Team Details

Team Name: Wafer Minds

SR. NO	ROLE	NAME	ACADEMIC YEAR
1	**Team Leader**	**Ebinesh K**	**3**
2	Member 1	**Kaviya Dharshini G**	**2**
3	Member 2	**Abishek J**	**2**

COLLEGE NAME

Chennai Institute of Technology

TEAM LEADER CONTACT NUMBER

+91 7845887115

TEAM LEADER EMAIL ADDRESS

ebineshk.vlsi2023@citchennai.net

Problem Statement Addressed

Edge AI–Based Defect Classification System for Semiconductor Wafer/Die Images.

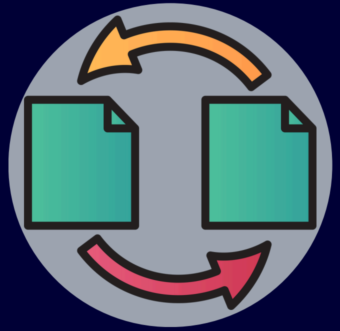
Semiconductor defect inspection currently relies on cloud processing or manual review, causing high latency, scalability issues, and delayed quality decisions.

High inspection latency

Cloud-based analysis delays real-time defect detection on production lines.

Manual Inspection Limitations

Human review is slow, subjective, and not scalable for high-volume manufacturing.



Bandwidth and infrastructure cost

Continuous transfer of high-resolution wafer images increases network load and operational expense.

Idea Description

A deep learning–based automated visual inspection system for wafer surface defect classification using transfer learning. The approach leverages a pretrained EfficientNet-B0 model fine-tuned on the Carinthia wafer defect dataset, enabling accurate multi-class defect identification with minimal training overhead and high generalization capability.

