WINTECHCON 2019

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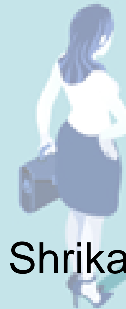
Automatic Defect Classification and Localisation of MURA Defects



Author - Ramya Bagavath Singh

Co-Authors - Gaurav Sultania, Gaurav Kumar, Priya Ranjan Sinha, Shashank Shrikant Agashe, Chulmoo Kang

***Samsung Semiconductor India R&D,* Bengaluru**

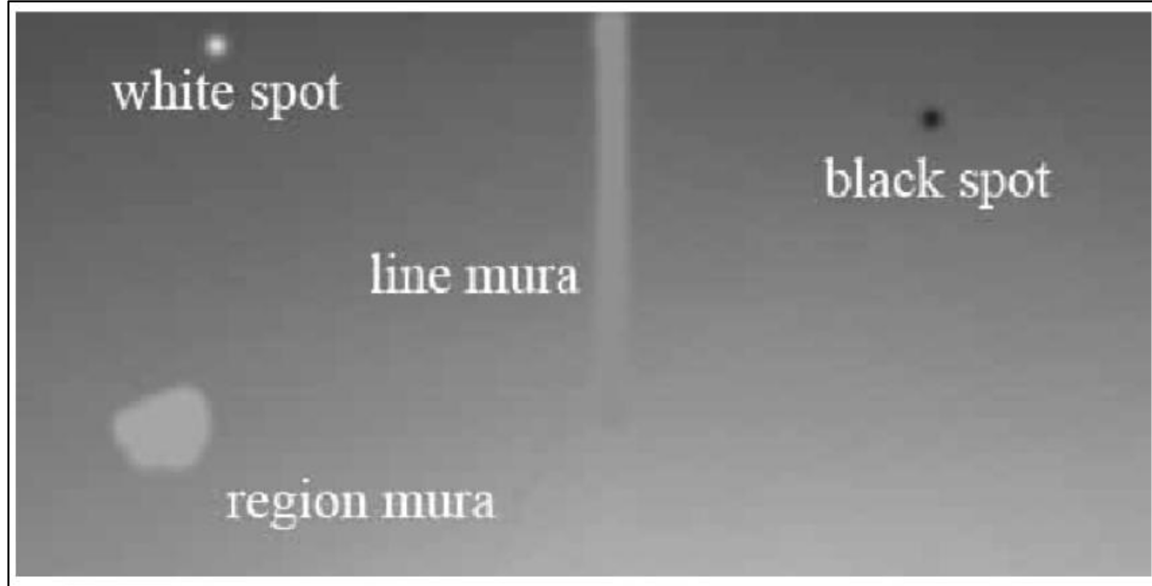
Problem statement

GOAL:

To provide an efficient and accurate network for automatic classification and localization of MURA defects

What is MURA ?

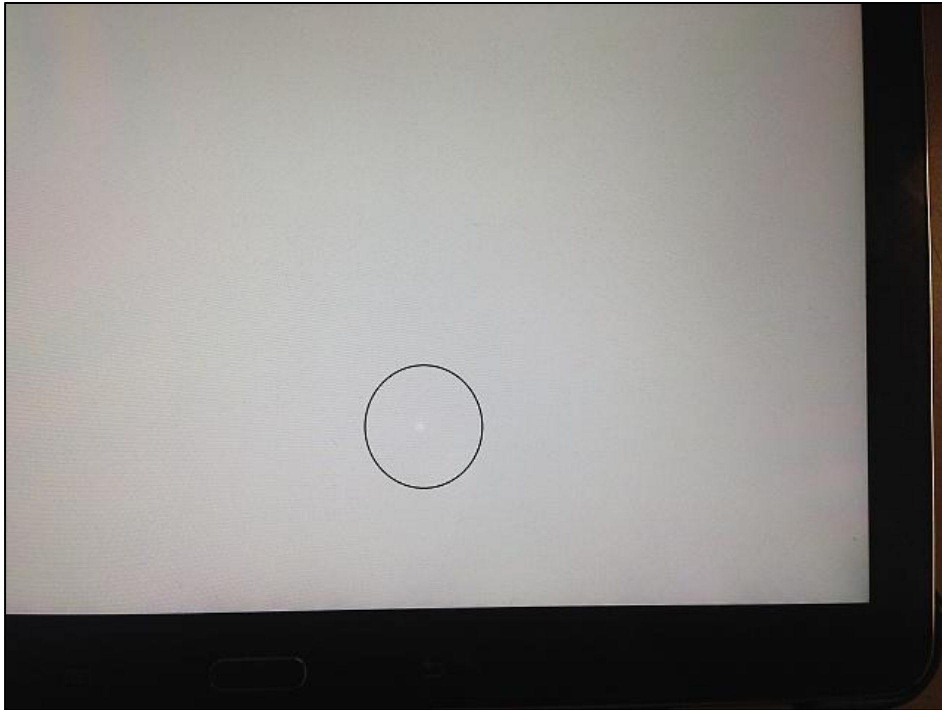
- MURA means blemish or stain, the common defect in any display panel manufacturing *(OLED/LED/LCD etc.)*
- Qualifying factor for display panels [1]



