

## Team Details

Team Name:

Ssqaure\_Tech

SR. NO	ROLE	NAME	ACADEMIC YEAR
1	Team Leader	Sakshee Umesh Gawde	3 <sup>rd</sup> year
2	Member 1	Shamita Mandar Lokhande	3 <sup>rd</sup> year
3	Member 2	{Enter Name}	{Enter Year}
4	Member 3	{Enter Name}	{Enter Year}

 A team can have up to 4 members including the team leader. Add rows if necessary.

 COLLEGE NAME

Terna Engineering College

 TEAM LEADER CONTACT NUMBER

+91 7039385078

 TEAM LEADER EMAILADDRESS

saksheegawde125@gmail.com

# Problem Statement

## 🎯 Edge-AI Based Defect Classification for Semiconductor Wafer Images

### ▪ *The Defect Challenge*

Semiconductor fabrication run hundreds of ultra-sensitive steps where even nanometer-scale defects can silently kill yield and reliability, directly translating to lost revenue and scrap.

### ▪ *Limitations*

Current centralized manual inspection can't keep up with terabytes of wafer images: data transfer to servers adds latency, cloud compute is costly, and human review is slow, inconsistent, and unable to scale to real-time line speeds.

### ▪ *Edge-AI Imperative*

Industries now need edge-AI so defect detection runs directly on or near the tool - cutting latency to milliseconds, reducing bandwidth and cloud dependence, and enabling Industry 4.0 lines that react instantly to defects instead of discovering problems batches later.

## Idea Description

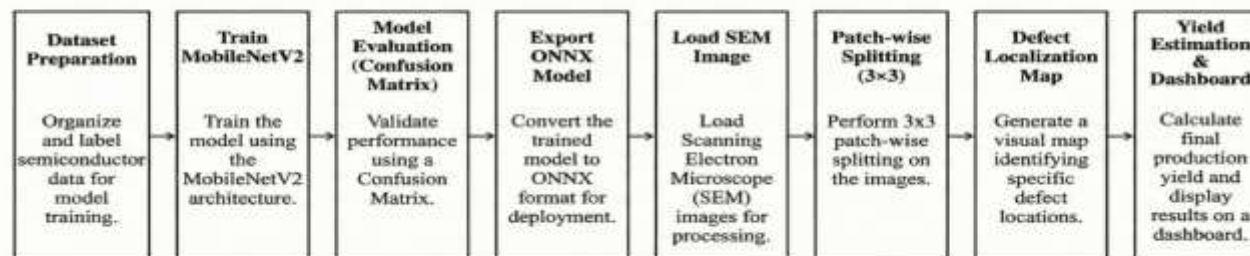
### Proposed Concept and Approach

An Edge-AI based multi-stage inspection pipeline is proposed for semiconductor wafer defect analysis. A lightweight CNN performs rapid whole-image defect classification, followed by patch-level analysis only when defects are detected, enabling low-latency and edge-deployable inspection.

### Methodology Overview

SEM images are first classified as Clean or Defective using a compact MobileNetV2 model. Defective images are spatially divided into patches to enable defect localization and yield estimation. The approach minimizes latency, eliminates cloud dependency, and directly links inspection results to manufacturing metrics.

### Application Flow: Defect Detection Pipeline



# Proposed Solution

## Wafer Images - Inspection Pipeline

### Stage 1: Dataset ingestion & preprocessing

SEM images are normalized and prepared for automated inspection.

### Stage 2: Image classification

Each image is classified as Clean or Defective using a lightweight deep learning model.

### Stage 3: Defect type identification

Defective images are further classified into specific defect categories.

### Stage 4: Patch-wise region analysis

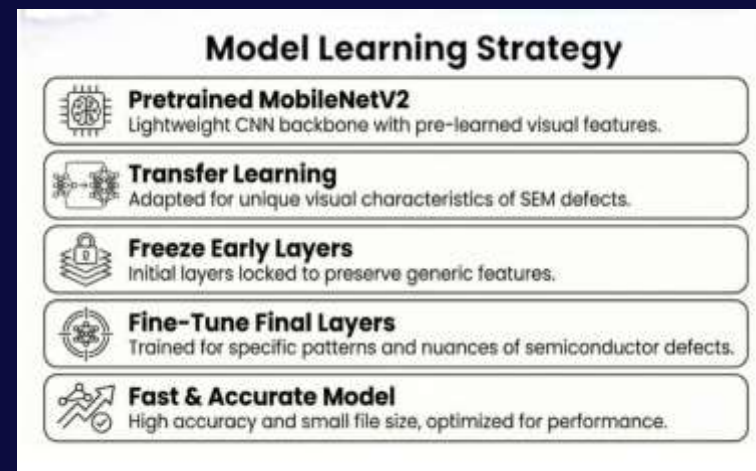
Both clean and defective images are divided into spatial patches for fine-grained inspection.

### Stage 5: Defect localization

Patch predictions are aggregated to highlight defective regions

### Stage 6: Yield estimation

Yield is computed as the percentage of clean patches for quality assessment.



### Development Tools



### System Components

Data Preprocessing, Model Training, Patch Analyzer, Result Visualization



### Deployment Format

- 1) ONNX Model – Cross-platform, fast inference
- 2) CPU Inference – Runs without GPU
- 3) Edge-Ready – Real-time, offline inspection

## Innovation and Uniqueness

💡 *The proposed system converts SEM images into actionable manufacturing decisions by integrating defect localization and AI-driven yield estimation .*

### *Technical Edge*

- Patch-based defect localization converts image-level predictions into spatial defect maps, *enabling accurate identification of faulty regions* without the need for costly pixel-level annotations.
- AI-driven yield estimation translates defect distribution into a quantitative usability metric, *directly supporting decisions to reject low-yield wafers, reprocess partially usable chips*, or advance high-yield wafers to fabrication.

