Deep Learning of Image Inpainting for Semiconductor Wafer Image Recognition

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Motivation

- AR / VR field advances and moving towards achieving 'Metaverse' in mixed reality world, creating the next generation devices – AR glasses is critical problem to solve.
- New challenges of handling transparent wafer auto handling.
- 'Universal' solution in fiducial mark image recognition pipeline.
- Sim2real solution for dataset with all confidential information under NDA.

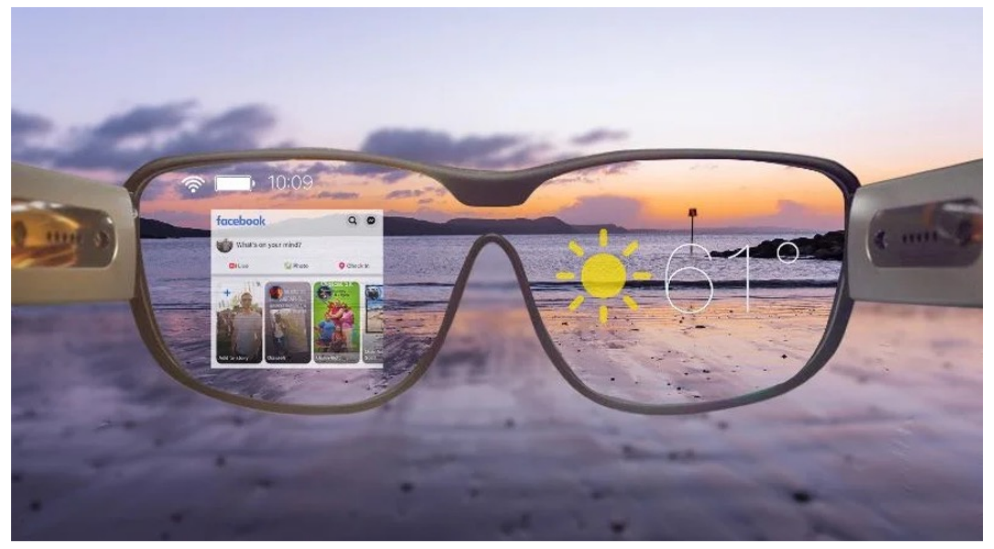

Fig 1. Metaverse AR glasses concept

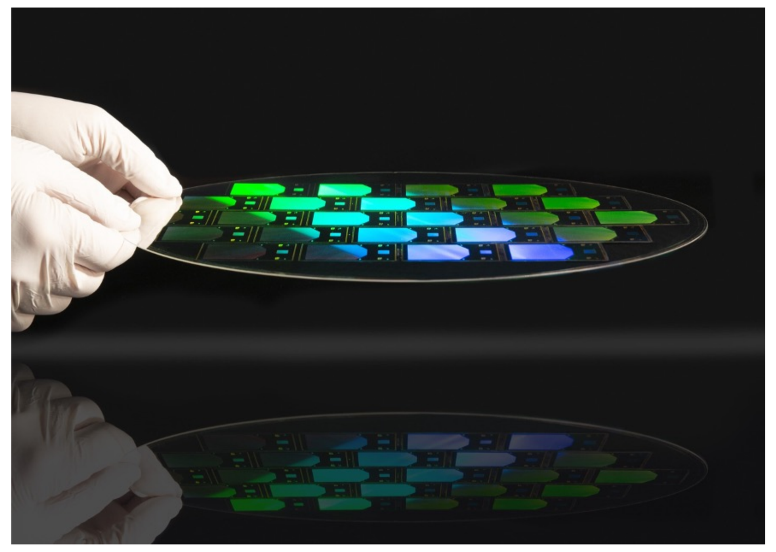

Fig 2. Next generation optical waveguide demo wafer. Image credit: EVG public

Dataset

- A set of simulated fiducial mark images and consider multiple factors to make the fiducial marks look as 'real' as possible to the ones on wafer surfaces.
- Second dataset of 'scratches' in background images to simulate the wafer conditions and model flexibility.

