KLE Technological University
Creating Value, Leveraging Knowledge
Dr. M. S. Sheshgiri Campus, Belagavi

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Department of
Electronics and Communication Engineering

GenAI

on

Generation Of Silicon Wafer Images Using Generative Adversarial Networks[GAN's]

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that project entitled **"Generation Of Silicon Wafer Images Using Generative Adversarial Networks[GAN's]"** is a bonafide work carried out by the student team of **" Sanskruti Mirajkar (02FE22BEC084) , Shraman Kanthi (02FE22BEC092) ,Swati Patil (02FE22BEC112),Darshan Modekar (02FE23BEC119)"**. The project report has been approved as it satisfies the requirements with respect to the mini project work prescribed by the university curriculum for B.E. (6th Semester) in Department of Electronics and Communication Engineering of KLE Technological University Dr. M. S. Sheshgiri CET Belagavi campus for the academic year 2024-2025.

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1.

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-The project team

ABSTRACT

The inspection and analysis of silicon wafers play a crucial role in semiconductor manufacturing, yet obtaining large and diverse datasets of wafer images is often expensive and limited. To overcome this challenge, our project focuses on the synthetic generation of silicon wafer images using Generative Adversarial Networks (GANs). The proposed approach employs a dataset of 1000 grayscale silicon wafer images, which are preprocessed by resizing and normalizing them for consistency. The GAN architecture used in this work consists of two primary components: a Generator, which creates synthetic images from random noise, and a Discriminator, which attempts to distinguish between real and fake images. Both models are trained simultaneously using Binary Cross-Entropy loss and optimized using the Adam optimizer. The training process is conducted over multiple epochs, alternating between updating the Generator and the Discriminator to achieve improved performance. Throughout the training, the generated images are periodically saved and analyzed to monitor quality and progression. The main objective is to produce realistic and diverse synthetic wafer images, including rare defect patterns, in order to augment existing datasets and reduce the reliance on costly data collection methods. The effectiveness of the model is evaluated based on the loss functions of both components and the visual similarity of the generated images to real samples. Results indicate that the GAN model is capable of generating high-quality silicon wafer images that can support tasks such as automated defect detection and quality assurance in semiconductor manufacturing.

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Chapter 1

Introduction

The semiconductor industry relies heavily on silicon wafers as the core material for manufacturing integrated circuits. These wafers must undergo rigorous inspection for defects, as even the smallest imperfection can lead to product failure or reduced performance. Detecting these defects requires a substantial amount of high-quality image data to train machine learning models effectively. However, collecting such large-scale, annotated datasets of silicon wafer defects is a resource-intensive and time-consuming process. This limitation creates a significant bottleneck in improving automated defect detection systems, particularly when it comes to identifying rare defect types that may not appear frequently in standard production samples.

To overcome this data scarcity challenge, our project introduces a deep learning-based solution that utilizes Generative Adversarial Networks (GANs) to synthetically generate realistic silicon wafer defect images. GANs are a class of neural networks where two models — a Generator and a Discriminator — are trained simultaneously in a competitive setup. The Generator creates fake images from random noise, while the Discriminator evaluates them against real images and learns to distinguish between real and fake. Through this adversarial training process, the Generator gradually improves its ability to create highly realistic synthetic images. For this project, we trained the GAN on 1000 grayscale images of silicon wafers, preprocessing them through resizing and normalization to ensure consistency and quality.

The primary goal of this work is to augment existing wafer image datasets with synthetic images that are nearly indistinguishable from real ones, thereby improving the performance of machine learning models in wafer defect classification and detection. By enriching the dataset with diverse and rare variations, we can help build more robust and accurate inspection systems. Furthermore, the project offers a scalable and cost-effective alternative to manual data collection and labeling. It demonstrates how AI, specifically GANs, can be harnessed to solve practical challenges in advanced manufacturing, enhance quality assurance processes, and ultimately support the development of more reliable semiconductor devices.