### *Why Our Solution Excels !!!*

- ✓ **Efficient:** Patch analysis runs when needed.
- ✓ **Cost-Smart:** Skips processing low-yield wafers.
- ✓ **Powerful:** Detection + Classification + localization + yield in one streamlined pipeline.
- ✓ **Actionable:** Delivers real-time, manufacturing-ready insights.

# DataSet Plan

Dataset link : [https://drive.google.com/file/d/1bWkKMjLqghkPmVGUKR6vS9YITUVqHSfq/view?usp=drive\\_link](https://drive.google.com/file/d/1bWkKMjLqghkPmVGUKR6vS9YITUVqHSfq/view?usp=drive_link)



## Dataset Overview

1. *Total Images*: 1,246 images
2. *Number of Classes*: 12
3. *Image Type*: Grayscale
4. *Labeling Method*: Manual
5. *Train/Validation/Test Split*:
  - Training: 865 images
  - Validation: 183 images
  - Testing: 198 images

Training set class distribution:

Bridge	: 147 images
CMP	: 117 images
Clean	: 58 images
Crackes	: 107 images
LER	: 62 images
Missing patterns	: 29 images
Multiple defects in one image	: 29 images
Open	: 93 images
Ripple	: 63 images
Scratch	: 127 images
Stain and Edge Contamination	: 19 images
VIAS	: 14 images

Dataset sizes:

Training:	865 images
Validation:	183 images
Testing:	198 images

## Model & Training Overview

1. *Model Architecture*: MobileNet V2
2. *Framework*: PyTorch 2.9.0 + CPU
3. *Training Method*: Transfer Learning
4. *Input Size*:  $224 \times 224$
5. *Deployment Format*: ONNX
6. *Model Size*: 8.78 MB
7. *Grid Size* :  $3 \times 3 = 9$  patches
8. *Best Validation Accuarcy* – 98.91%



## Results

The proposed multi-stage Edge-AI inspection pipeline effectively analyzes SEM images, performing global classification to detect defects and patch-wise inspection to localize them precisely. *Clean regions are filtered out, reducing unnecessary computation, while defective areas are highlighted with high confidence.* The detailed results can be reviewed in the attached pdf , and the inspection process is demonstrated in the provided video link. This pipeline consistently delivers reliable and efficient inspection outcomes.

Result PDF link: [https://drive.google.com/file/d/1\\_2wJ0CjZtMisRUFGmkAGMm2a1di-IMXg/view?usp=drive\\_link](https://drive.google.com/file/d/1_2wJ0CjZtMisRUFGmkAGMm2a1di-IMXg/view?usp=drive_link)

Video link : [https://drive.google.com/file/d/1Ty\\_v-RtYwknDIJPZPqQu-KFZtBBg-kVi/view?usp=drive\\_link](https://drive.google.com/file/d/1Ty_v-RtYwknDIJPZPqQu-KFZtBBg-kVi/view?usp=drive_link)

# Links and References



## Links

GITHUB link: <https://github.com/teamssquaretech-ai/edge-sem-vision>

ONNX model : [https://github.com/teamssquaretech-ai/edge-sem-vision/blob/main/model/sem\\_mobilenetv2\\_model.onnx](https://github.com/teamssquaretech-ai/edge-sem-vision/blob/main/model/sem_mobilenetv2_model.onnx)

Collab link: [https://colab.research.google.com/drive/1eGhJz2G76D1BvSxKUrBoElm6r1F3a-mA?usp=drive\\_link](https://colab.research.google.com/drive/1eGhJz2G76D1BvSxKUrBoElm6r1F3a-mA?usp=drive_link)

ONNX model GD link: [https://drive.google.com/file/d/1vZKyGKL8H-iyY\\_8gd09ceoa4kYy1A6Yz/view?usp=drive\\_link](https://drive.google.com/file/d/1vZKyGKL8H-iyY_8gd09ceoa4kYy1A6Yz/view?usp=drive_link)

Dataset GD link: [https://drive.google.com/file/d/1bWkKMjLqghkPmVGUKR6vS9YITUVqHSfg/view?usp=drive\\_link](https://drive.google.com/file/d/1bWkKMjLqghkPmVGUKR6vS9YITUVqHSfg/view?usp=drive_link)



## References & Citations

Research papers - [https://drive.google.com/file/d/15vDQ6DvxI9WH8IVBctgh1o3Uo7Ln5Tiz/view?usp=drive\\_link](https://drive.google.com/file/d/15vDQ6DvxI9WH8IVBctgh1o3Uo7Ln5Tiz/view?usp=drive_link)

[https://drive.google.com/file/d/10k-9Z5UxRIu-VV-osK7TnY5bYP417Kad/view?usp=drive\\_link](https://drive.google.com/file/d/10k-9Z5UxRIu-VV-osK7TnY5bYP417Kad/view?usp=drive_link)

Image classification models - <https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html>

Root Cause Identification in Wafer Fabs- <https://www.foamtecintlwcc.com/scratch-defects-troubleshooting-root-cause-identification-in-wafer-fabs/>