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Deep Learning Based Image Denoising Model for Electronic Manufacturing Industry using NanuNet

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Abstract: Recent advancement in technology has led the electronic manufacturing industry to be more efficient, robust and fast. The advent of Artificial Intelligence in various domains of engineering has brought many positive changes in production and testing. Since most of the work is based on electronic machines and apparatus in various fields, it is important to work on challenges in different steps of manufacturing and testing of such electronic equipments. Semiconductor wafers are the core and most important part in gadgets and apparatus thus testing and detection of any kind of defect present in the wafer is cardinal for better efficiency. For that it is customary to deal with the noise problem in PCB wafer images. In this paper we have proposed a deep learning based image denoising method for semiconductor wafer testing and noise removal.

Keywords: *Deep Learning, Artificial Intelligence, Image Denoising, Semiconductor wafer*

1. Introduction

Semiconductor wafers are the heart of all electronic equipments which work on logical circuits, carefully designed on a printed circuit board (PCB). This wafer is mostly made up of silicon and responsible for all the essential decision making and logical operations within a device. A big challenge in the process of wafer manufacturing is to detect defective or non-defective wafers in order to scrutinize them at the testing and quality check step. In this regard significant work is being done to automate the process of testing the wafers and segregating them on the basis of pre-installed computerized system at the facility.

The recent research and development methods include application of deep learning and computer vision techniques to detect the defect present in the wafer. In this process a deep learning model will take the wafer image as input and automatically give defective or non-defective result using pre trained algorithm.[7] The hardship in this process is the availability of clean high quality images of wafers, which can be used to train and test the model to detect the defects. Noisy images cannot give efficiency in detection because of poor quality or blur pictures. Therefore it is important to first develop a model which can efficiently de-noise all the images before they can be fed to the detection model for better accuracy.

Image- image is a multidimensional array of numbers which ranges from 0- 255. Each number is represented by a combination of horizontal and vertical coordinates that is called pixel. Color image consist of 3 channels Red, Green and Blue. All color images are combination of these 3 channels in different proportion.

Noise – Random variation in color information or brightness, some undesirable element of image, other factors which obscures the wanted information from the image.

Types of Noise

- → Gaussian noise
- → Salt and pepper noise
- → Poisson noise
- → Quantization noise
- → Anisotropic noise
- → Speckle noise

In this regard a lot of work has already been done to denoise the noisy images for better visibility to the model[**8**]. Both deep learning based and other kind of filters are used for the task. But still efficiency is not up to the mark. There is more room for improvement in enhancing the quality of images by using deep learning based models which are more accurate. We have studied the already available recently published literature with respect to the same domain and found many research gaps present. We have prepared a brief summary of literature review and discussed all the pros and cons of each research paper referred in this work. The proposed methods are discussed and research gaps are listed out for clear understanding of work flow.

2. Literature Review

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Amirhosein Ghasemabadi et al (2024) paper first talks about the convolutional neural network and its application in capturing the global information. After that it discuss the pros and cons of transformers, lastly they have presented CascadedGaze Network, an encoder–decoder architecture which employed global context extractor. GCE module further train kernels for global dependencies learning with no requirement of self attention.[1]

Cagatay Isil, Tianyi Gan et al. (2024) developed a physical image denoiser with spatially engineer diffractive layer for noisy input image processing and synthesizing without any usage of digital compute. After the proper training the visual processor is fabricated with diffractive layers results into a image denoiser used to scatter the optical modes attached with spatial artifacts and noise. The proposed model claims to have low power consumption, compact size and high speed, further it also address the problems of sensing and imaging.[2]

Shijie Liu et al. (2023) paper talks about the importance of expanding the width of neural network instead of increasing depth to enhance model performance. It points out on the fact that feature filtering can enhance learning ability of model. Further they have proposed Dual Branch Attention Network (DRANet) which has 2 different parallel branches used to capture complement features to boost learning ability in model. Proposed model is demonstrated to be better than other state of the art models in terms of synthetic and real noise denoising.[3]

Chi-Mao-Fan et al. (2022) talks about the success of convolutional neural network in the field of computer vision after that they have proposed blind real image denoising network SRMNet. SRMNet uses hierarchical architecture which is an improvement on U-Net. In this work they have used selective kernel along with residual block on hierarchical structure M-Net for multi scale semantic information.[4]

Shen Cheng et al.(2021) this paper introduced NBNet, a framework for image denoising which works on noise reduction by image adaptive projection. Here the authors have presented to train network which can separate both signal and noise after learning reconstruction basis. Further they have worked on selection of corresponding basis of signal subspace and also projecting the i/p to signal subspace. Dataset used for experiments are SIDD and DND for the state of the art performance in terms of PSNR and SSIM having lesser computation cost.[5]

Saeed Anwar et al. (2019) paper discuss about the performance of deep convolutional networks on invariant noise which is limited on real time noisy photographs. Further it proposed a single stage blind image network (RIDNet) using modular architecture. They have used residual structure for low freq. information and feature attention for channel dependencies.[6]

After a survey of literature related to the pre-defined available methods and computer vision based models it is observed that significant work is already been done in this regard and many such efficient and fast models are tested and their performance is published. The application and performance of such models are tested on publically available dataset which does not contain any image related to semiconductor wafers. That's why it is important to point out the research gaps present in the literature both in terms of performance and application in the concerned field of wafer manufacturing industry.