1.1 Motivation

The motivation behind this project stems from the pressing need to modernize traditional farming practices and address the challenges faced by farmers in today's agricultural landscape. Many farmers still rely on guesswork or manual observation to decide which crop to sow, often leading to poor yield due to mismatched crop-soil conditions or improper planting techniques. Additionally, manual seed sowing is time-consuming, labor-intensive, and often lacks precision, resulting in uneven spacing and inefficient use of land. With the advancement of technology, especially in the areas of embedded systems, IoT, and machine learning, there is an opportunity to make agriculture smarter, more accurate, and less dependent on manual intervention. This project aims to empower farmers with a predictive tool that recommends the most suitable seed based on real-time environmental data and automates the seed-sowing process using a simple, cost-effective vehicle. By doing so, it hopes to reduce labor costs, increase productivity, and bring intelligent decision-making to even small and medium-scale farms, where resources and access to advanced tools are often limited.

1.2 Objectives

- **To develop a Generative Adversarial Network (GAN) model:** The core aim of the project is to design and implement a GAN architecture tailored for the generation of high-quality silicon wafer defect images. This involves defining a custom Generator that learns to produce defect images from random noise, and a Discriminator that evaluates those images for authenticity. The adversarial nature of GAN training ensures that both models improve simultaneously, resulting in increasingly realistic outputs that can mimic actual silicon wafer defects.
- **To preprocess a dataset of 1000 grayscale silicon wafer images:** Before training the GAN, the input images must be standardized to ensure consistent model behavior. This involves resizing all images to a uniform resolution suitable for the model architecture and normalizing pixel values to a range between 0 and 1. This step reduces noise, improves learning efficiency, and ensures the Generator can learn important features of defect patterns more effectively.
- **To train the GAN model using Binary Cross-Entropy loss and the Adam optimizer:** Training a GAN involves a delicate balance between the Generator and Discriminator. The Discriminator learns to classify images as real or fake using Binary Cross-Entropy loss, while the Generator learns to fool the Discriminator. The Adam optimizer is chosen for its ability to handle sparse gradients and noise in data. Training is done in alternating cycles (epochs), improving both networks iteratively, and ensuring the model converges to a point where generated images closely resemble real wafer defects.

1.3 Literature Survey

- **Rohan Ingle (2025)** presents *"Deep learning driven silicon wafer defect segmentation and classification"*, The paper presents a deep learning approach to automate the detection and classification of defects in silicon wafers. The study achieved high accuracy in both segmentation and classification tasks and integrated a large language model (LLM) to provide interactive defect analysis and guidance.
- **Shuyu Wang (2021)** introduces an *"A Variational Autoencoder Enhanced Deep Learning Model for Wafer Defect Imbalanced Classification"* The paper proposes a Variational Autoencoder-Enhanced Deep Learning Model (VAEDLM) to tackle the wafer defect classification problem caused by class imbalance. By generating realistic synthetic wafer images for rare defect types,accuracy, recall, and F1-score, significantly outperforming existing methods while also improving interpretability through saliency maps and t-SNE visualization.
- **Vic De Ridder (2023)** in *"SEMI- Diffusioninst: A Diffusion Model Based Approach for Semiconductor Defect Classification and Segmentation"* a novel diffusion model-based deep learning framework for accurately detecting and segmenting semiconductor defects in SEM images. The proposed SEMI- Diffusioninst model outperforms previous methods in both bounding box and segmentation precision, particularly improving detection of line collapse and It also explores backbone networks,

sampling strategies, and inference optimizations to enhance performance without synthetic data.

1.4 Problem statement

Silicon wafer images requires large, diverse datasets, which are often costly and limited. This project uses Generative Adversarial Networks (GANs) to synthetically generate realistic wafer images, enhancing data availability.

1.5 Application in Societal Context

- Enhanced Quality Control in Electronics
- Accelerating Innovation in AI and Semiconductor Technology
- Boosting National Capability in AI and Electronics
- Promoting Fair Access to Technology for Startups
- Reducing reliance on costly real-world datasets
- The generation of wafer images using GANs is allowing researchers to simulate rare defect scenarios.