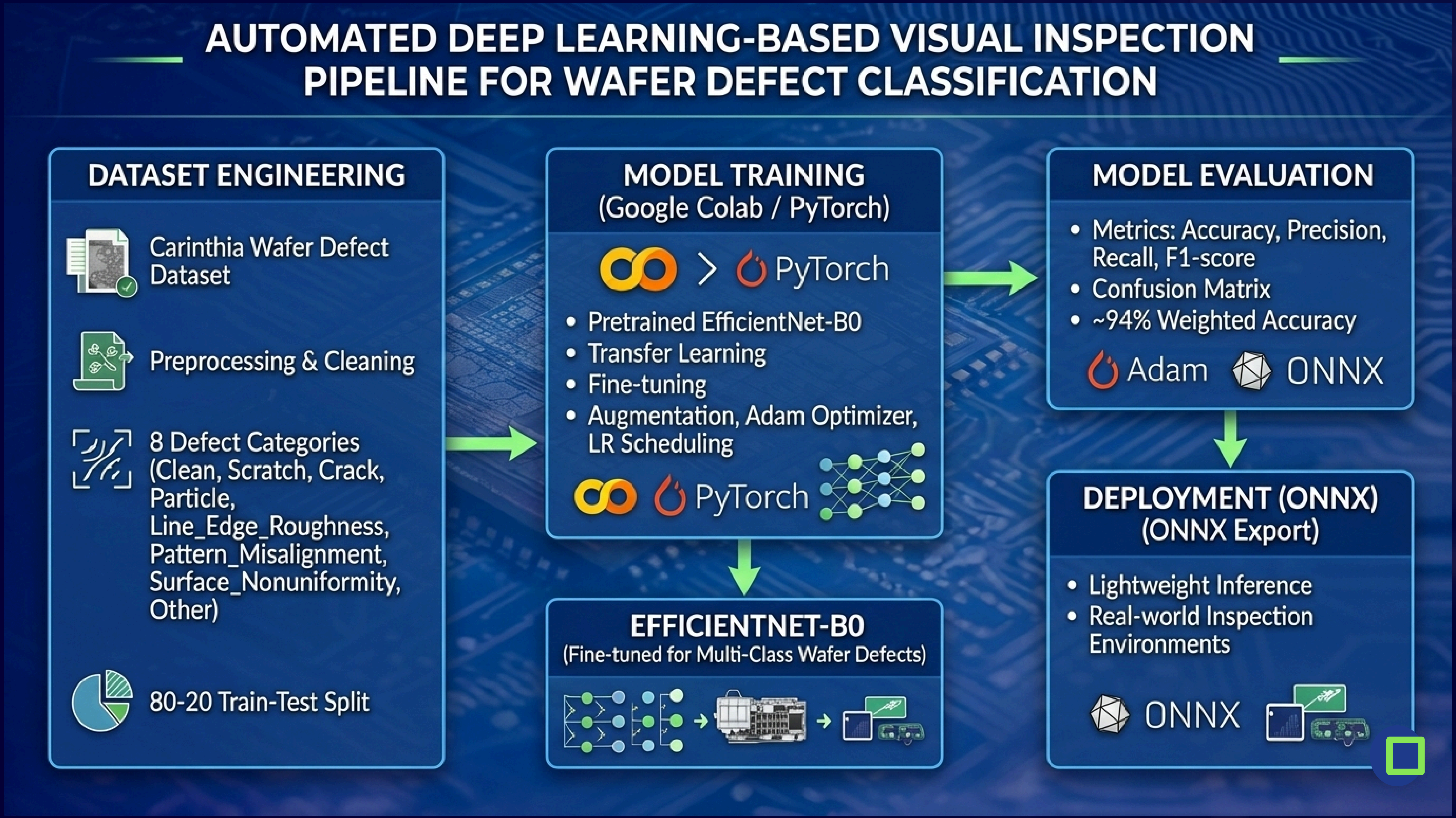
KEY CONCEPT & APPROACH

A transfer-learning based deep learning system using **EfficientNet-B0** for automated multi-class wafer defect classification.

SOLUTION OVERVIEW

A fine-tuned EfficientNet-B0 classifies wafer images into **8 classes**: Clean, Scratch, Crack, Particle, Line_Edge_Roughness, Pattern_Misalignment, Surface_Nonuniformity, and Other for fast, automated quality inspection

Proposed Solution



Dataset Plan & Class Design

Carinthia dataset ← click here for dataset

Class List	Training Set	Testing Set
Clean	180	40
Crack	181	46
Line_Edge_Roughness	801	201
Pattern_Misalignment	801	201
Surface_Nonuniformity	801	201
Particle	231	58
Scratch	44	11
Other	810	204

Total images: 4,591 images

No. of classes: 8 (6 defect classes + Clean + Other)

Train/Validation/Test split: 80 / 10 / 10

Image type: Grayscale wafer inspection images (preferred for defect visibility and reduced computation)

Labeling method: Manual

Results (Phase 1)

Model Details

- Architecture: EfficientNet-B0 (lightweight CNN backbone)
- Training approach: Transfer Learning (ImageNet pretraining + fine-tuning)
- Input size: 224 × 224 (grayscale replicated to 3 channels)
- Model size: ~ 20 MB (ONNX-ready compact variant)
- Framework: PyTorch (trained in Google Colab)

ONNX File Link

Training Strategy

- Optimizer: Adam
- Learning rate: Scheduled (StepLR decay)
- Loss: Cross-Entropy Loss
- Data Augmentation: Random rotation, horizontal/vertical flip, normalization
- Train/Test split: 80/20

Metrics on Test Split (962 images)

- Overall Accuracy: 94.3%
- Weighted Precision: 0.9464
- Weighted Recall: 0.9428
- Weighted F1-score: 0.9437

GitHub & Video Link

GitHub Repository

https://github.com/Ebiinesh/wafer_minds_deeptech_hackathon2026

Prototype / Simulation Video

https://drive.google.com/file/d/1m2CR6tNh1pl29nN5pMSDvudTbNMbTQoC/view?usp=sharing

Research and References

Research Background & Methodology

Deep learning–based automated wafer defect inspection offers higher accuracy, consistency, and scalability compared to traditional manual and rule-based methods. In our work, we adopted a transfer learning approach by fine-tuning a pretrained EfficientNet-B0 model on the Carinthia wafer defect dataset, applying systematic data preprocessing and augmentation, and evaluating performance using accuracy, precision, recall, F1-score, and a confusion matrix to ensure reliable multi-class defect classification.

References & Citations

List key papers, articles, or data sources.

[Ref 1] Carinthia Wafer Surface Defect Database – Public Dataset Repository / https://zenodo.org/records/10715190

[Ref 2] Tan, M., & Le, Q. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks / https://arxiv.org/abs/1905.11946

[Ref 3] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition / https://arxiv.org/abs/1512.03385