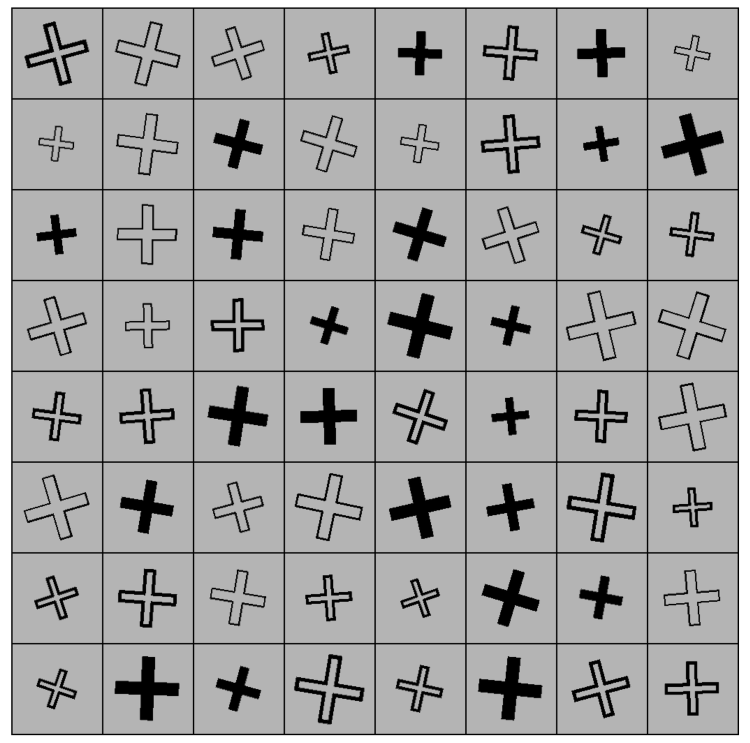

Fig 3. Fiducial mark dataset example

References

[1] Pathak, Deepak et al. "Context Encoders: Feature Learning by Inpainting." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): 2536-2544.
[2] Senzer, Zachary et al. "Photobombs begone with Magic Eraser in Google Photo", https://blog.google/products/photos/magic-eraser/
[3] M. Chen, Y. Ho and S. Wang, "A fast positioning method with pattern tracking for automatic wafer alignment," 2010 3rd International Congress on Image and Signal Processing, 2010, pp. 1594-1598

Methods – Context Encoder for Image Inpainting

- Baseline: Part of the fiducial mark missing – 0% success rate in image recognition for wafer alignment.
- Proposed Method: Using image inpainting to 'guess' the missing fiducial mark pattern – higher success rate in image recognition, so wafer can be aligned properly!
- A context encoder and decoder pipeline are implemented in the model. The context encoder uses convolutional neural network to learn the surrounding feature of an image, simulated fiducial mark images will be pass through the encoder to study the feature based on the remaining part of the image.
- Encoder: 5 conv layers -> Fully connected layers -> Decoder: 5 conv layers
- Joint loss function: Reconstruction L2 loss function + Adversarial loss function (real or fake)

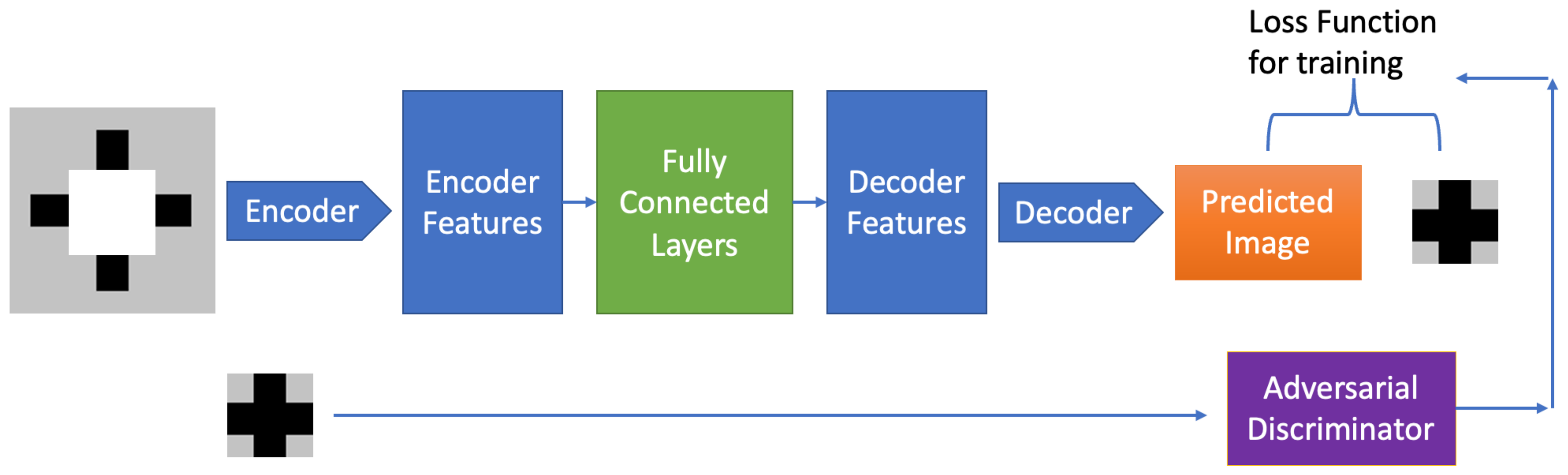

Fig 4. Context encoder trained with joint reconstruction and adversarial loss for fiducial mark inpainting.

