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Smart Condition Assessment of Bridges and Underground Structures using Image Data and Deep Learning

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Outline of Presentation

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- 1. Introduction to smart condition assessment
- 2. Application to bridge ASR damage: *Overcoming the challenge of complicated image backgrounds*
- 3. Application to underground sewer pipe defects: *Result of two object detection models*
- 4. Conclusion

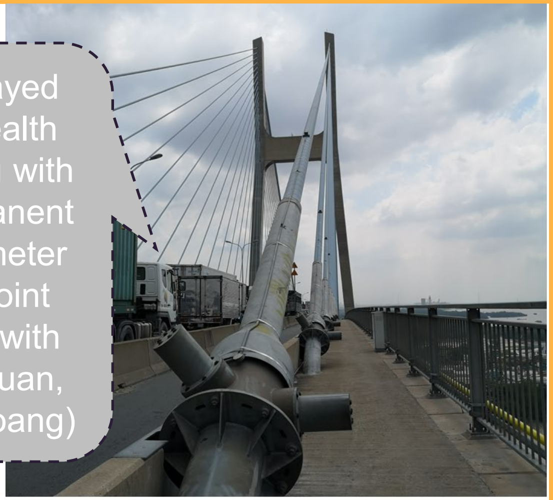
1. Introduction to Smart Condition Assessment

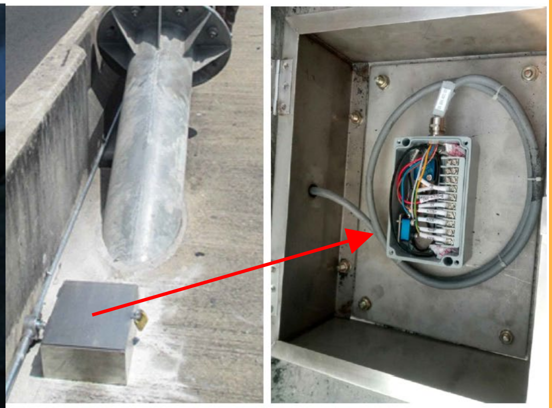
Condition Assessment Overview

Main assessment approaches for ageing civil infrastructure:

- Health monitoring methods *(i.e. using continuous automated measurements of structural response and/or loading over a period)*
- Condition assessment methods (***<u>our focus today</u>***)

Cable-stayed bridge health monitoring with one permanent accelerometer shown (joint research with Sharry, Guan, Oh and Hoang)





Traditional condition assessment:

- <u>How</u>: Use of trained inspectors

+ decision-making criteria (e.g. condition rating)

- <u>Pros</u>: Established, intuitive
- <u>Cons</u>: Time-consuming, laborious

+ sometimes dangerous

Inspectors from the US Army Corps of Engineers rappel down a Tainter gate to inspect for surface damage [4] (in Spencer 2019)

Condition Assessment Overview

Smart condition assessment:

- <u>How</u>: use of remote cameras (to capture image data) + AI deep learning/image processing techniques (for feature recognition, extraction and classification)
- <u>Pros</u>: → fast, affordable and safe features offered by computer vision system
- <u>Cons</u>: still new → requiring time for full development + knowledge transfer

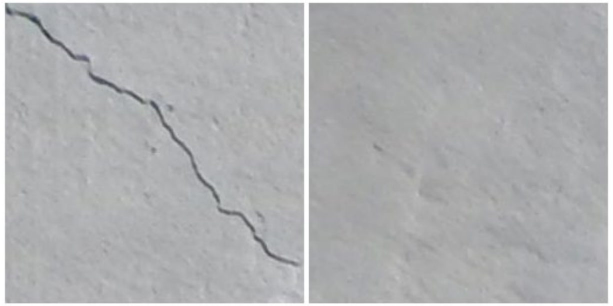
<u>Aim:</u> **Camera + AI algorithm** replaces **Human eye + Brain**

Source of figures: Application of artificial intelligence on assessing surface damage of concrete bridges (Courtesy of Luong and Ngo, 2022)

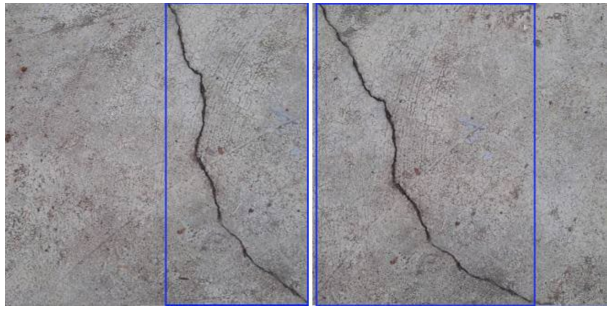
Hierarchy of Smart Condition Assessment

03 common levels:

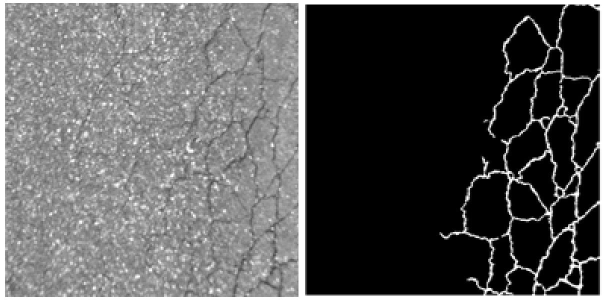
- <u>Level 1</u>: Detecting the occurrence of damage/defect through image classification, *e.g., most CNNs can do this*



- <u>Level 2</u>: Locating damage through object detection (i.e. damaged region recognition) *e.g., R-CNN, faster R-CNN and YOLO*



- <u>Level 3</u>: Assessing more detail damage characteristics (e.g. severity) through semantic segmentation, i.e. working at the pixel level for precise interpretation of the geometrical space around objects, *e.g., U-Net, Mask R-CNN*



Sources of some Figures: Luong and Ngo (2022) and joint work with Khuc et al. (2022)

Current Status of Smart Condition Assessment

Achievements:

- Attracted numerous high-quality studies in all these three levels…
- …partly because of recent rapid advancement in image acquisition and AI computing technologies

Image acquisition using UAV (Luong and Ngo, 2022)

Challenges & research need:

- Most existing assessment models were developed using images with clear damage/defects
  - *C1: More research is needed for real-world image datasets i.e. with increased complexities*
- Most existing assessment models were developed for deployment onto powerful/sever-/cloud-based AI computing machines
  - *C2: More research is needed for emerging mobile/ embedded systems for real-time implementations*

