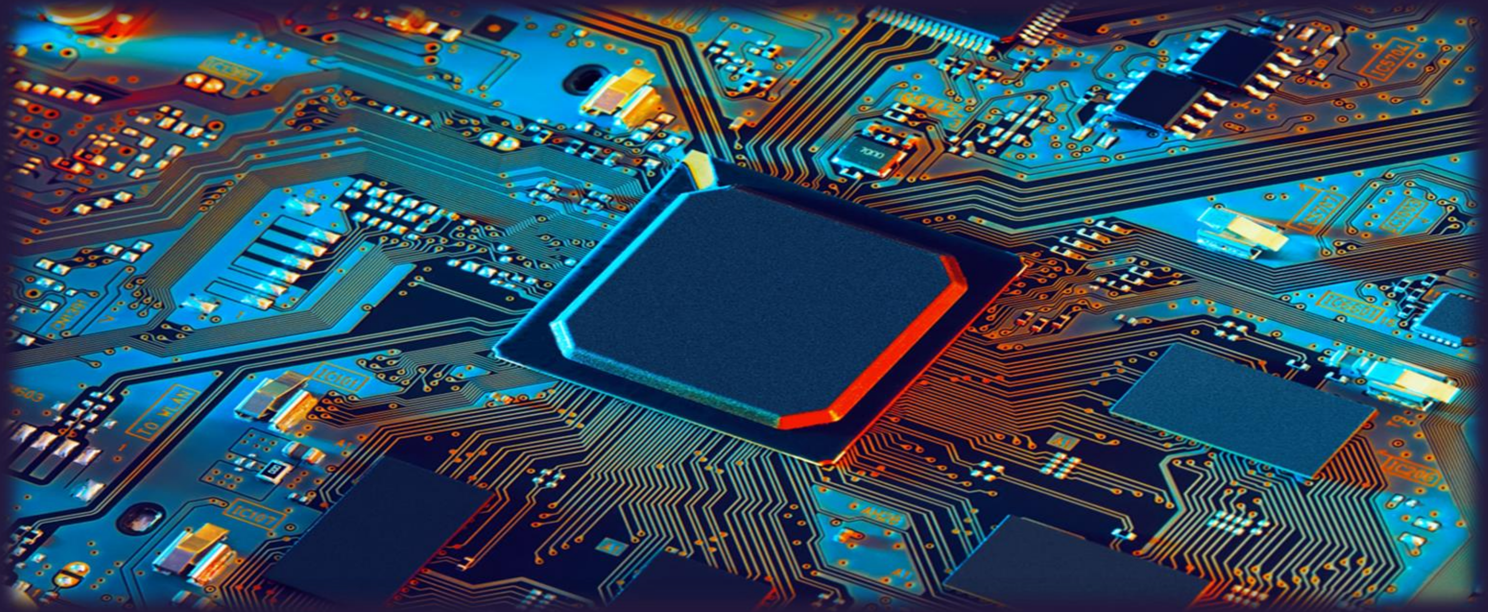
Semiconductor Wafer Map Defect Pattern Classification

Shaalini
DSIF2 Capstone project

Contents

Introduction

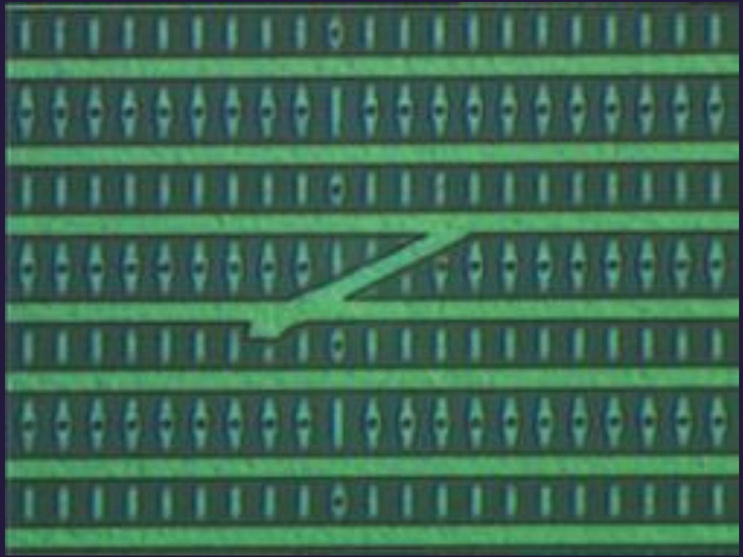
Our Life's are powered by System on Chip Integrated Circuits