Chapter 2

Dataset and Algorithms

2.1 Dataset Description

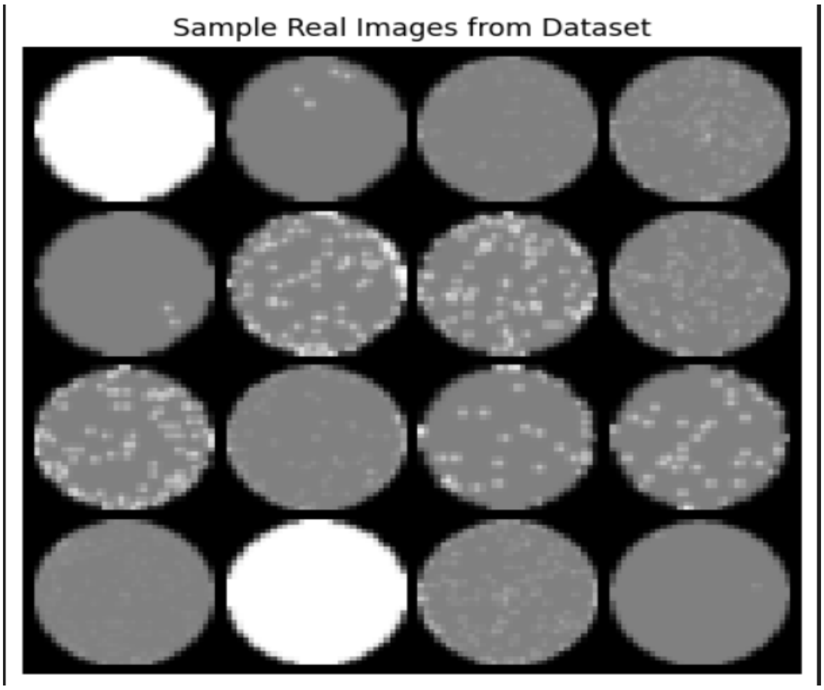

Figure 2.1: Dataset

Dataset used in this study is the WM-811K Wafer Map Dataset, publicly available on Kaggle. It comprises a large collection of silicon wafer maps used for defect detection and classification. The dataset contains a total of 811,457 wafer map entries, out of which 172,950 are labeled with specific defect types, while the remaining 638,507 entries are unlabeled.

SL NO.	ATTRIBUTE NAME	DESCRIPTION
1.	Dataset Name	WM-811K Wafer Map Dataset
2.	Total Entries	811,457 wafer map samples
3.	Labeled Samples	172,950 labeled entries
4.	Unlabeled Samples	638,507 entries without specific labels
5.	Format	2D grayscale matrix with intensity values (image-like wafer map)
6.	Preprocessing Needed	Yes – to reduce noise and standardize sample quality

Table 2.1: Dataset Attributes Overview

2.2 Dataset Information

The data set used in this study is the WM-811K wafer map data set. It comprises a large collection of silicon wafer maps used for defect detection and classification. The data set contains a total of 811,457 wafer map entries, of which 172,950 are labeled with specific defect types, while the remaining 638,507 entries are unlabeled.

Each wafer map represents a silicon wafer and may contain one of several types of defects. However, the data set does not include pixel-level annotations; instead, defect areas are indicated with intensity values, often "1", scattered throughout the maps. This introduces significant noise, requiring preprocessing to enhance the quality and utility of the data. 2000 images were used to train the model from WM-811k

