



Title : Edge AI-Driven Semiconductor Defect Classification

Team Details

Team Name:

Die-Trying

SR. NO	ROLE	NAME	ACADEMIC YEAR
1	Team Leader	Aditya Malpani	3 rd year B.Tech
2	Member 1	Yash Dobariya	3 rd year B.Tech
3	Member 2	Krins Italiya	3 rd year B.Tech
4	Member 3	Pratyush Maheshwari	3 rd year B.Tech

COLLEGE NAME

Pandit Deendayal Energy University Gandhinagar Gujarat

TEAM LEADER CONTACT NUMBER

+ 91 6352589940

TEAM LEADER EMAIL ADDRESS

adityamalpani006@gmail.com

Problem Statement Addressed



Edge AI-Based Defect Classification System for Semiconductor Wafer and Die Images

- ◆ **High-Volume Inspection Challenge**

Modern semiconductor fabs generate massive volumes of die inspection images, where even microscopic defects can significantly impact **yield, performance, and long-term reliability**.

- ◆ **Limitations of Conventional Inspection**

Centralized and manual inspection pipelines suffer from **high latency, bandwidth bottlenecks, rising infrastructure costs, and limited scalability**, making them unsuitable for real-time, high-throughput production.

- ◆ **Need for Edge AI-Driven Inspection**

There is a critical need for **real-time, on-device defect detection and classification**, enabling **low-latency, scalable, and Industry-4.0-ready semiconductor manufacturing**.

Idea Description



➤ IDEA SUMMARY :

- ◆ Develop a **custom, semiconductor-specific wafer and die defect dataset** to address the lack of reliable public inspection data.
- ◆ Focus on **realistic defect classes and imaging conditions**, ensuring the data reflects actual inspection scenarios.
- ◆ Train a **lightweight CNN baseline (MobileNetV2)** to learn domain-relevant defect patterns effectively.
- ◆ Validate **Phase-1 feasibility** through model accuracy, class-wise performance, and compact model size suitable for edge execution.

➤ KEY CONCEPT & APPROACH :

- ◆ **Edge-first AI architecture** that brings defect intelligence closer to wafer and die inspection, minimizing dependence on centralized analysis.
- ◆ **Constraint-driven model design** where accuracy, latency, and memory are co-optimized for edge feasibility from the outset.
- ◆ **Scalable inspection strategy** designed for consistent use across multiple inspection points in high-throughput fabs.

Proposed Solution



➤ SOLUTION DETAILS :

◆ Methodology

- Design, train, and validate a defect classification model using wafer and die inspection images, with emphasis on robustness across defect categories and imaging variations.

◆ Technology

- Adopt MobileNetV2 as the core architecture for its strong accuracy–efficiency balance, supported by task-specific preprocessing and lightweight model optimization.

◆ Implementation Strategy

- Establish a **model-development workflow** where training and validation are performed on standard compute systems, with architectural decisions explicitly aligned to edge execution constraints to ensure smooth transition to on-device inference in later phases.

➤ IMPLEMENTATION STRATEGY :

SEM / Die
Images



Dataset Prep



Preprocessing



MobileNetV2



Edge
Inference

Dataset Plan & Class Design

- ◆ **Dataset Overview**
- ◆ **Total images current : 22,672**
- ◆ **No. of classes: 8 (6 defect + Clean + Other)**
- ◆ **Class balance plan: 2500 Images Per Class**
- ◆ **Train/Validate/Test split: 70 % / 20% / 10%**
- ◆ **Image type: Grayscale**
- ◆ **Labeling method/source: Generated / Python**

- ◆ **Class Design (8 Classes) :**
 - **Defect_1 – Open**
 - **Defect_2 – Via**
 - **Defect_3 – Crack**
 - **Defect_4 – LER**
 - **Defect_5 – CMP**
 - **Defect_6 – Bridge**
 - **Clean**
 - **Other**