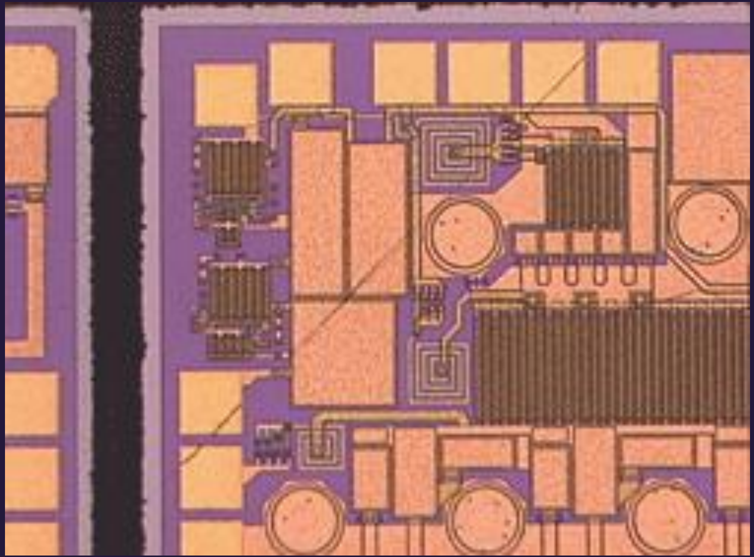


Making these ICs are no mean feat

Courtesy: Fab1 ArsTechnica Web

- Semiconductor Wafer/IC Fabrication involves hundreds of Process steps, takes a month or few to complete and costs thousand of dollars for each wafers
- With such huge investment, consistent Yield Improvement is crucial for Profitability





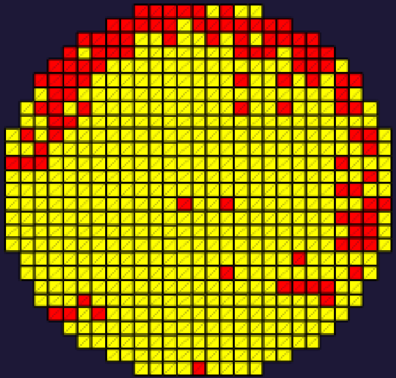
Images of wafer defects

- One of the major cause for yield loss is the errors from Process
- Identifying these fabrication errors in shorter time is crucial in improving the yield

Wafer Bin Map Pattern

Wafer/IC Fabrication Process → Wafer Electrical Test → Assembly (Dicing & Packaging) → Test and Distribution

Wafer Bin Map



ICs Passed for Electrical Test
ICs Failed for Electrical Test

- **Wafer Bin Map -> pictorial representation of Defective ICs**
- **Fail (Defect) Patterns -> can be related to different Fabrication errors**
  Scratch pattern: Handling Issues, Localised pattern: Uneven Cleaning

Classification of Wafer Map Defect Pattern → **Identify Defect root cause at Process** → **Timely Fix and Enhance the Yield**

Problem Statement

Build Deep Learning based Multi-Label Image Classifier Model for Wafer Map Mixed-type Defect pattern

Less complex (Less training time)
Achieving overall AccuracyScore/ExactMatchRatio > 90%
Achieving Precision/Recall/F1-score > 90% for each individual defect pattern

Multilabel classification : Single sample may belong to more than one class

Machine Learning Process

Data Gathering

Mixed-type Wafer Defect Datasets (Public dataset)
By Institute of Intelligent Manufacturing, Donghua University
https://www.kaggle.com/co1d7era/mixedtype-wafer-defect-datasets

Wafer Map Image: Numpy array format (52 X 52)
Image Labels: 8-bit one-hot encoding format (1 X 8)

38,000 Images
(Real data obtained from Testing & some generated data using GAN)

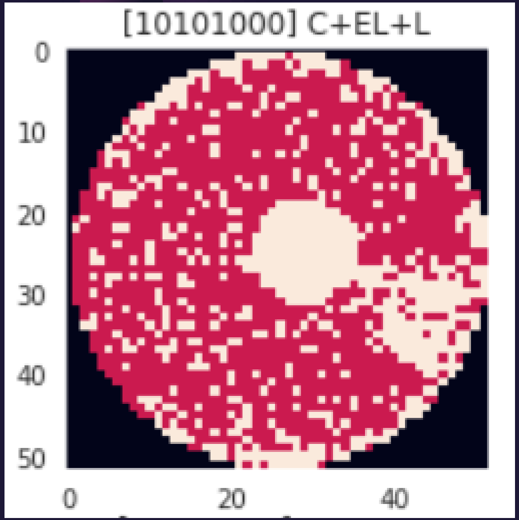
8 Different Individual Defect patterns
Defects: Center, Donut, Localized Edge, Ring Edge, Localized, Near Full, Scratch, Random