2.3 Generative Adversarial Networks GAN

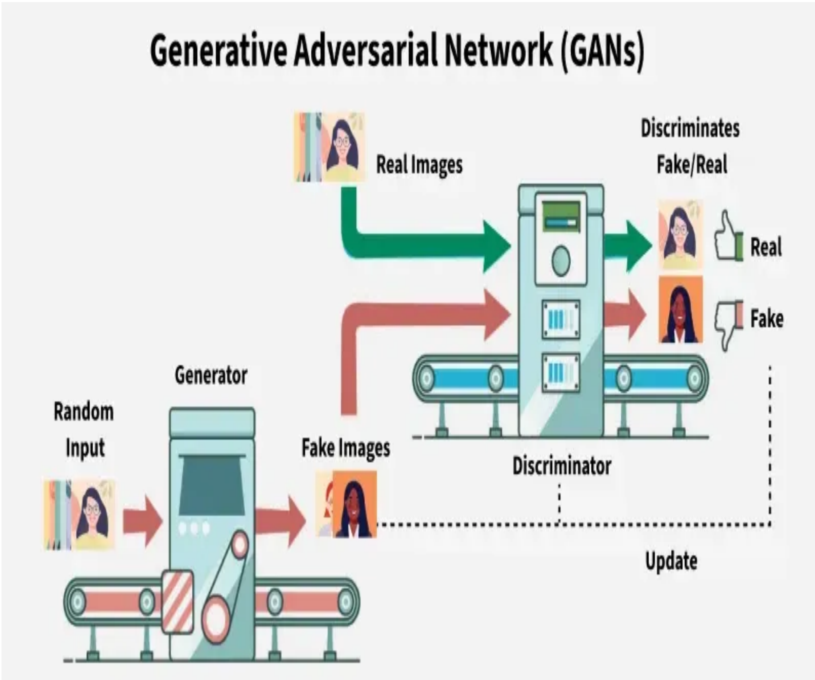

Figure 2.2: GAN

Generative Adversarial Networks (GANs) are a type of deep learning model introduced by Ian Goodfellow in 2014, consisting of two neural networks: a Generator and a Discriminator. The Generator creates synthetic data (like images) from random noise, while the Discriminator evaluates whether the data is real (from the dataset) or fake (from the Generator). Both networks are trained simultaneously in a competitive setting: The generator tries to fool the Discriminator, and the Discriminator tries to correctly identify real from fake. This adversarial process helps the Generator improve over time, ultimately producing highly realistic data. GANs are widely used in image generation, data augmentation, super-resolution, and even in creating deepfakes. Despite their impressive capabilities, GANs can be difficult to train and may suffer from issues like mode collapse and training instability.

Chapter 3

Methodology

3.1 Data Collection and Preprocessing

We collected a dataset of 2000 grayscale silicon wafer images from WM-811K WaferMap Dataset. Each image was resized to a consistent resolution and normalized to a pixel intensity range between 0 and 1 to ensure uniformity and efficient training.

3.2 Model Architecture

A Generative Adversarial Network (GAN) was employed, consisting of two components:

- **Generator:** Accepts a random noise vector as input and produces synthetic silicon wafer images.
- **Discriminator:** Takes an image as input and determines whether it is real (from the dataset) or fake (from the Generator).

Both models were built using convolutional neural network (CNN) layers to capture complex spatial features of wafer patterns.

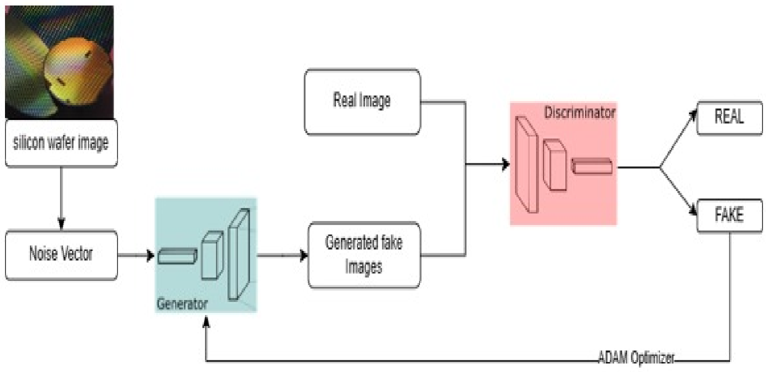

Figure 3.1: GAN

3.3 Training Strategy

The GAN was trained using the Binary Cross-Entropy loss function and optimized using the Adam optimizer. The training process alternated between:

– Updating the Discriminator to improve its ability to distinguish real from fake images.

– Updating the Generator to enhance its capability to fool the Discriminator.

This adversarial training continued over multiple epochs.

3.4 Monitoring and Evaluation

To evaluate the model:

– The loss values of the Generator and Discriminator were monitored and smoothed to assess convergence.

– Generated images were periodically saved for visual inspection.

– Pixel intensity distributions of real and generated images were compared to verify similarity and realism.