Challenging inspection photos from Queensland bridges

2. Application to bridge ASR damage: *Overcoming the challenge of complicated image backgrounds*

Project Background

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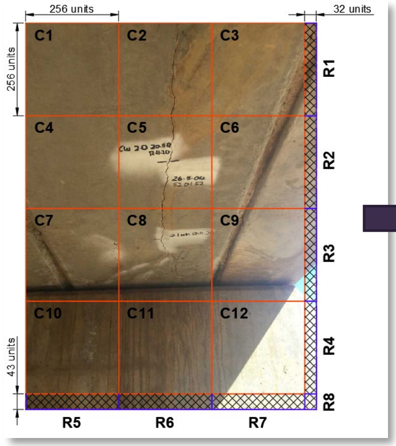
Research significance/highlights:

- ASR: destructive phenomenon known as 'concrete cancer'
- Timely detection of ASR cracks ensure long-term durability, structural integrity for civil structures
- ASR damage is heavily affected by texture backgrounds, causing CNN evaluation confusion
- First time ASR damage detection is tackled by AI vision

Original Inspection Photos Taken from ASR Affected Bridges in Queensland

Creation of Image Dataset:

- Use 35 inspection photos (ranging from 800x600 to 5184x3888 pixels), cropped to 256x256 patches to suit most CNNs and retain image quality
- Final dataset has 1706 images (609 with ASR defect)



Example of an 800×1067 Photo Cropped to 256×256 Patches

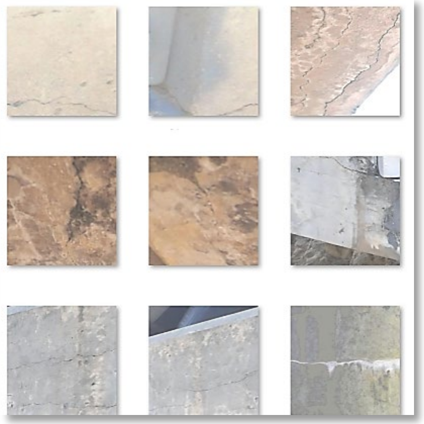
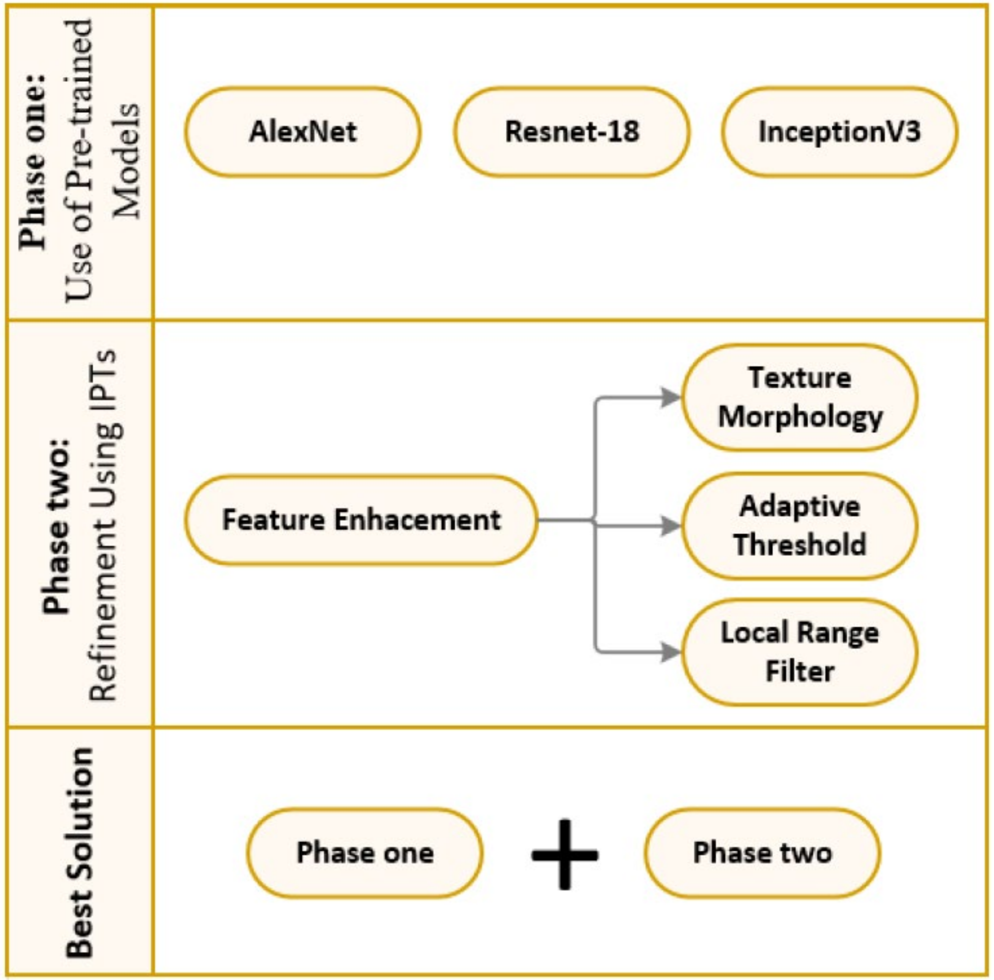


Image Dataset

Framework & Phase I- Use of Pre-trained Models

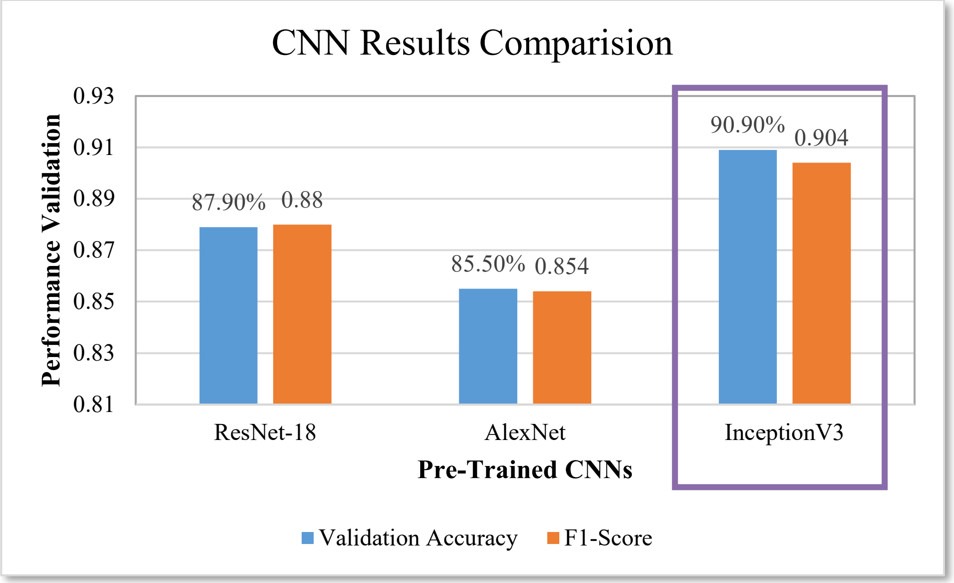
Damage detection framework



IPTs: Image Processing Techniques

Phase I- Use of Pre-trained models

- Selected 3 representative CNN models based on our previous study (Nguyen *et al.*, 2022)
- InceptionV3 found the best performing CNN to deal with ASR damage