* image from public dataset, not from Samsung [2]

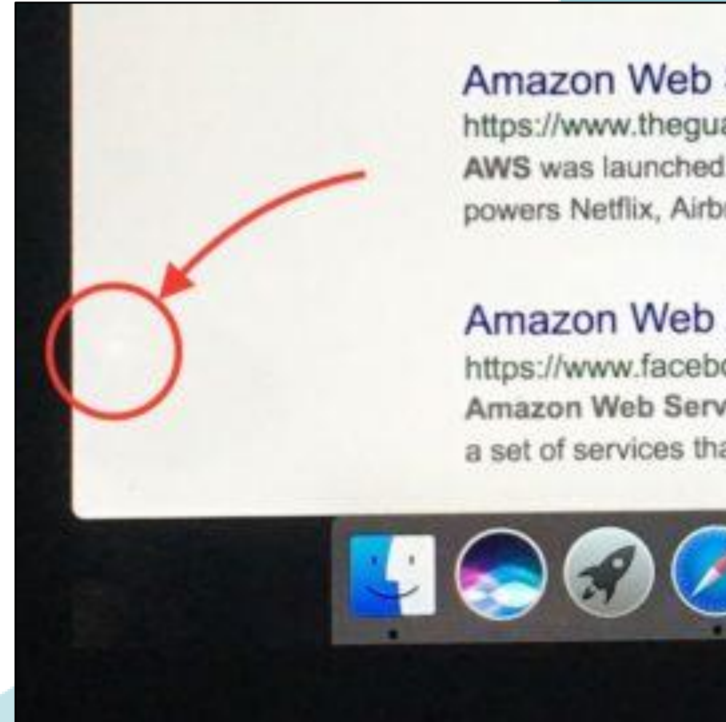
Challenges

MURA – Why classification and localization is challenging ?



* image from public dataset, not from Samsung [3]

Extremely low contrast with the background



* image from public dataset, not from Samsung [4]

Invisible to naked eye

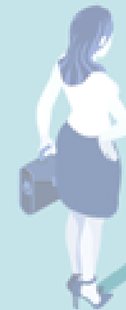
Challenges cont…

- Visually similar defect types
- Arbitrary shape defects → hard to determine exact bounding box
- No standard MURA defect classes or dataset
- Occurrence of multi label defects at multiple locations → Multi-Label classification and localization problem
- Manual detection is highly error prone
- Varied size defect (range from few pixels to covering whole image)

Business Impact

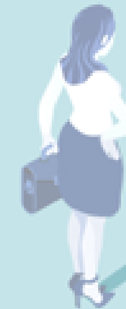
Why Automatic Defect Classification and Localization ?

- High error rate in manual detection → Automatic detection with no tuning threshold
- Root cause Analysis(RCA) is difficult → Classification and localization fastens RCA
- Affects overall display panel quality → Improves display panel quality



Existing Approaches

- *Lu et al. [5] applied the Independent Component Analysis (ICA) to detect defects in patterned LCDs. These approaches defines hand-crafted heuristics and threshold and had to be separately designed for different MURA defects. –* Heuristic Image processing based approach
- *Liu et al. [6] used the Locally Linear Embedding (LLE) to extract image features, and then applied the Support Vector Machine (SVM) for classification, without localization. –* Machine learning approach without localization
- *Hua yang et al. [7] applies transfer learning and deploy an Extreme Learning Machine (ELM) for online MURA defect classification and shows impressive result. –* DL based approach with no localization