3.5 Role of Binary Cross-Entropy Loss and Adam Optimizer

In this project, we trained a Generative Adversarial Network (GAN) to generate synthetic silicon wafer images. Two key components that played a crucial role in the success of our training process were the Binary Cross-Entropy (BCE) loss function and the Adam optimizer. Their roles are described in detail below.

Binary Cross-Entropy Loss

The Binary Cross-Entropy (BCE) loss function was used to train both the Generator and the Discriminator in our GAN architecture. As the GAN operates in a minimax game setting, BCE served as the core objective function for adversarial learning.

– **Discriminator:** The Discriminator is trained to distinguish real silicon wafer images (labeled as 1) from synthetic images produced by the Generator (labeled as 0). BCE penalizes incorrect predictions, thus improving the Discriminator's ability to identify fake images. This helps in learning detailed features of real wafer patterns and defects.

– **Generator:** The Generator is trained to produce images that the Discriminator classifies as real. By minimizing the BCE loss, the Generator learns to generate images that are increasingly realistic. As training progresses, the feedback from BCE loss drives the Generator to improve the visual quality and authenticity of the generated wafer images.

The BCE loss thus facilitates effective adversarial training, ensuring both networks improve simultaneously.

Adam Optimizer

The Adam optimizer was used for both the Generator and Discriminator. GAN training is known for being unstable due to the adversarial nature of its components. Adam was chosen for its adaptive learning rate and momentum-based updates, which help mitigate this instability.

- Adam maintains running averages of both the gradients (first moment) and the squared gradients (second moment), allowing for smoother and more adaptive updates during backpropagation.
- It enabled stable convergence during the early training stages when the Generator produced low-quality images, and later stages when the image complexity increased.
- It also prevented gradient explosion or vanishing, ensuring the learning signal remained strong for both networks throughout training.

Overall, the Adam optimizer played a vital role in stabilizing and accelerating training, leading to more efficient convergence and higher-quality synthetic wafer image generation.

3.6 Algorithm for Synthetic Wafer Image Generation using GAN

Input: Dataset of 2000 grayscale silicon wafer images, Noise vector z sampled from a standard distribution
Output: Synthetic silicon wafer images generated by the GAN

1. **Data Preprocessing**
   - Load the grayscale wafer image dataset
   - Resize all images to a fixed size
   - Normalize pixel values to the range
2. **Initialize GAN Architecture**
   - Define the **Generator** network:
     * Input: random noise vector z
     * Output: synthetic image resembling a wafer
   - Define the **Discriminator** network:
     * Input: real or generated image
     * Output: probability indicating whether image is real or fake
3. **Define Loss and Optimization**
   - Use Binary Cross-Entropy loss for both Generator and Discriminator
   - Optimize using Adam optimizer (e.g., learning rate = 0.0002)
4. **Training Loop (Repeat for N epochs)**
   - **Train Discriminator**
     * Sample real images from dataset
     * Generate fake images using Generator
     * Compute Discriminator loss:
       · Real loss = BCE(D(real), 1)

- - - · Fake loss = BCE(D(fake), 0)
    - ∗ Update Discriminator weights
  - **Train Generator**
    - ∗ Generate fake images from random noise
    - ∗ Compute Generator loss = BCE(D(fake), 1)
    - ∗ Update Generator weights
  - Log and monitor losses
  - Periodically save generated images

5. **Evaluation**
   - Plot smoothed Generator and Discriminator loss
   - Compare pixel intensity distribution of real and generated images
   - Visually inspect generated images

6. **Final Output**
   - Use trained Generator to synthesize realistic wafer images
   - Use synthetic images to augment datasets for further use

Chapter 4

Results and Analysis

4.1 Training Progress Evaluation

To assess the training performance of the GAN, we monitored the Generator and Discriminator loss across training iterations. The following figures show both raw and smoothed loss values, indicating the adversarial learning dynamics.