CNN: Convolutional Neural Network

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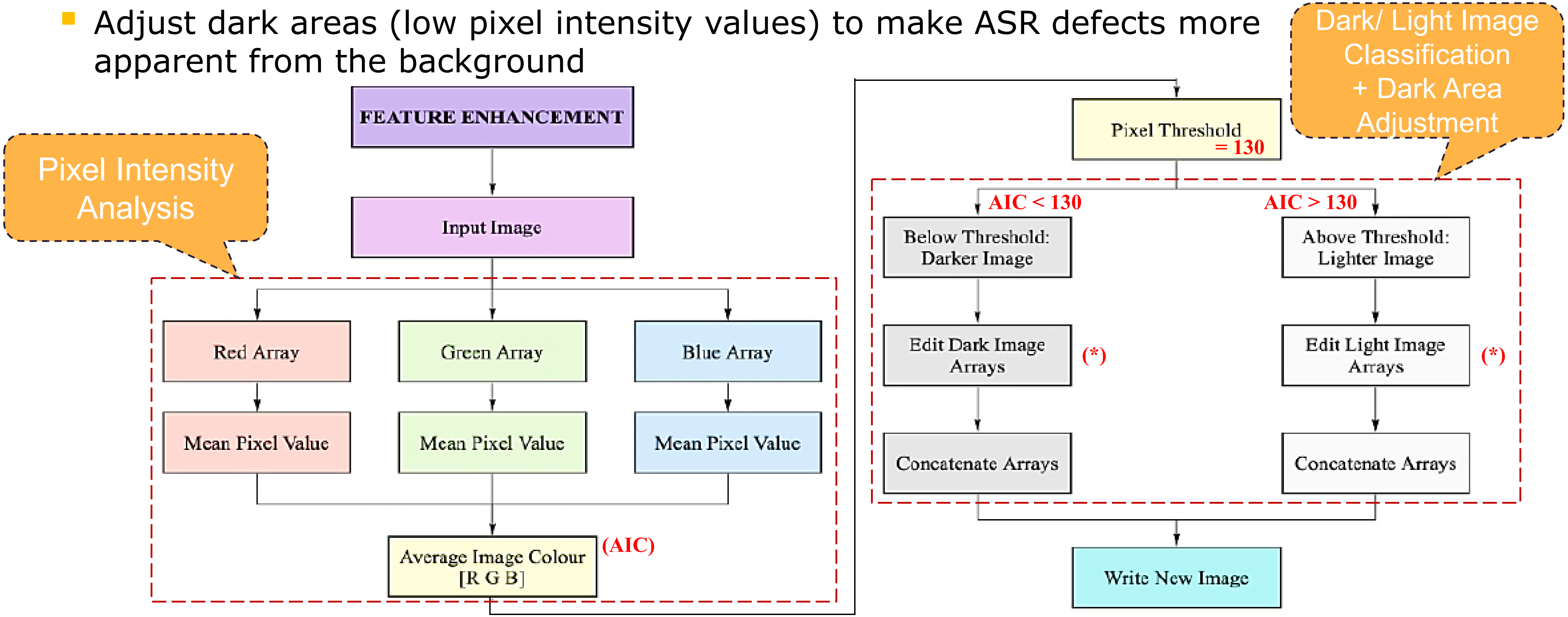
Feature Enhancement flow chart

- Adjust dark areas (low pixel intensity values) to make ASR defects more apparent from the background



AIC represents the average intensities of the colour image

(*) Adjust **pixel of dark areas** (for each array):

- In dark images: Pixel (Pixel< 130-X)= Mean Pixel Value- 100
- In light images: Pixel (Pixel< 180-X)= Mean Pixel Value– 50

X: Feature Adjustment Value (to be determined – **see next**)

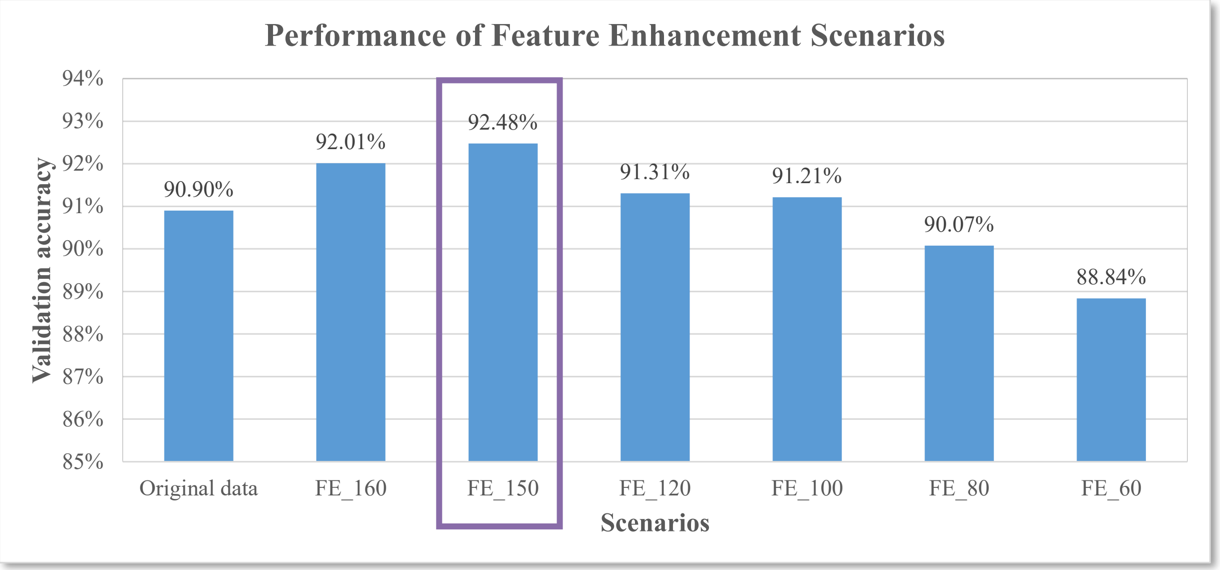
Phase II- Refinements using Image Processing Techniques