Our Solution

Base DL Network Pre-trained externally (Generally state of art DL pipeline for normal object classification and localization)

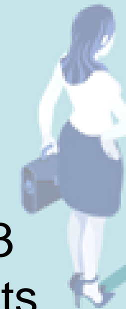
→ DL Network specific optimization (Regularizer, loss function modification)

→ Domain specific data preprocessing and augmentation (preferably non-heuristic based)

→ Ensemble Network (Breaking similar looking defect into different network)

→ Domain knowledge to aid ensemble network (like knowledge from manufacturing process step, inspection setup etc.)

Repeat Till Accuracy or Test Coverage Improves



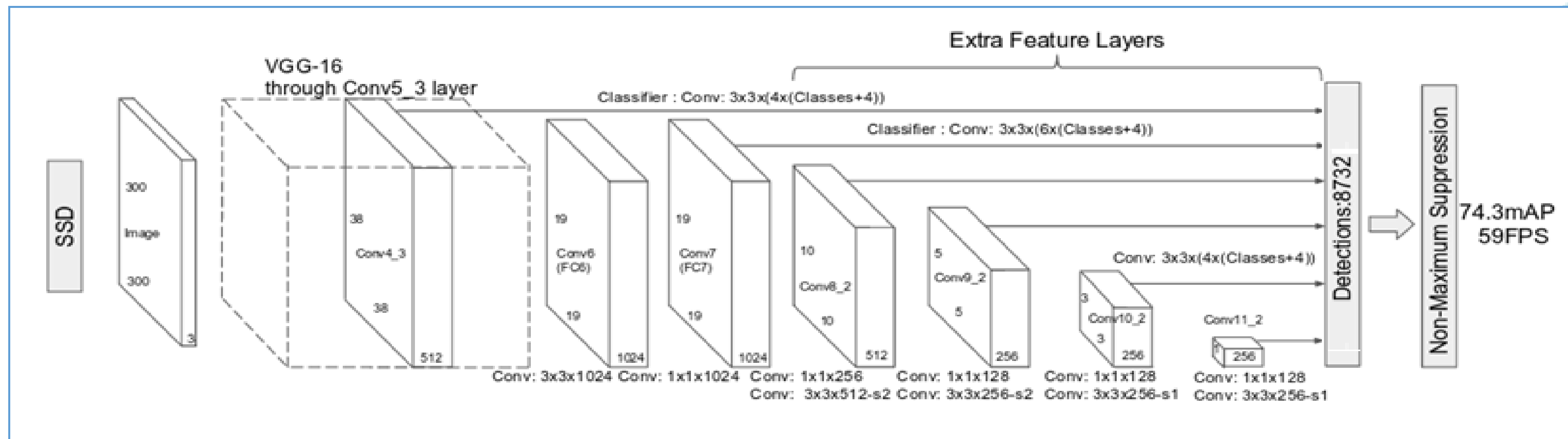
Dataset Description:

1. # of images - 344
2. Defect Classes - Type 0,1,2,3
   1. Type 0,1,3 – small defects
   2. Type 2 – bigger defect

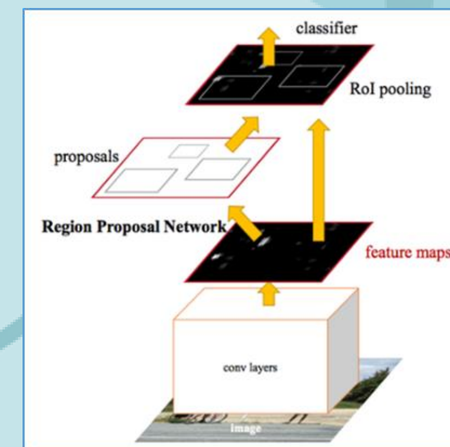
Our Solution cont…

Block 1- Base DL Network :

- Experimented with both single stage (SSD [8]) and two stage (FasterRCNN [9]) networks
- Faster RCNN performed poorly (default training configuration), low performance of RPN
- Tried transfer learning with pre-trained weights(ImageNet) of VGG16 [10] and RESNET [11] for feature generation
- Only fine tuned last layer for our dataset
- RESNET performs marginally better (~1%) but with increased training time
- Chose SSD with pre-trained VGG 16, gave a combined F1 score of ~30%