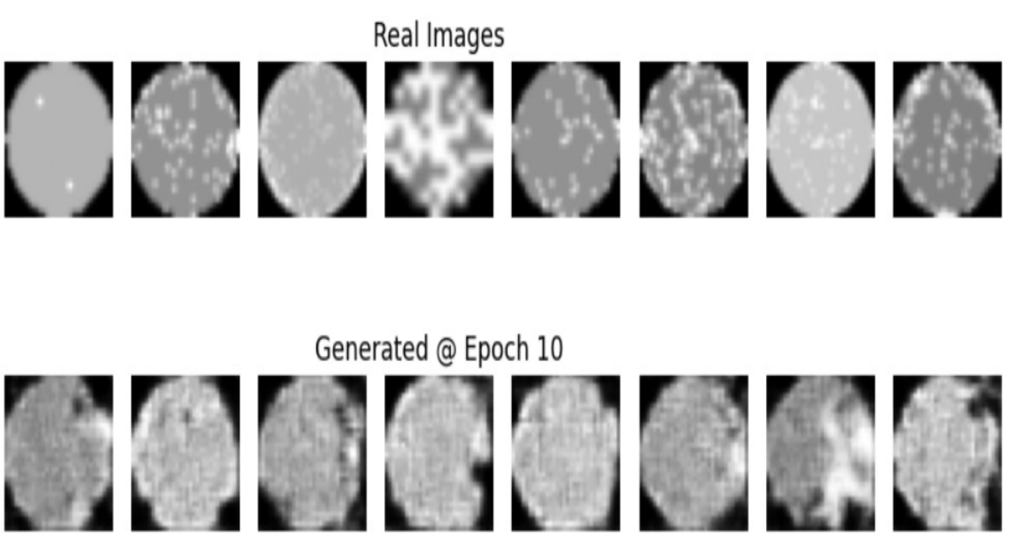

Figure 4.1: confusion matrix

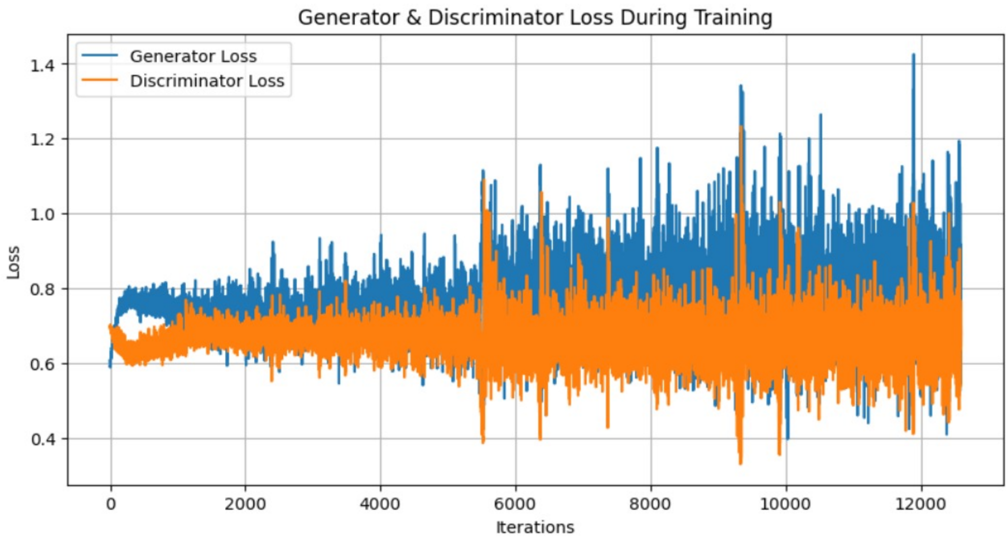

Figure 4.2: confusion matrix

4.2 Pixel Intensity Distribution

We analyzed the pixel intensity distribution of both real and generated wafer images to evaluate how closely the synthetic images match the statistical features of the real dataset.