Result - Best FE:

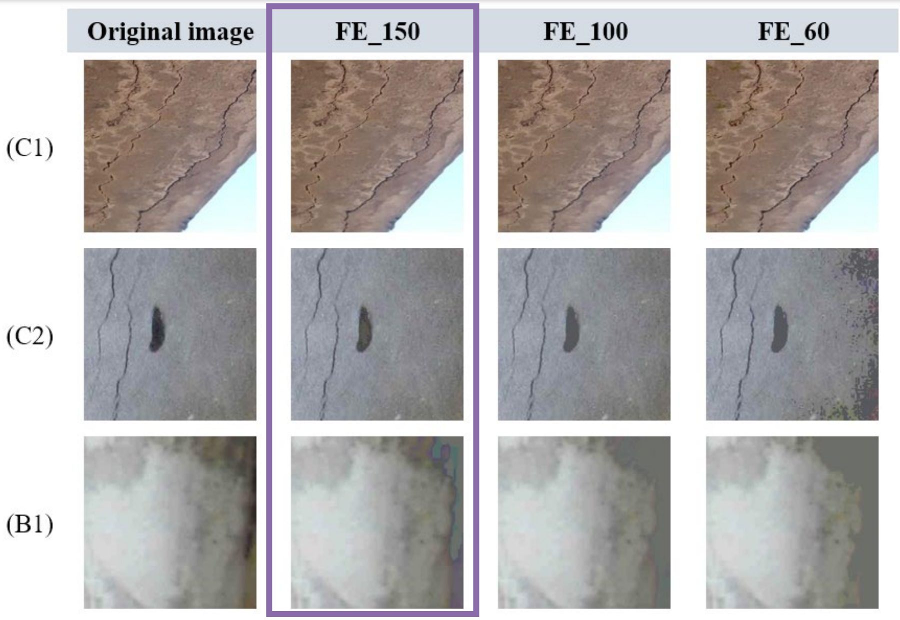
- Parametric study: X= [60÷160] →
- Best FE option:
  - X=150, highest VA = **92.48%**
  - +1.59% from original result

FE Scenarios and Validation Accuracy results

Feature enhancement scenarios	FE_160	**FE_150**	FE_120	FE_100	FE_80	FE_60
Feature adjustment value (*x*)	160	**150**	120	100	80	60
Condition dark (darker images)	0	**0**	10	30	50	70
Condition dark (lighter images)	20	**30**	60	80	100	120
Percentage of Crack image adjusted	17.1%	**23.7%**	58.4%	77.8%	92.7%	98.9%
Percentage of Base image adjusted	5.3%	**7.5%**	28.6%	53.8%	74.4%	89.5%
Validation accuracy with InceptionV3	92.01%	**92.48%**	91.31%	91.21%	90.07%	88.84%



Performance of Feature Enhancement Scenarios with InceptionV3



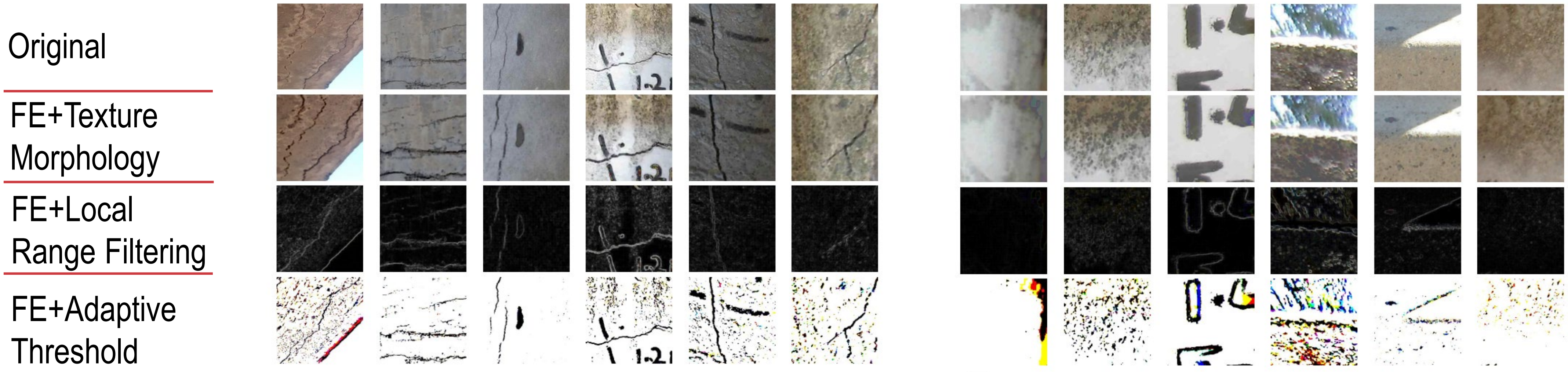
(C1) A clear crack image, adjustment is unrecogniseable
(C2) A crack image with heavy texture background
(B1) A base images with local dark area

Result - FE+ Texture Analysis (TA):