SSD – Single Shot multi-box Detector



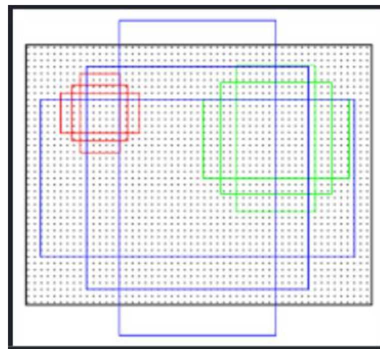
FasterRCNN – Faster Region based CNN

Our Solution cont…

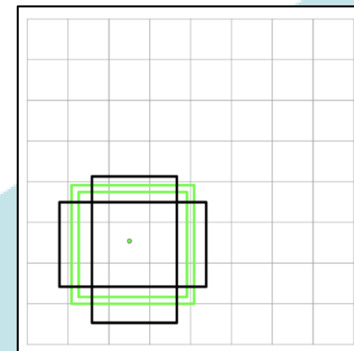
Block 2- DL Network Specific Optimization

- ***2a - Loss Function Optimization:-***
  - In multi-box loss(used in SSD pipeline), the loss gradients are applied only to the overlapping boxes and equal number of non-overlapping boxes randomly chosen from all the proposals
  - Less than 1% of boxes being trained per batch mainly due to low training set size of about 344 images
  - Modify multi-box loss with **weighted loss** where all the proposal are simultaneously trained with loss gradient, which get proportionately divided between overlapping and non-overlapping boxes as per the ration of their count.

This improves the **test F1 score by ~10%**



Trained boxes for MS COCO



Trained boxes for Mura

Our Solution cont…

- ***2b - Generic network optimization:-***
  - Use of regularization such as **dropout**
  - Add **batch normalization** to control the variation between layers etc.
  - **Augment** training dataset to 4x by using generic optimization such as image flip.

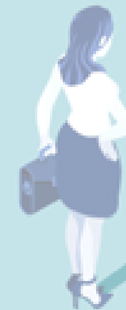
  These result in improvement of **test F1 score by ~10%**

Block 3- Domain Specific Optimization

- ***3a - Image Pre-processing:-***
  - Modified standardization works best to increase contrast difference defect and background

  This improves F1 score by ~10%

```
def standardize_adv(im, gt=None, newshape=None):
    avg = np.mean(im)
    std_dev = np.std(im)
    im[:,:,0] = (im[:,:,0] - avg)/ (0.5*std_dev)
    im[:,:,1] = (im[:,:,1] - avg)/ 1*std_dev
    im[:,:,2] = (im[:,:,2] - avg)/ 2*std_dev
    return im, gt
```



Our Solution cont…

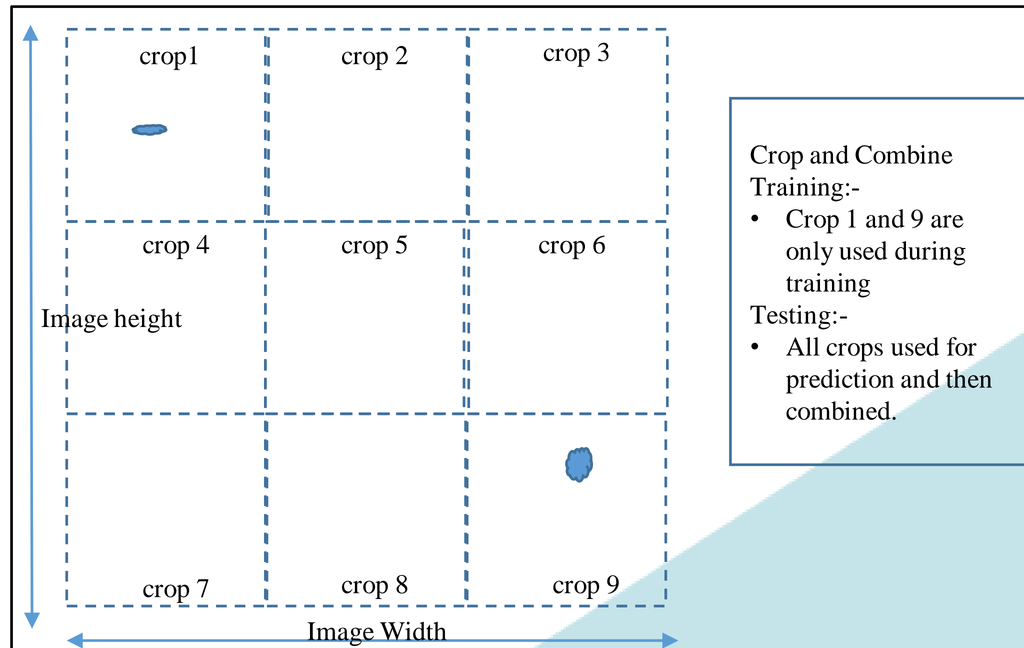
- ***3b - Crop and Combine data augmentation:-***
  - – Crop and combine is defined exclusively for small defect.

