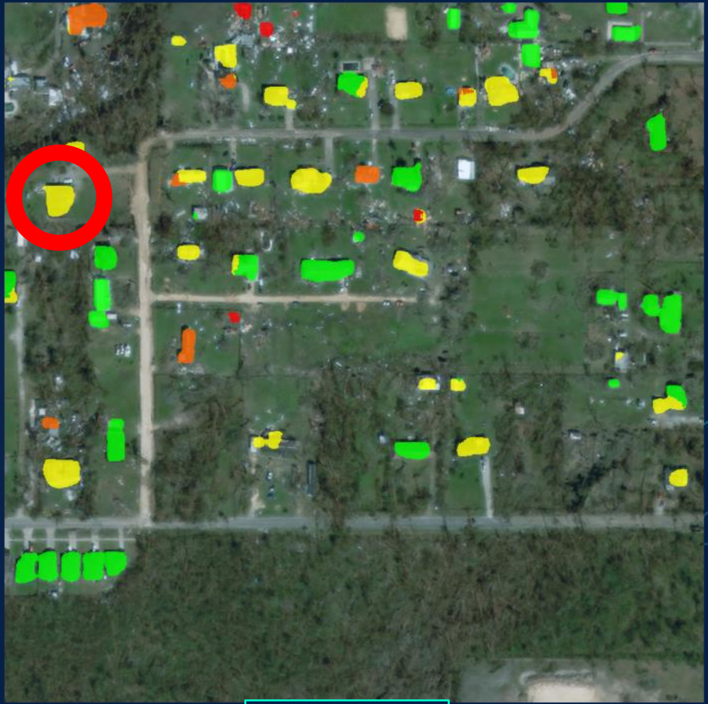
RESULTS

CASE #2
MANY BUILDINGS

3.2 - RESULTS #1



True Mask



Pred Mask

Metrics

Accuracy: 0.96

F1 score: 0.96

3.2 - RESULTS #2

True Mask

Pred Mask

Metrics

Accuracy: 0.85

F1 score: 0.86

05

FINAL RESULTS

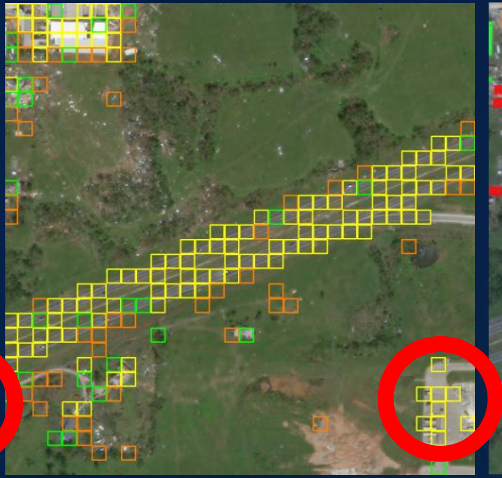
CASE #1
FEW BUILDINGS

LABELED RESULTS COMPARISON

CASE #2
MANY BUILDINGS

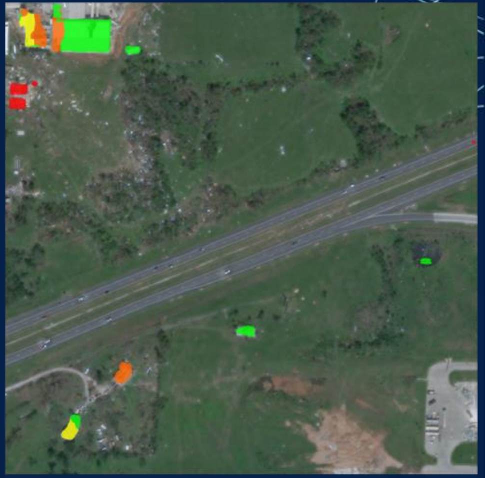
LABELED RESULTS COMPARISON - Case #1

True Mask



Pred Mask

True Mask



Pred Mask

Approach #1 - CNN

Metrics:

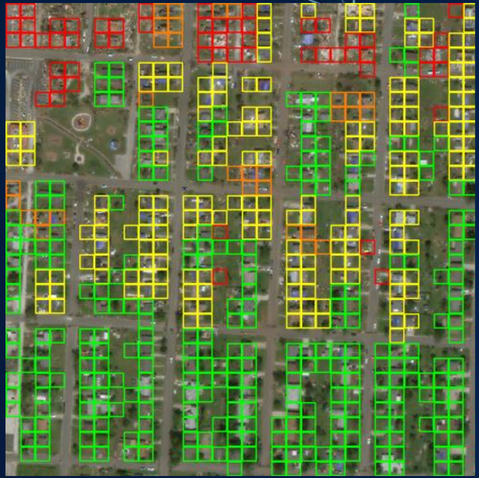
- Accuracy: 0.81
- F1 score: 0.75

Approach #2 - UNET

Metrics:

- Accuracy: 0.98
- F1 score: 0.98

LABELED RESULTS COMPARISON - Case #2



True Mask

Pred Mask

True Mask

Pred Mask

Approach #1 - CNN

Metrics:

- Accuracy: 0.45
- F1 score: 0.44

Approach #2 - UNET

Metrics:

- Accuracy: 0.91
- F1 score: 0.91

CASE #1
FEW BUILDINGS

Pre

Post

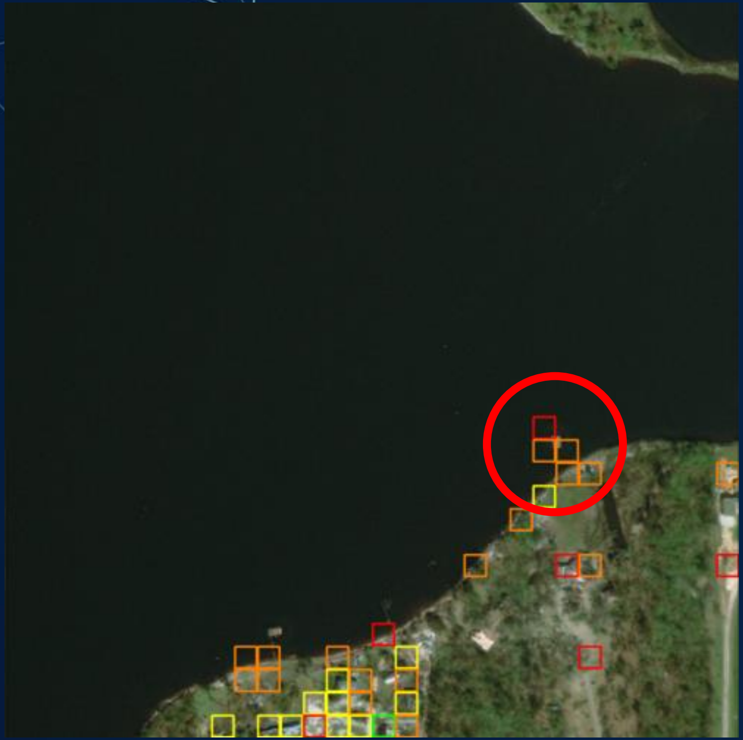
UNLABELED RESULTS COMPARISON

Pre

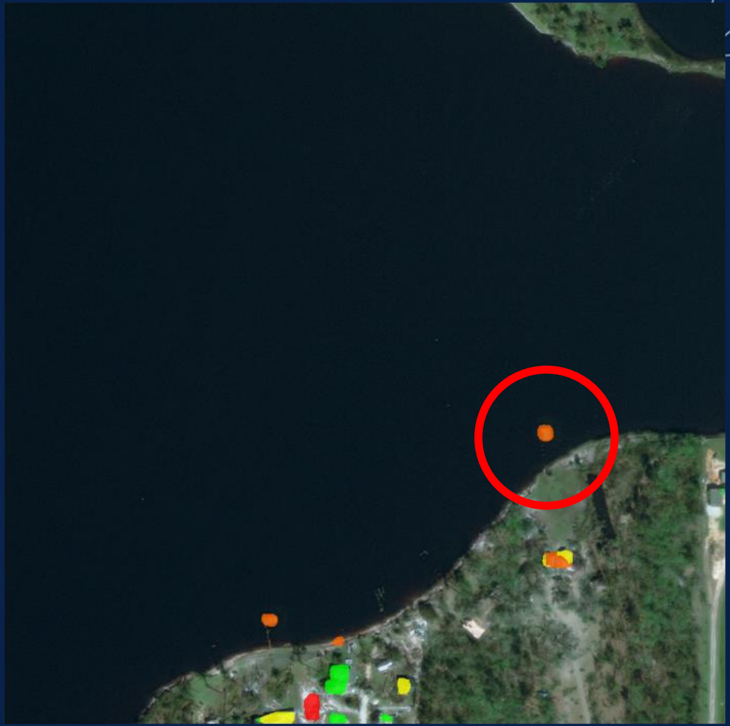
Post

CASE #2
MANY BUILDINGS

RESULTS COMPARISON (Case #1)