- FE + Texture morphology/ Local Range Filtering/ Adaptive Thresholding

Crack Images after Processed by FE+Texture Analysis

Base Images after Processed by FE+Texture Analysis



Phase II- Refinements using Image Processing Techniques

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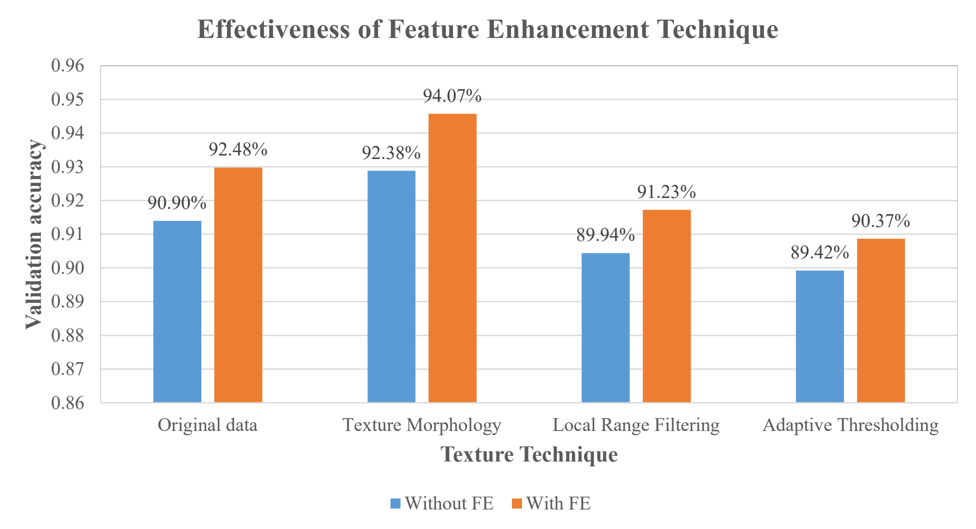
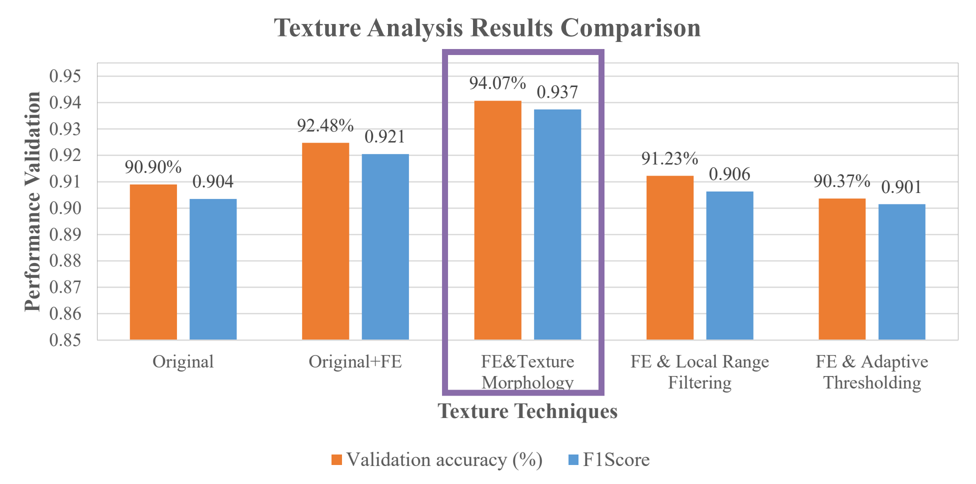
Result - FE+ TA vs TA only:

- **TA only**: Texture morphology improved VA to 92.38% (+1.59%), while the other two TAs reduced VA by -1.25% & -2.11%
- **FE + TA**: FE helps to improve VA of all three TAs
  - **Best IPTs**: FE+ Texture Morphology, VA=94.07% (+3.17% from original 90.9%)

Performance Assessment criteria	Original	FE_150	FE & Texture Morphology	FE & Local Range Filtering	FE & Adaptive Thresholding
Validation accuracy	90.90%	92.48	94.07%	91.23%	90.37%
Compared to Original	0%	1.58%	3.17%	0.33%	-0.53%
Compared to FE_150	-	0%	1.59%	-1.25%	-2.11%
F1-score	0.904	0.921	0.937	0.906	0.901
Overfitting	Negligible	Negligible	Negligible	Negligible	Negligible





3. Application to underground sewer structures:
Result of two object detection models

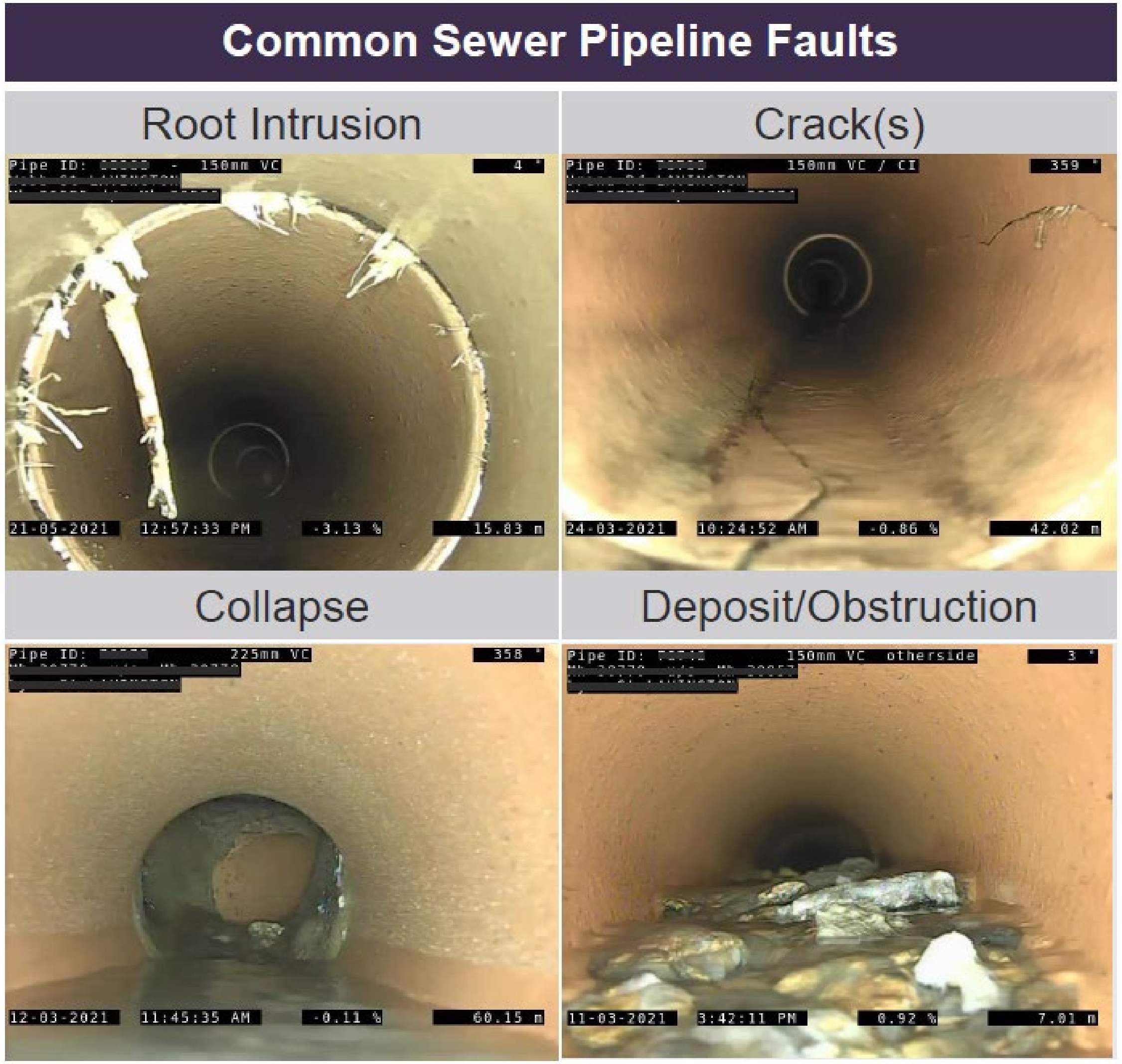
Project Background

Research aim/highlights:

- Increase efficiency in review of sewer inspection CCTV data (through automation)
- Improved accuracy and reliability of fault detection ($\rightarrow$ direct economic and qualitative benefit to industry)

Background on Sewer Network:

- Complex systems of pipes, manholes and associated infrastructure (to convey wastewater from the property junction to a treatment facility)
- Common damage/defects (faults) are shown, *we start with Crack (important), then expand to Root and Deposit*

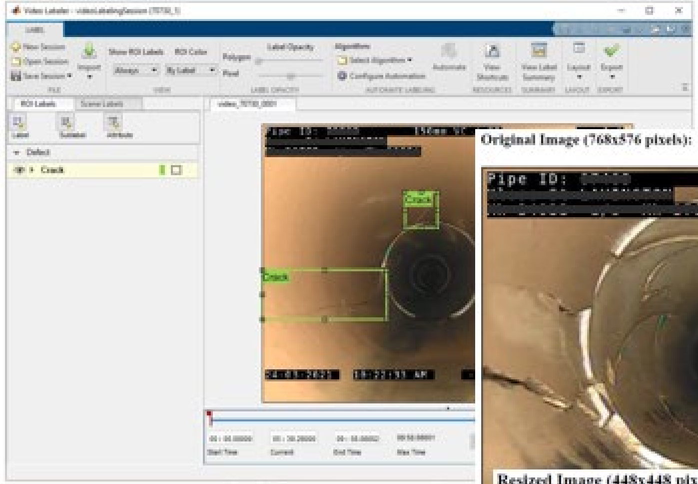


(note: some pipe information has been deidentified)

Project Background

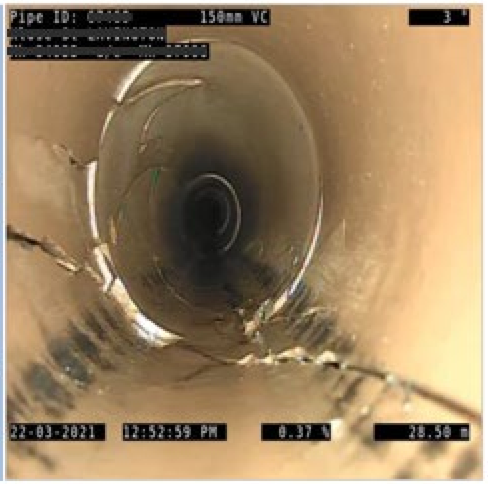
Creation of Labelled Image Datasets:

- Labelling done directly on CCTV footage
- Image splitting done autonomously from the video using a predetermined sampling rate n
- Train/Validation/Test proportion: 70/10/20 (%)
- Image conversion
- Image augmentation



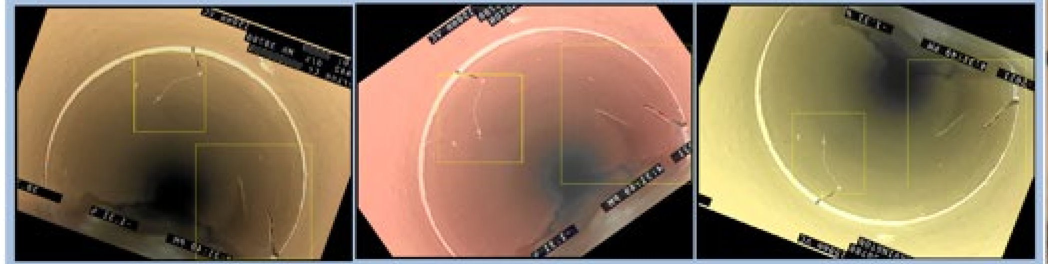
Original Image (768x576 pixels):

Resized Image (448x448 pixels):



AUGMENTATION DATASET

- For stimulating the real life conditions, dataset has been augmented with
  - Random flip (vertical and horizontal)
  - Random rotation
  - Colour Jitter (contrast, hue)