  This impacts F1 score as,

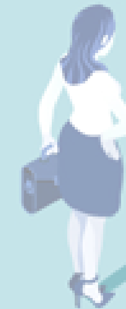
  Increase in Smaller defects (Type 3 → more than ~10% increase)

  Decrease for the bigger defect – As crop can change the characteristics of defect

  Overall Score increased marginally by ~5% as our dataset was biased toward smaller defects



Type 0,1,3 – Smaller defects
Type 2 – Bigger defect

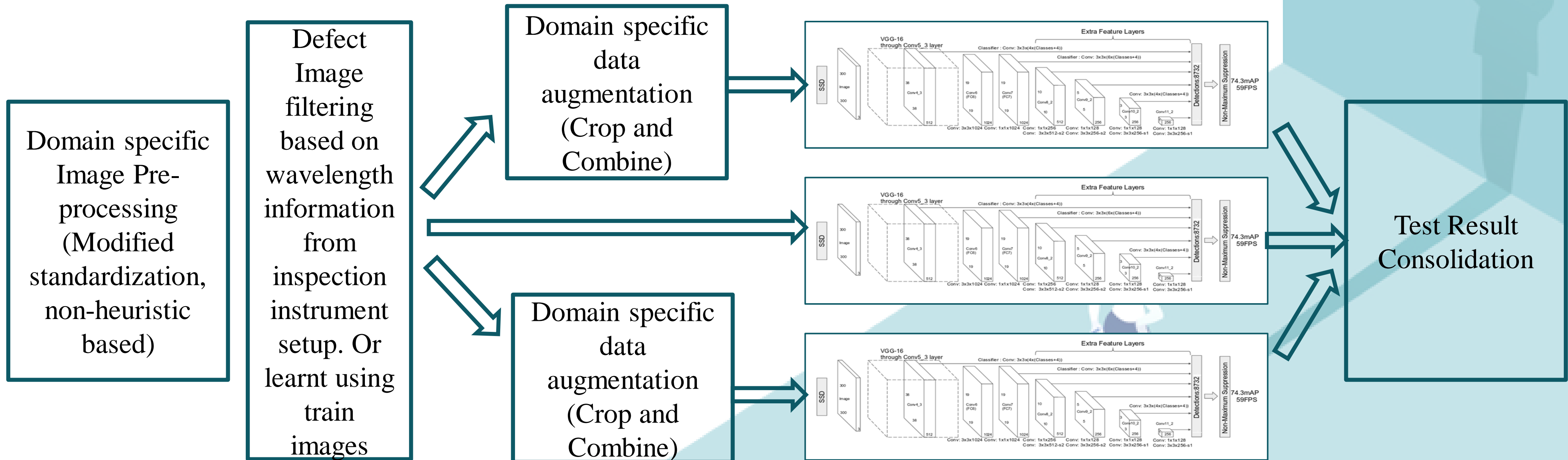


Our Solution cont…

Block 4 - Ensemble Network

– Network is divided into three separate networks.
  - First network is trained for type 0 and 1
  - Second network is trained for type 2 and
  - Third network is trained for type 3

– Pass test images to all three networks during inference and consolidate the output



Our Solution cont…

Block 5 - Domain knowledge to aid ensemble network

- ***Wavelength based filtering before final prediction :-***
  - All defects images in the dataset are captured using different wavelength
  - **A filtering rule based on wavelength** was created for each defect class based on training history
  - This information is specific to Inspection setup instrument