Table 1. Deep Learning based models [11][12][13][14]

Model	***Epochs***	***Loss Function***	***Train loss***	***Test loss***	***PSNR***	***SSIM***
AUTOENCODER	25	MSE	0.0014	0.0011	29.12	0.67
CBDNET	25	MSE+λX	0.00054	0.00045	33.1	0.71
PRIDNET	25	MSE	0.000591	0.000576	34.15	0.73
RIDNET	**25**	**MSE**	**0.000321**	**0.000323**	**35.9**	**0.81**

Here we are listing some research gaps found in the survey:

- → Deep learning model for semiconductor wafer denoising- most of the methods are applied and tested for different dataset, however very less work is done on image denoising of semiconductor wafers.
- → Computation cost- computation cost is too high in terms of device configuration.
- → Performance – performance is good but not as per the requirement of industry.
- → Model size – Deep learning model size is huge which requires big space on hard disk and RAM.

Problem statement and research objective

We have the dataset of semiconductor wafers images from manufacturing facility and by processing these images on various deep learning models we have to design and develop an outstanding deep learning model for de-noising the image to become clear. The objective of this work is to develop a model based on deep neural networks which can remove all noises from the images and make them ready for industry applications.

3. Solving approach: Implementation of state of the art models

Performance metrics

(1) Peak signal to noise ratio (PSNR) **[9]** – ratio of maximum signal power to corrupt noise power, usually expressed in log decibel scale.

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

(2) Structural Similarity Index (SSIM**) [10]** measure of similarity between noisy image and ground truth clean image based on luminance, Contrast, Structure.

Exploratory Data Analysis

We have the image dataset containing a total of 672 images from industry. In order to pass them through deep learning models we have divided it into 3 parts training, validation and testing in the ratio of 70/15/15. The training part contains 472 images while validation and testing set contains 100 images.

Further EDA on the dataset consist of visualizing the images, plotting their pixel distribution, PSNR, SSIM, PDF and Histogram. At last all images were converted into small pixels in both training and testing set before feeding to deep learning models.

X_train_patches.shape = (7562,256,256,3)- GT images

Y_train_patches.shape = (7562,256,256,3)- Noisy images

X_test_patches.shape = (1878,256,256,3) – GT images

Y_test_patches.shape = (1878,256,256,3)- Noisy images

By analyzing the results achieved in the above DL models mentioned in the table 1, it is observed that the performance of RIDNet is better among all the 4 models. Although the performance of RIDNet is comparatively better still it is not perfect and there is room for improvement.

Limitations of RIDNet:

1. Output parameters values are not satisfactory i.e. PSNR value can be enhanced and SSIM can be brought down at lowest level.
2. Inefficient Architecture
3. Insufficient use of Enhancement Attention Module (EAM)

4. Proposed Model: NanuNet

NanuNet consists of major 3 major blocks as shown in diagram:

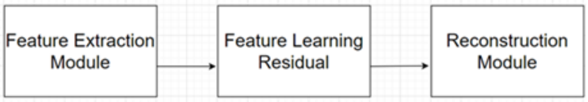

Fig.1: Block Diagram of NanuNet

1. Feature extraction module

It uses convolution layer for initial feature extraction from the noisy image dataset.

F0 = Me(x)

F0 is initial features extracted from noisy image

M(x) is convolution on noisy image

F0 is passed to next module i.e. feature learning module called as Mf()

Fr = Mf1(f0)

Fr = learned features

Mf1(x) is main feature learning residual with EAM

Output features of layer are given to reconstruction module which uses convolution layer

Y’ = Mr(fr), Mr = reconstruction layer

Loss function

L(w) = 1/Ni=1-N||NanuNet(xi)-yi||,

NanuNet is proposed network and w is learned network parameters

2. Feature learning residual

Number of enhancement attention module is increased which internally uses local skip and short skip connections. EAM is made up of D blocks which are followed by feature attention module. Feature attention module enhance the weights of predominant features from the feature maps.

It uses

- Novel merge and run unit
- Features are divided and passed in 2 dilated convolutions
- Feature learning happens using residual block
- Compression is achieved using residual block of 3 convolution layers

3. Feature attention

Attention is focused on the relationship of channel features. Global average pooling is applied to present the numerical data denoting the entire noisy image; further aggregation of features is displayed for image descriptor.

Global Average Pooling GP = 1/hxwi= 1-hi=1-wfc(I,j)

Fc(i,j) is feature value at position (I,j)

Implementation

The noisy semiconductor wafer image dataset was divided in to three parts as 3 subsets. Training set, validation set and testing set in the ratio of 70/15/15 percent. The images are first converted into small patches of size 256*256 after that network parameters are tuned after many permutation and combinations of various values of parameters.