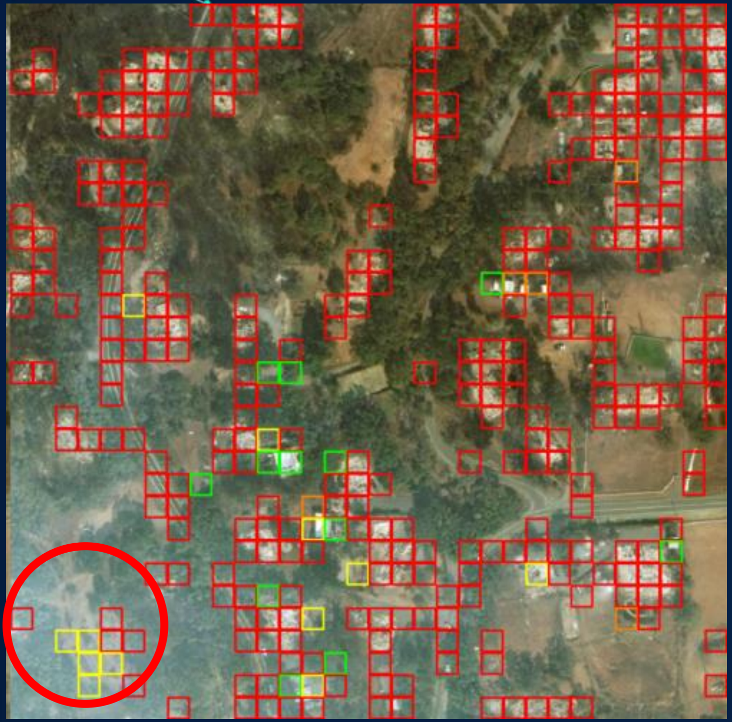


Approach #1

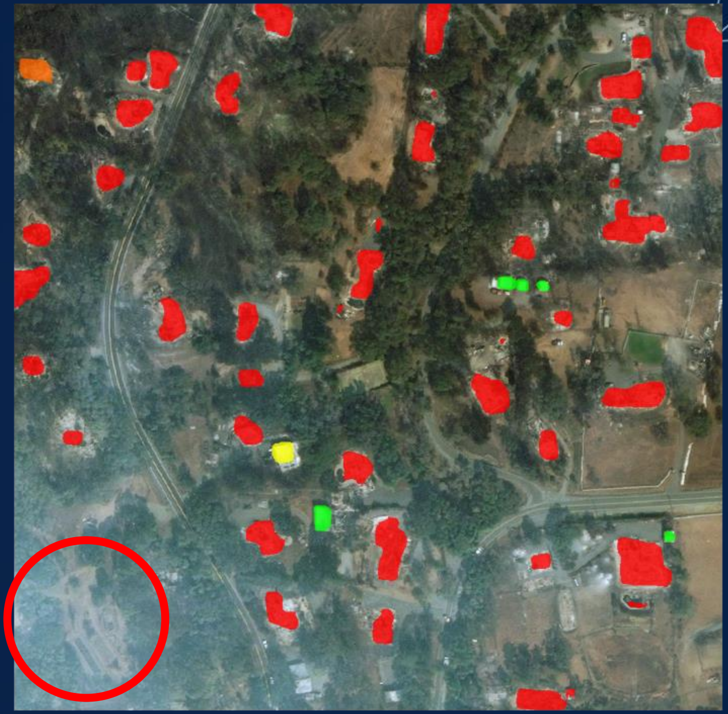


Approach #2

RESULTS COMPARISON (Case #2)



Approach #1



Approach #2

THANKS

REFERENCES

- (PDF) Disaster detection from aerial imagery with convolutional neural network
- (PDF) Analysis of satellite images for disaster detection
- xView2
- xBD: A Dataset for Assessing Building Damage from Satellite Imagery, https://arxiv.org/pdf/1911.09296.pdf
- U-Net: Convolutional Networks for Biomedical Image Segmentation
- GitHub - qubvel/segmentation_models: Segmentation models with pretrained backbones. Keras and TensorFlow Keras.

INDEX