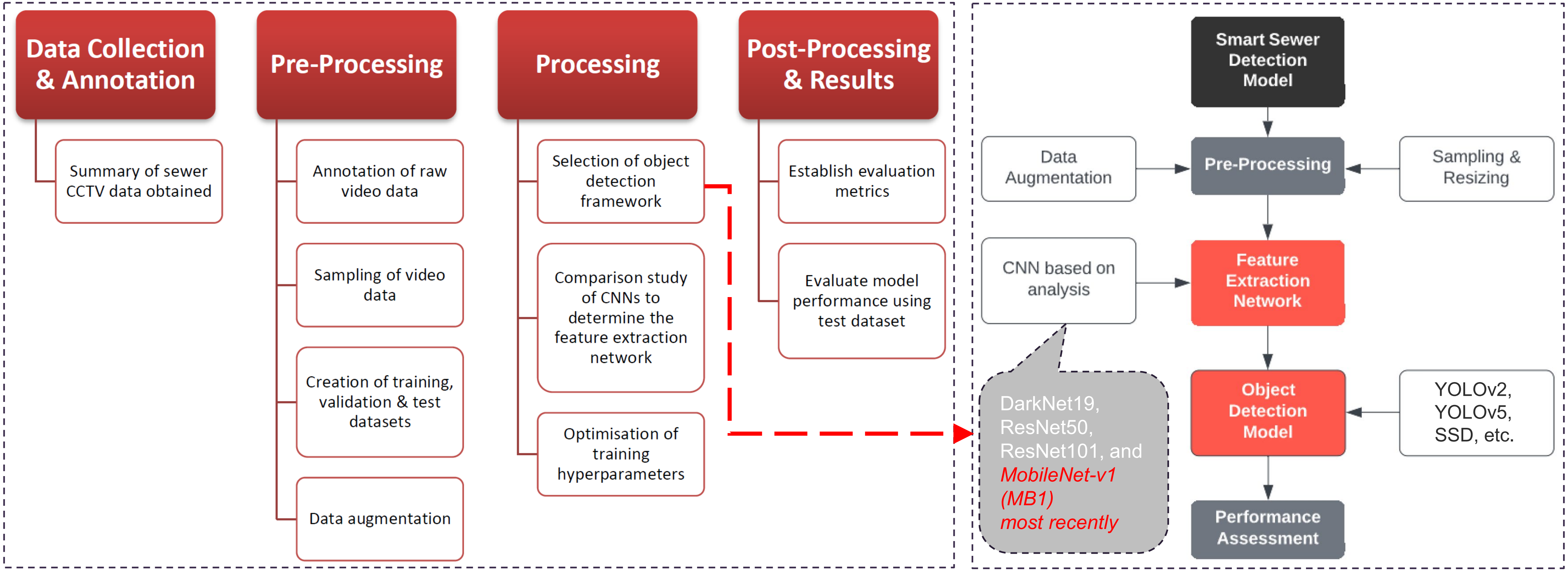
Example of Dataset Augmentations

(note: some pipe information has been deidentified)

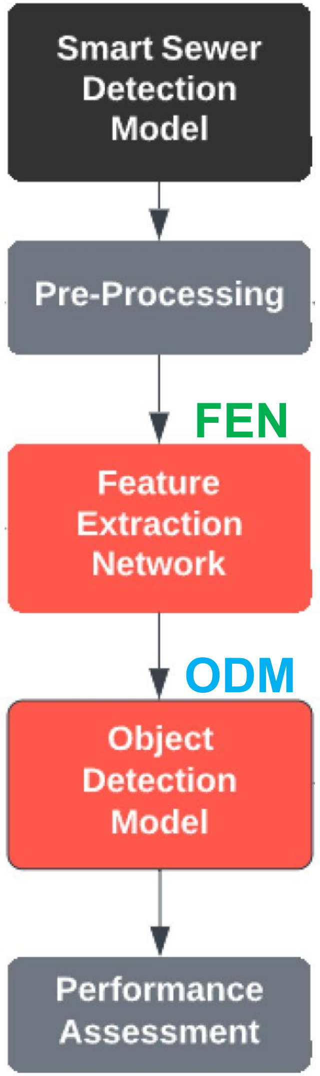
Framework of Model Development and Assessment

Model development & evaluation methodology

Flow Diagram of Smart Sewer Detection Model



Architectures of Fault Object Detection Models



1. Large models for conventional AI computing system:

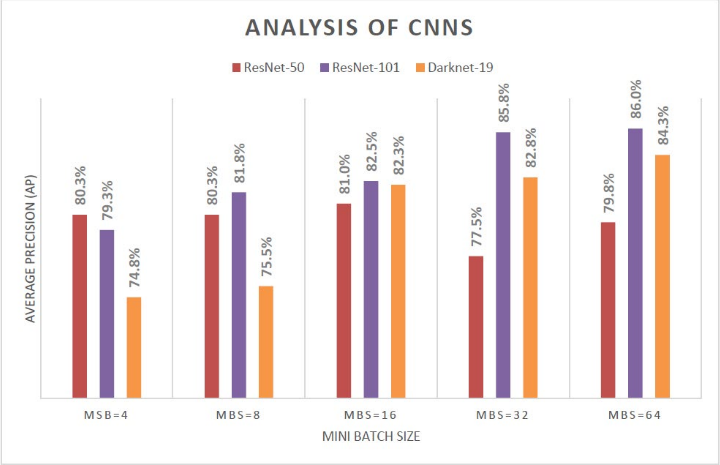
- Target computing systems: Nvidia DGX system, Google Colab, etc.
- **FEN**: best CNN=ResNet101 with MBS = 32, MaxEpochs=30 (from CNN, etc. analyses)
- ODM: YOLOv2

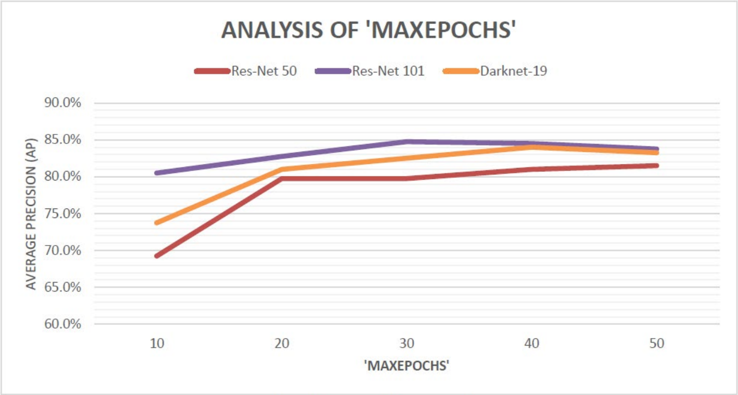
2. Computationally efficient/small models for embedded computing systems:

- Target computing systems: BrainChip devices, or those from Google/Nvidia
- **FEN**: MB1 (MobileNet-v1)
- ODM: SSD (Single Shot Detection)
- Effective Distribution of Workers