→ Optimizer – Adam (Adaptive Moment Estimation) optimizer is used out of all the other optimizers which is derived from Root Mean Square propagation (RMSProp)

→ Learning rate (n)- n value is kept at 0.0001 initially and divided by 100 after each passing batch changing it by 0.01 every time

→ Batch Size – number of samples in every iteration we have kept it at 30

→ Epochs – epochs are set on 25

→ Loss function – Sigmoid loss function is used

→ Error – MSE error was used

The model was build and tested on the test set of dataset we separated in the beginning consists of 15% images from entire dataset. We have tested the model using the 2 parameter matrices defined in the beginning i.e. PSNR, SSIM.

All the experiments were conducted in Google Colaboratory platform using the libraries tensorflow and keras. Google colab GPUs are found to be better in simulation and speed.

NanuNet Model Quantization

Quantization is used in model size reduction and improvement in CPU latency by bringing down the number of parameters in NanuNet model. By quantization we have achieved light weight model with faster outputs. We have used pre-trained tensorflow model for quantization task.

Table 2. PSNR, SSIM and Model Size of RIDNet, NanuNet and Quantized NanuNet Comparison

Model	*PSNR - Test data*	*SSIM- Test data*	*Model size*
RIDnet	35.32	0.93	19.88 MB
NanuNet	36.67	0.8	19.87 MB
NanuNet-Quantized	36.78	0.79	8.98 MB

Table 3. Architecture comparison of RIDNet and NanuNet

Sr.No	*Feature detail*	*RIDNet*	*NanuNet*
1	Convolution layers in Feature Extraction Module	1	2
2	Convolution layers in ERM block	3	4
3	Kernel Dilation	1*1	2*2
5	Image patch size	80*80	256*256
6	No of ERM blocks	3	2

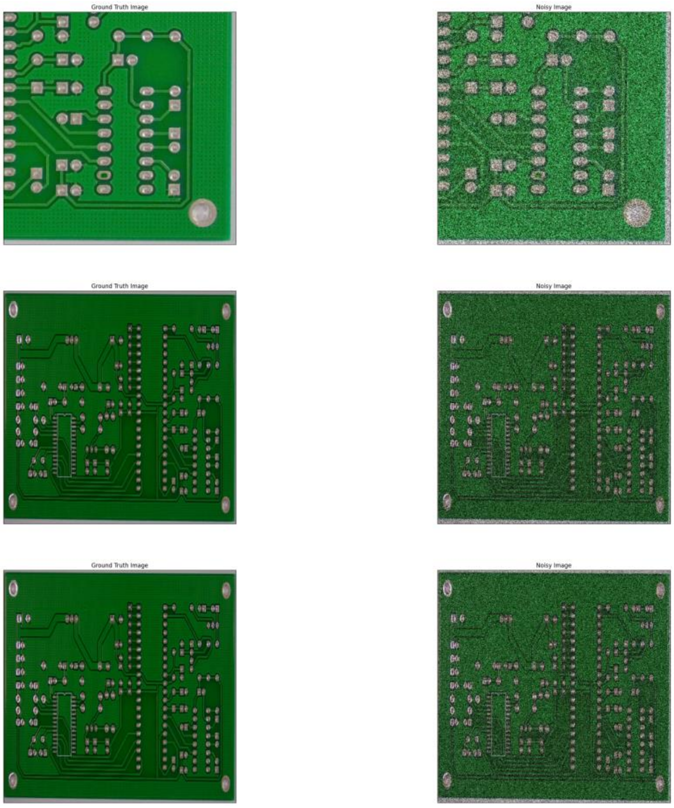

Fig. 2: image data test samples of noisy and clean images using NanuNet

Table 4. Performance of NanuNet-Quantized Model for Test Samples

Sample	*PSNR before De-noising (DB)*	*PSNR after De-noising (DB)*	*SSIM before De-noising*	*SSIM after De-noising*	*Prediction time*
Sample1	17.67	33.66	0.43	0.66	1.2 sec
Sample2	20.65	32.33	0.54	0.79	1.4 sec
Sample3	21.8	30.67	0.49	0.71	1.4 sec

Conclusion and Future Scope

A state of the art model is designed and tested for semiconductor wafer noise removal for the betterment of electronic manufacturing industry. We have compared our model with the best performing model in terms of architecture and efficiency as shown in table no 3, in both parameters the proposed network NanuNet has performed better than the already available network i.e. RIDNet. The calculated values of PSNR and SSIM shows the superiority of NanuNet model from its predecessors as shown in table no 4.

Further more work can be done to reduce the size of the model a little and to enhance the overall efficiency of the model. The training and testing time of the model can be improved with the advent of newer processing power in future.

Author contributions

Pankaj Kumar Sharma: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation.

Dr. Sandhya Sharma: Visualization, Software, Investigation, Writing-Reviewing and Editing, Validation.

Conflicts of interest

The authors declare no conflicts of interest.

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