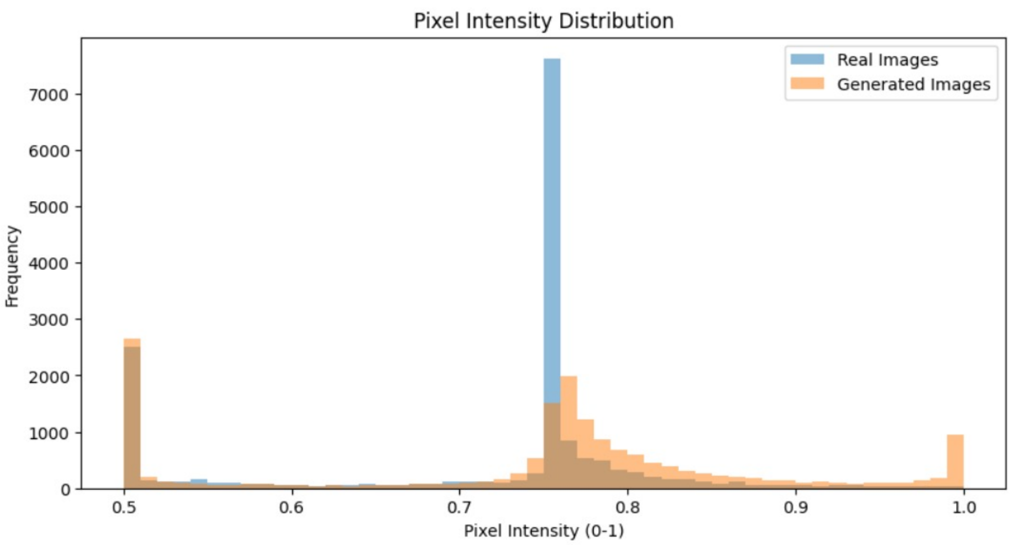

Figure 4.3: confusion matrix

4.3 Visual Comparison of Images

Visual inspection provides qualitative evidence of model learning. Below, we compare real wafer images with generated images at different epochs.

4.3.1 Epoch 10

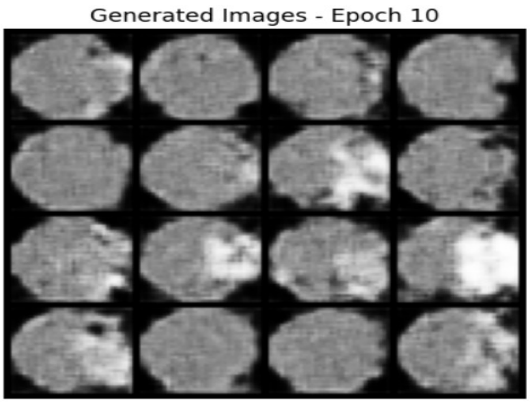

Figure 4.4: 10 Epochs

4.3.2 Epoch 200

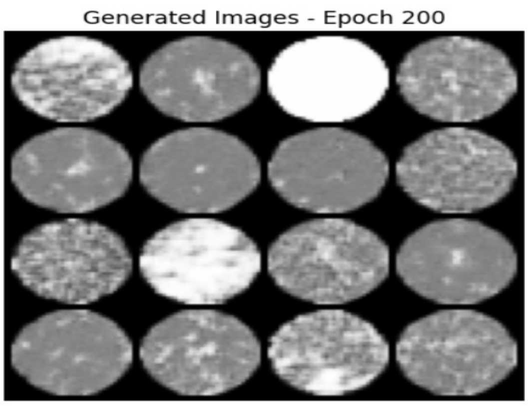

Figure 4.5: 200 Epochs

4.4 Observations

– The Generator and Discriminator losses remained relatively stable, indicating a balanced adversarial training process.

– Pixel intensity distributions of generated images closely matched those of real images.

- Visual results improved significantly from Epoch 10 to Epoch 200, indicating effective learning by the Generator.

Overall, the model was able to generate high-quality, realistic silicon wafer images, which can be used for dataset augmentation and further research in semiconductor defect analysis.

Chapter 5

Conclusion

This project demonstrates the successful application of Generative Adversarial Networks (GANs) for the synthetic generation of silicon wafer images. A dataset of 1000 grayscale wafer images was preprocessed and used to train a GAN composed of a Generator and a Discriminator. Through adversarial training using Binary Cross-Entropy loss and the Adam optimizer, the model effectively learned to generate images that closely resemble real silicon wafer data.

The Generator progressively improved the realism of outputs, as evidenced by both visual comparisons and statistical analysis of pixel intensity distributions. The generated images captured key structural features and rare defect patterns, offering a promising method to augment limited datasets in semiconductor manufacturing.