MURA Defect Class	Wavelength Rule
Type 0	All wavelength except wavelength index 0
Type 1	Only wavelength index 1
Type 2	Only wavelength index 2
Type 3	Only wavelength index 0

The **overall final F1 score as ~80% shows about ~30% improvement**

Experimental Results

- MURA dataset consists of 344 images, a train and test split of 80:20
- 5 fold cross-validation, each fold train and test evaluation was run for 5 times
- The number of training epoch as 100 and model state was saved after each epoch
- For reporting F1 metric, the best model was selected

TABLE I. CUSTOM F1 SCORE

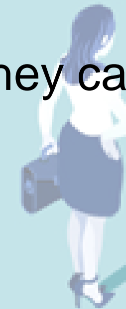
	Predicted Class			
Actual Class	Type A		Other	
IOU	>0.5	<0.5	>0.5	<0.5
Type A	TP^{A}	FP^{A}, FN^{A}	FP^{other}, FN^{A}	FN^{A}, FP^{other}
Other	FP^{A}, FN^{other}	FP^{A}, FN^{other}	TP^{other}	FN^{other}, FP^{other}

Experimental Results

Dataset (MURA (1480X720)(344 images)	F1 Score (Table 1) in percentage on 20% test split	Processing Time in milli-sec (ms)
Base Network (SSD) **(1 model to train)**	Type0=11.6, Type1=10.5, Type2=84, Type3 = 7 Overall=30.2(2.66)	Train: 30000 ms/epoch Test: 50 ms/image
++[a] generic network optimization **(1 model to train)**	Type0=38.5, Type1=44.6, Type2=74.6, Type3 = 33.3 Overall=42.3(5.26)	Train: 30000 ms/epoch Test: 50 ms/image
++[a] Image prep-processing **(1 model to train)**	Type0=54.5, Type1=57.1, Type2=100, Type3=30.8 Overall=57.1(5.12)	Train: 30000 ms/epoch Test: 50 ms/image
++[a] Domain specific data augmentation(1 model to train)	Type0=59.3, Type1=66.7, Type2=83.3, Type3=40.5 Overall=61.5(3.86)	Train: 30000 ms/epoch Test: 50 ms/image
++[a] Ensemble Network **(3 models to train)**	Type0=73, Type1=72.2, Type2=100.0, Type3=64.1 Overall=56.3(4.86)	Train: 70000 ms/epoch Test: 150 ms/image
++[a] Wavelength based filtering before final prediction (3 models to train)	Type0=74, Type1=100, Type2=100, Type3=86.36 Overall=83.1(1.98)	Train: 70000 ms/epoch Test: 150 ms/image

Conclusions

- The First attempt with DL so far, automatic classification and localisation for MURA kind of defects. In our DL pipeline,
  - Wavelength based filtering from inspection process setup as minimum heuristics (no tunable thresholds can be common across different MURA dataset)
  - Easily adaptable for newer MURA dataset (OLED/LED/LCD panels)
- Present technique for re-use of state of the art DL pipeline for classification and localization trained on normal object
  - Rely heavily on transfer learning concept and inherited DL pipelines are fine-tuned over our dataset
  - Some part of domain specific optimization techniques described can be applied over any DL pipeline
- State of the art DL pipeline was improved for normal object and they can be directly plugged here for MURA kind of datasets



References

1. *A New Mura Defect Inspection Way for TFT-LCD Using Level Set Method (Xin Bi, Chungang Zhuang, and Han Ding, Senior Member, IEEE)*
2. Yu-Chiang Chuang, Shu-Kai S. Fan - Automatic Detection of Region-Mura Defects in TFT-LCD Based on Regression Diagnostics
3. *https://www.overclock.net/forum/44-monitors-displays/1626677-spot-screen-sometimes-appear-sometimes-not-iiyama-monitor-help.html*
4. Blog by STEVEN STULTZ - http://sqsystems.com/?p=609
5. C.-J. Lu and D.-M. Tsai, "*Independent component analysis based defect detection in patterned liquid crystal display surfaces," Image and Vision Computing, , vol. 26, 2008, pp. 955-970*
6. Y.-H. Liu, Y.-K. Huang and M.-J. Lee, "*Automatic inline defect detection for a thin film transistor-liquid crystal display array process using locally linear embedding and support vector data description," Measurement Science and Technology, vol. 19, 2008, 095501*
7. H. Yang, S. Mei, K. Song, B. Tao and Z. Yin, *"Transfer-Learning-Based Online Mura Defect Classification," in IEEE Transactions on Semiconductor Manufacturing, vol. 31, no. 1, pp. 116-123, Feb. 2018*
8. Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, Alexander C. Berg, *"SSD: Single Shot MultiBox Detector", in ECCV (2016)*