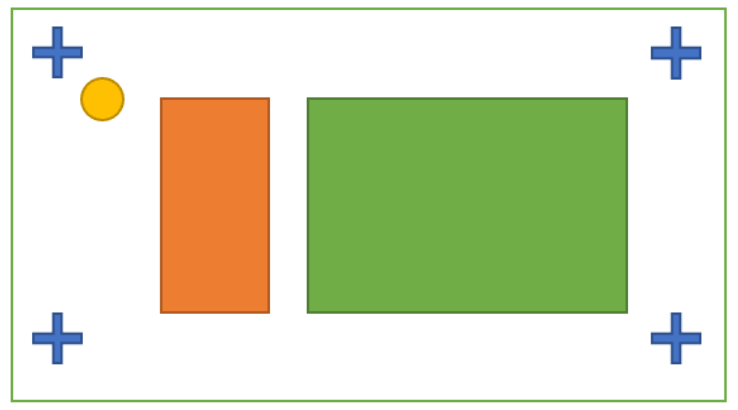

Fig 5. Wafer die illustration with potential fiducial marks positions for automatic positioning.

Experimental Results

- Two sets of data used for testing.
- Most fiducial images were successfully inpainted. -> Success rate > 50%
- Simulated background scratch wafer fiducial image. -> Denoising

Dataset	L2 Loss	PSNR
Test Dataset with clean background	0.1651	15.2995
Test Dataset with 'scratch pattern' background	0.0828	20.0537

Table 1. Test datasets results.

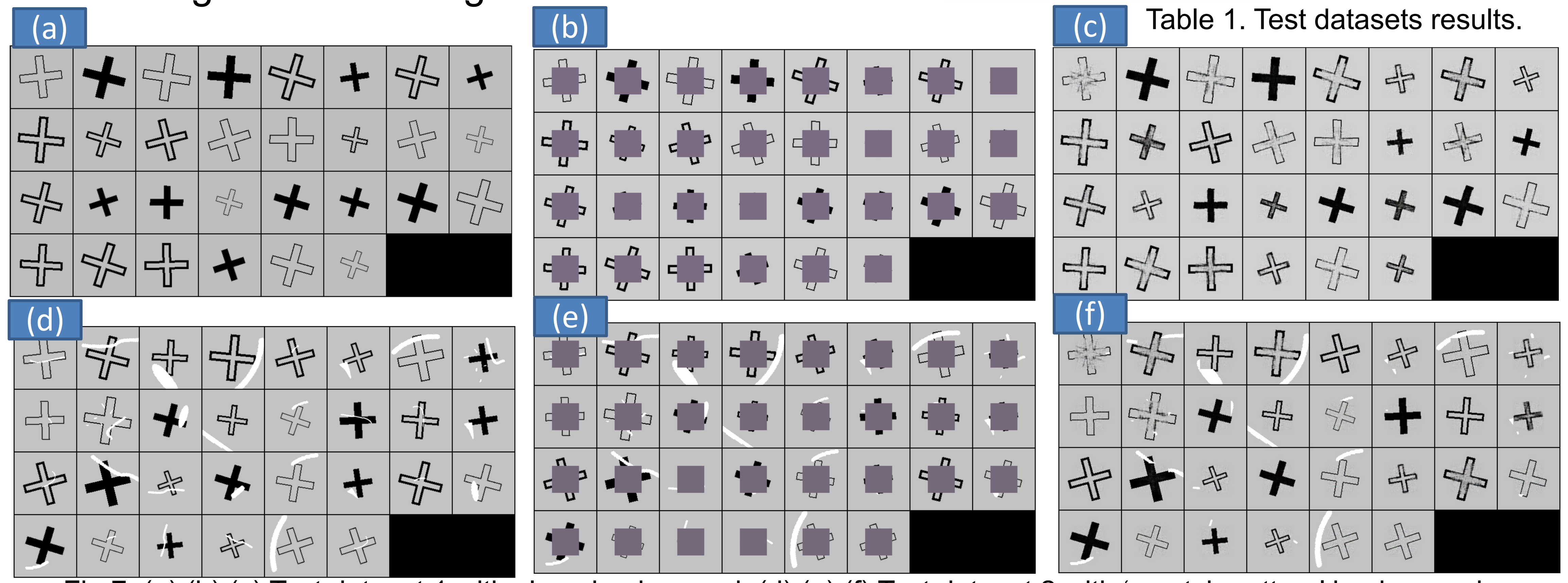

Fig 7. (a) (b) (c) Test dataset 1 with clean background, (d) (e) (f) Test dataset 2 with 'scratch pattern' background.

Future Work

- Using the real wafer and fiducial mark data for training and testing.
- Hardware + Software Creating a camera ISP with denoising and image inpainting algorithm for dealing with real environment.
- Sim2Real adaption, solve wafer alignment issue in real product.

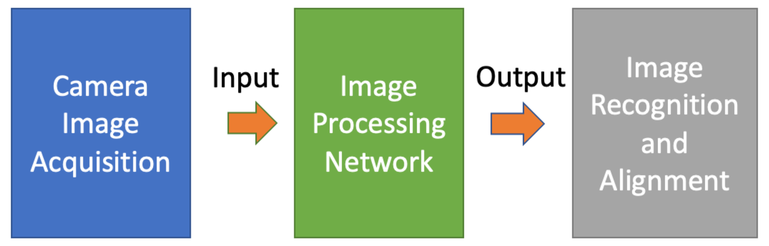

Fig 8. Wafer alignment image processing pipeline