In conclusion, the proposed approach enhances the availability of training data for defect detection models without incurring high acquisition costs. This work lays the foundation for future research in automated semiconductor inspection and could be extended by incorporating conditional GANs, higher-resolution architectures, or domain-specific evaluation metrics.

Bibliography

[1] H. Zheng, S.W.A. Sherazi, S.H. Son, J.Y. Lee, "A Deep Convolutional Neural Network-Based Multi-Class Image Classification for Automatic Wafer Map Failure Recognition in Semiconductor Manufacturing," *Applied Sciences*, vol. 11, no. 20, p. 9769, 2021.

[2] Y. Li, H. Zhao, H. Jiang, et al., "Large Language Models for Manufacturing," *arXiv preprint*, arXiv:2403.12345, 2024.

[3] U. Batool, M.I. Shapiai, M. Tahir, Z.H. Ismail, N.J. Zakaria, A. Elfakharany, "A Systematic Review of Deep Learning for Silicon Wafer Defect Recognition," *IEEE Access*, vol. 9, pp. 116572–116593, 2021.

[4] S.P. Bates, "Silicon Wafer Processing," *Industry Initiatives for Science and Math Education (IISME)*, San Jose, CA, 2000.

[5] M.C. Chiu, T.M. Chen, "Applying Data Augmentation and Mask R-CNN-Based Instance Segmentation Method for Mixed-Type Wafer Maps Defect Patterns Classification," *IEEE Transactions on Semiconductor Manufacturing*, vol. 34, no. 4, pp. 455–463, Nov. 2021.

[6] R. Lakatos, P. Pollner, A. Hajdu, T. Joo, "Investigating the Performance of Retrieval-Augmented Generation and Fine-Tuning for the Development of AI-Driven Knowledge-Based Systems," *arXiv preprint*, arXiv:2403.09727, 2024.

[7] M. Nasr, N. Carlini, J. Hayase, et al., "Scalable Extraction of Training Data from (Production) Language Models," 2023.

[8] Q. Shu, "WM811K Wafer Map Dataset," Kaggle. [Online]. Available: https://www.kaggle.com

[9] C. Zhou, R.C. Paffenroth, "Anomaly Detection with Robust Deep Autoencoders," *Proc. 23rd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD '17)*, New York, USA, pp. 665–674, 2017.

[10] S.R. Dubey, S.K. Singh, B.B. Chaudhuri, "Activation Functions in Deep Learning: A Comprehensive Survey and Benchmark," *Neurocomputing*, vol. 503, pp. 92–108, 2022.

[11] M.A. Hossain, M.S.A. Sajib, "Classification of Image Using Convolutional Neural Network (CNN)," *Global Journal of Computer Science and Technology*, vol. 19, no. 2, pp. 13–14, 2019.

[12] Y. Wang, Y. Li, Y. Song, X. Rong, "The Influence of the Activation Function in a Convolution Neural Network Model of Facial Expression Recognition," *Applied Sciences*, vol. 10, no. 5, p. 1897, 2020.

[13] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.T. Yih, T. Rocktäschel, S. Riedel, D. Kiela, "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks," *arXiv preprint*, arXiv:2101.05453, 2021.

[14] Z. Jiang, F.F. Xu, L. Gao, et al., “Active Retrieval Augmented Generation,” *arXiv preprint*, arXiv:2305.06983, 2023.

[15] H. Touvron, T. Lavril, G. Izacard, et al., “Llama: Open and Efficient Foundation Language Models,” *arXiv preprint*, arXiv:2302.13971, 2023.

[16] M. Hossin, M.N. Sulaiman, “A Review on Evaluation Metrics for Data Classification Evaluations,” *International Journal of Data Mining & Knowledge Management Process*, vol. 5, no. 2, pp. 1–12, 2015.

[17] D. Müller, I. Soto-Rey, F. Kramer, “Towards a Guideline for Evaluation Metrics in Medical Image Segmentation,” *BMC Research Notes*, vol. 15, no. 1, p. 210, 2022.