Baseline Model & Results

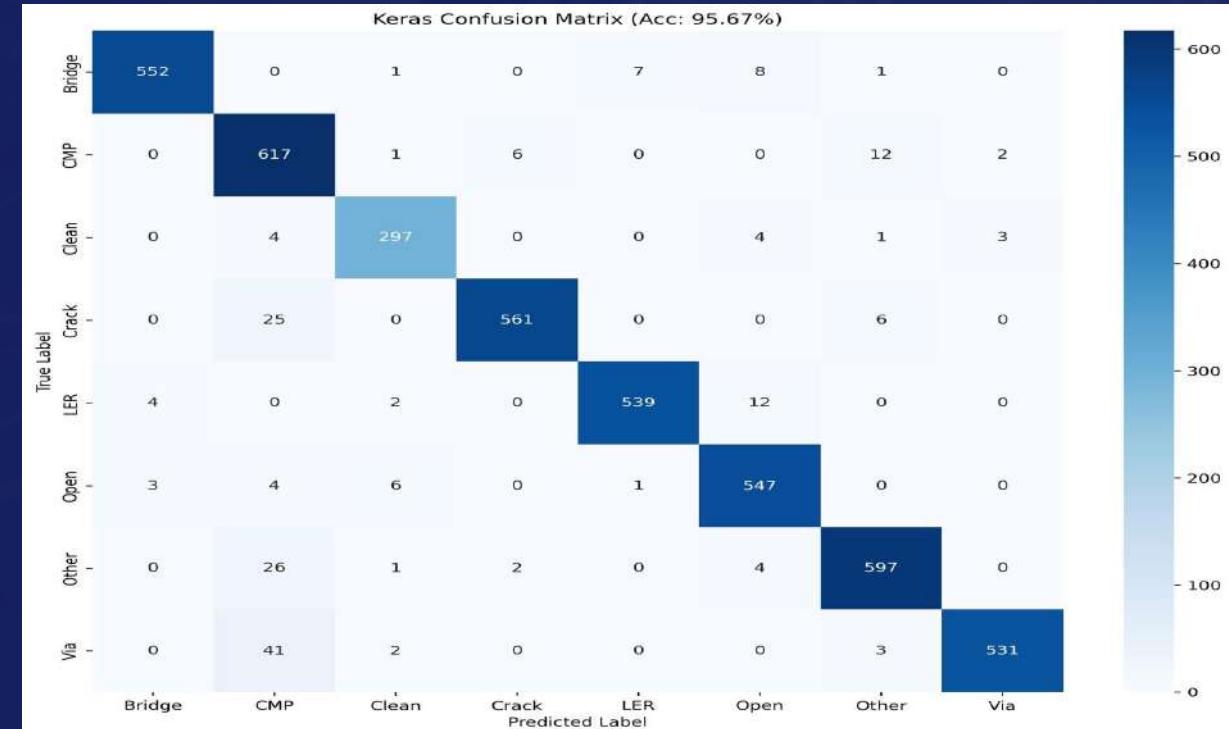
➤ Model details :

- Architecture : MobileNetV2
- Training approach : Transfer Learning
- Input size : 224x224
- Model size : 5 MB
- Framework : TensorFlow 2.x [Keras API]

➤ Metrics on your test split :

- Accuracy : 96%
- Precision/Recall : 96% / 96%

➤ Confusion Matrix:



GitHub & Video Link



GitHub Repository



<https://github.com/yash4959/Die-Trying>



Dataset ZIP link: (Drive)



<https://drive.google.com/file/d/1aESAhJMB3ur3kpgqoUetGvQf6I2wuAiW/view>



ONNX model link:



<https://drive.google.com/file/d/1qF1G4cor4Z5GbD9xmd6pGoq5miGSplLI/view>



Results report link :



https://drive.google.com/drive/folders/17m2kinjPerkSyWzLjhIzqza4CHVz_CmX



Simulation Video :



<https://drive.google.com/file/d/1xw8oAEsZ2deSmF13DgoUed1c7Vpq72vX/view>