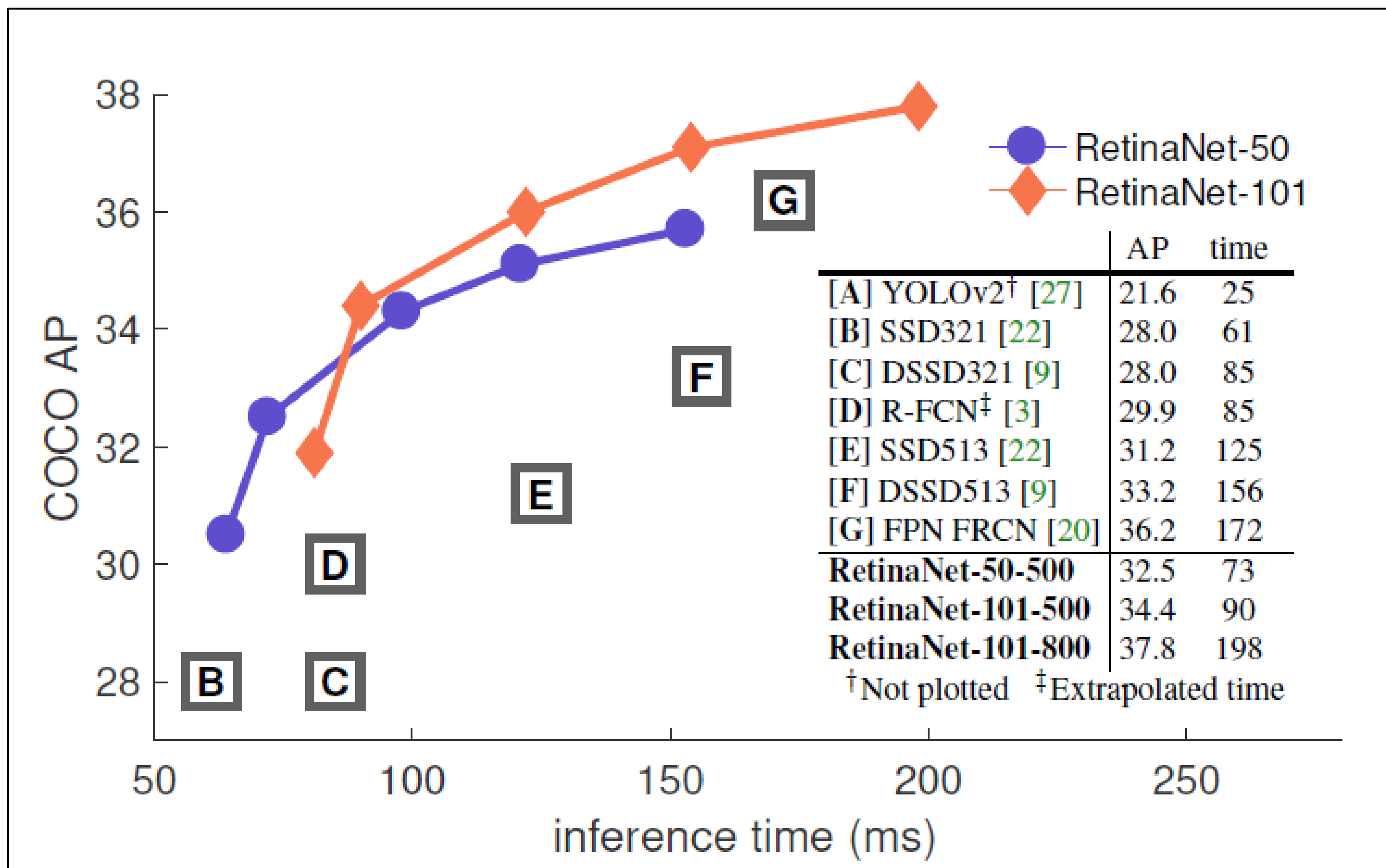
References

9. S. Ren, K. He, R. Girshick, and J. Sun. *Faster R-CNN: Towards real-time object detection with region proposal networks. In NIPS, 2015*