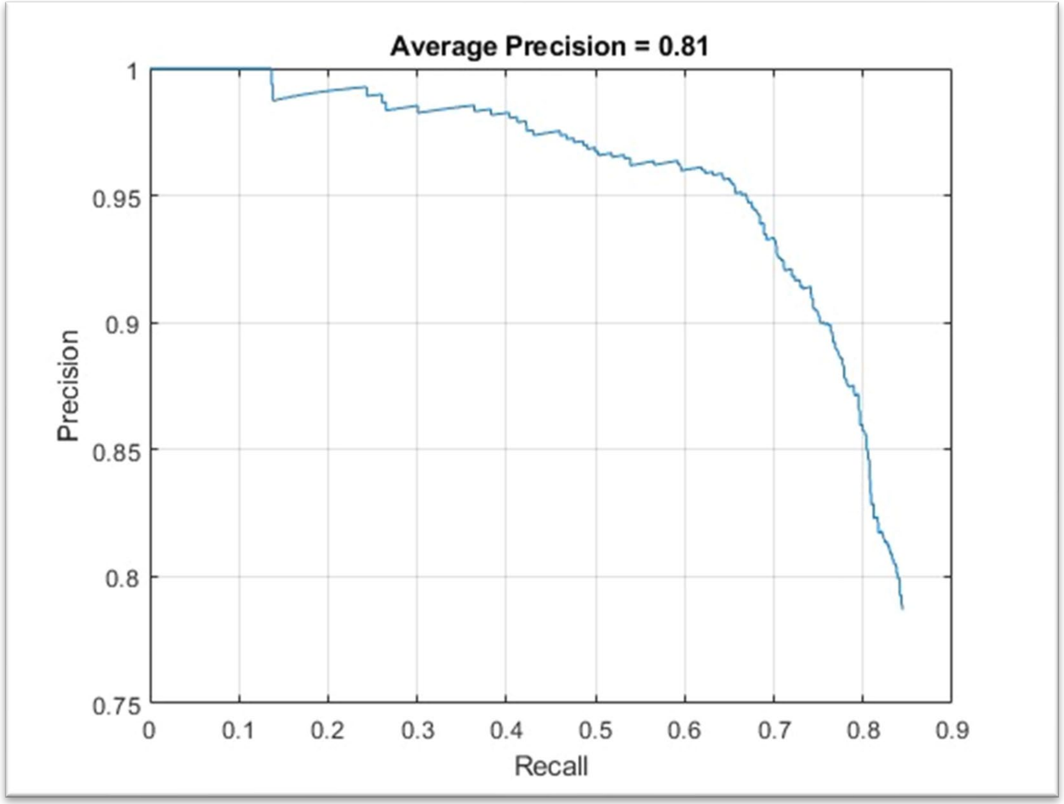
Source: www.nvidia.com

Source: www.brainchip.com





Framework of Model Development and Assessment



Example of Precision-Recall Curve (YOLOv2 Model)

Evaluation Metrics

- **Precision** – ability to detect correctly classify positive ground truth data

$$Precision = \frac{TP}{TP + FP}$$

- **Recall** – ability to detect positive ground truth data

$$Recall = \frac{TP}{TP + FN}$$

- **Average Precision (AP)** – ability to find all relevant objects and the ability to detect objects correctly

$$AP = \sum_{k=0}^{k=n-1} [Recall(k) - Recall(k+1)] \times Precision(k)$$

- **Mean Average Precision (mAP)** - the average of APs of faults in multi-fault object detection process

Results of Object Detection using Large Model

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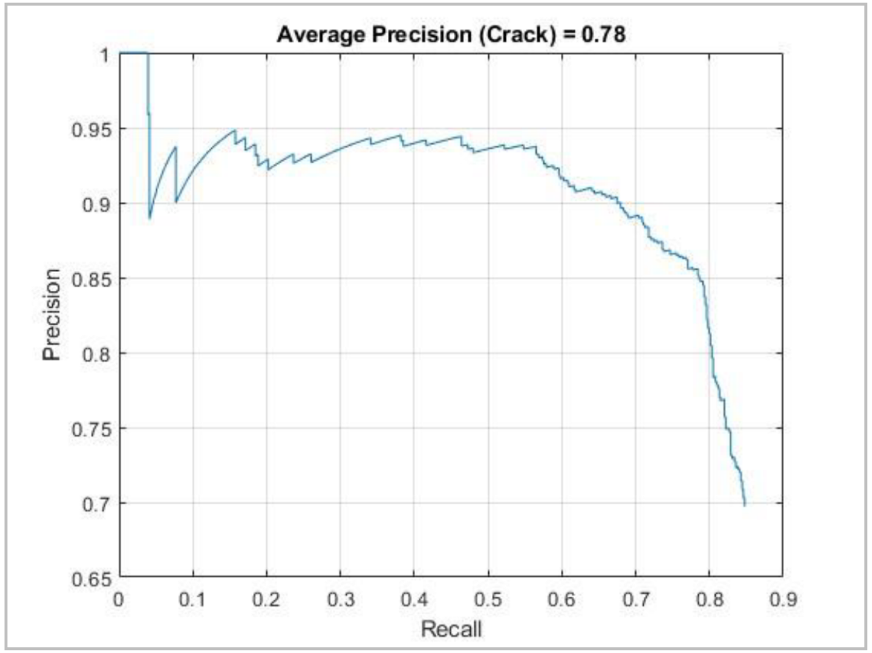
Smart Sewer Detection Model – Multiclass Analysis			
AP			mAP
Crack	Deposit	Root Intrusion	
77.5%	96.3%	94.8%	89.3%

Table 4.8: Multiclass Object Detection Results

Precision-Recall Curve: ‘Cracking’ Defects



Results of Object Detection using Small Model

- Using a new way of distributing workers (16), we can use a larger MBS e.g. 16 or 32 which significantly improve AP and mAP.
- Below are some of our recent initial outcome: results by embedded systems are well comparable to those by the large systems

3 Classes (Crack – Deposit – Root) by Embeded AI system					Mean				Std		
Net	MBS	LearningRate	Workers	Epoch	AP Crack	AP Deposit	AP Root	mAP	AP Crack	AP Deposit	AP Root
mb1-ssd	8	0.01	2	30	0.764	0.865	0.893	0.841	0.011	0.017	0.004
mb1-ssd	16	0.01	16	100	Result still under Analysis						
mb1-ssd	32	0.01	16	100	0.827	0.883	0.899	0.870	0.006	0.006	0.001

3 Classes (Crack – Deposit – Root) by Conventional AI system					Mean				Std		
Net	MBS	LearningRate	Workers	Epoch	AP Crack	AP Deposit	AP Root	mAP	AP Crack	AP Deposit	AP Root
mb1-ssd	8	0.01	2	30	0.775	0.860	0.887	0.841	0.010	0.026	0.012
mb1-ssd	16	0.01	16	100	0.853	0.887	0.901	0.880	0.006	0.005	0.001
mb1-ssd	32	0.01	16	100	0.831	0.877	0.899	0.869	0.005	0.008	0.001

- Detail developments and final result will be reported in our upcoming publication

Conclusion

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Our research have:

- Found useful way of using IPTs to boost the performance of CNN when dealing with complicated backgrounds of images

- Successfully developed two object detection models for two different AI computing platforms (conventional vs. embedded system)

Acknowledgements

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- External collaborators (S. Crawford, C. Luong, T. Khuc, etc.) and industry organisations that supplied image/video datasets for these studies

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Thanks for your attentions!

Questions?

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