10. Karen Simonyan and Andrew Zisserman, *"Very Deep Convolutional Networks for Large-Scale Image Recognition" in CVPR (2014)*

11. Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun, *"Deep Residual Learning for Image Recognition" in CVPR (2015)*

Appendix I

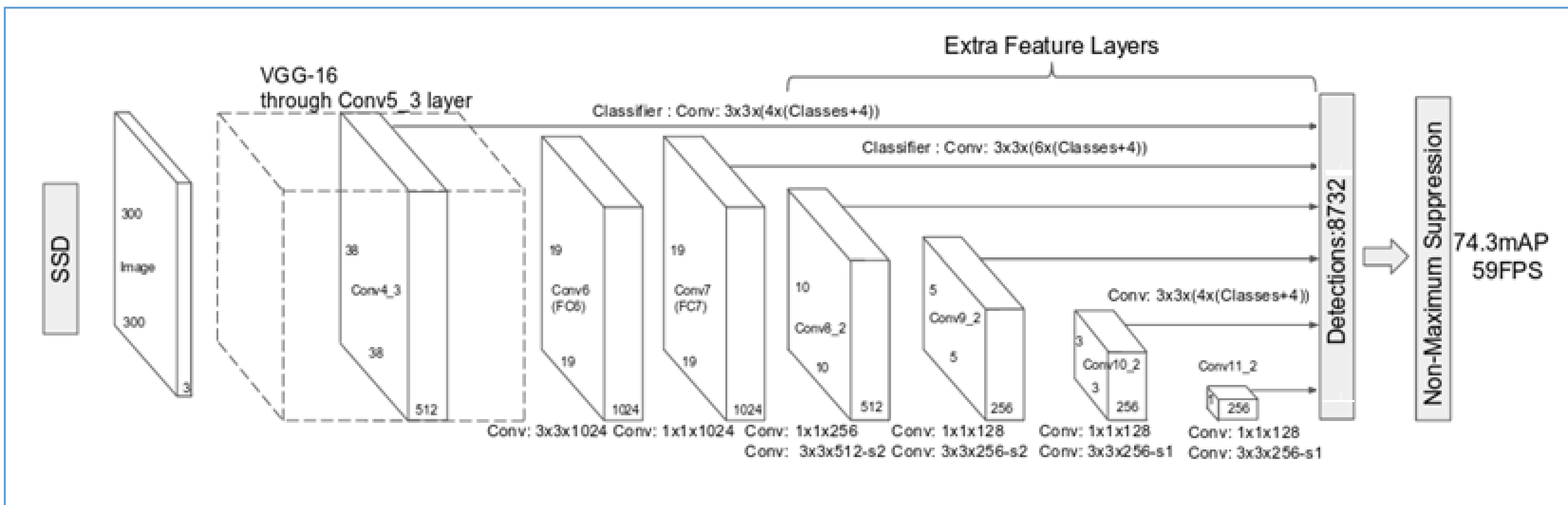


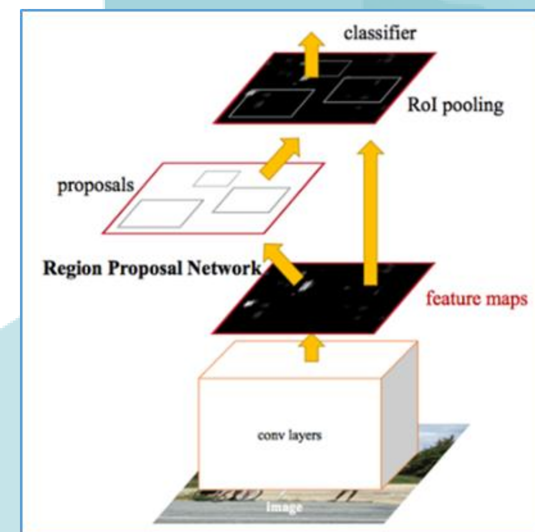
	AP	time
[A] YOLOv2† [27]	21.6	25
[B] SSD321 [22]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [22]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [20]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

Literature Survey result for state of art DL for normal object detection

Appendix II





SSD

Faster RCNN

Thank You