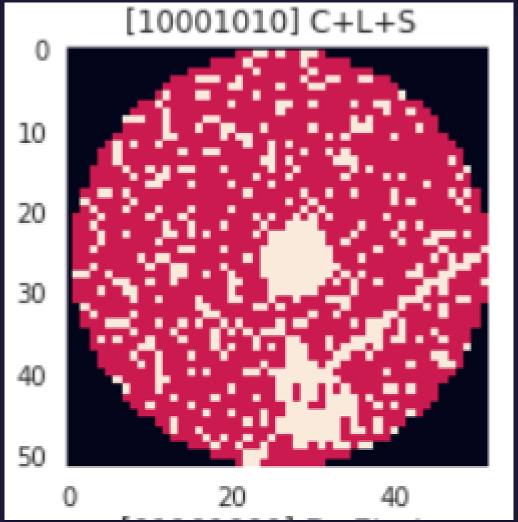
38 Mixed Defect Types
1 normal (no defect)
8 single (1 defect)
28 mixed type (2 different defects, 3 different defects, 4 different defects)

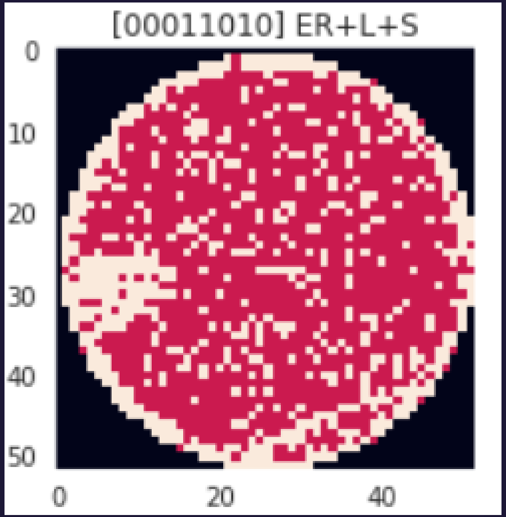
Data Preprocessing

- Replaced invalid pixel values
- Normalized the Image data
- Calculated Class weights
- Stratified Train-Val-Test split
- Convert to RGB representation

Exploratory Data Analysis

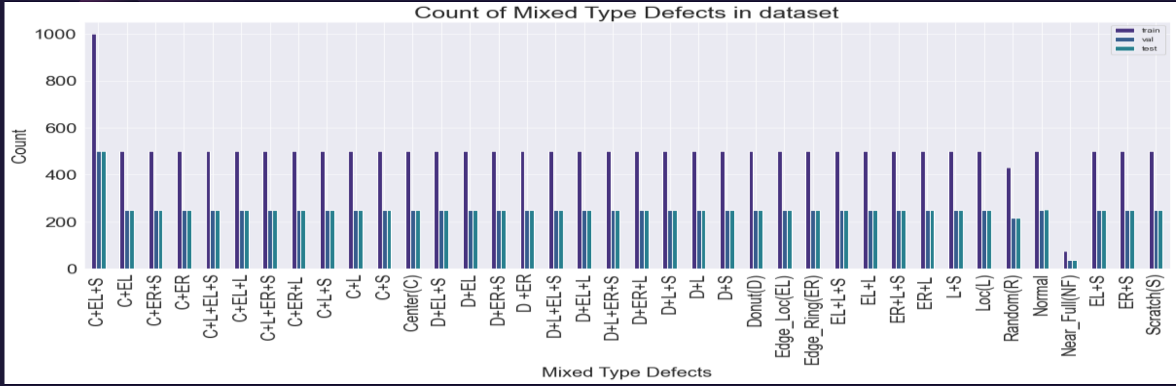




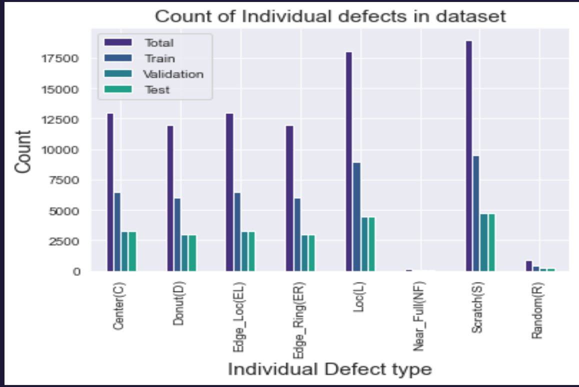


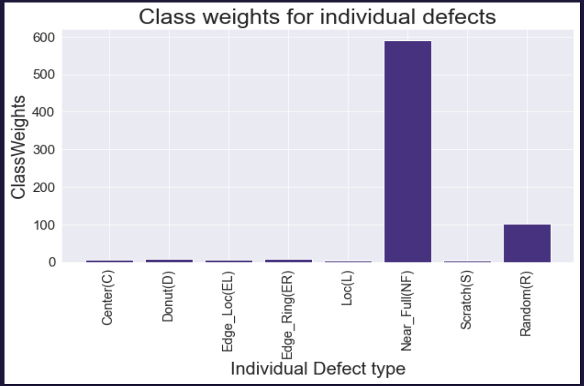
Same type of defect pattern can be at different size/position/angle

Exploratory Data Analysis



Stratified split: 50% in Train set, 25% in Validation set, 25% in Test set
- For both Mixed defect types and also the individual defect counts



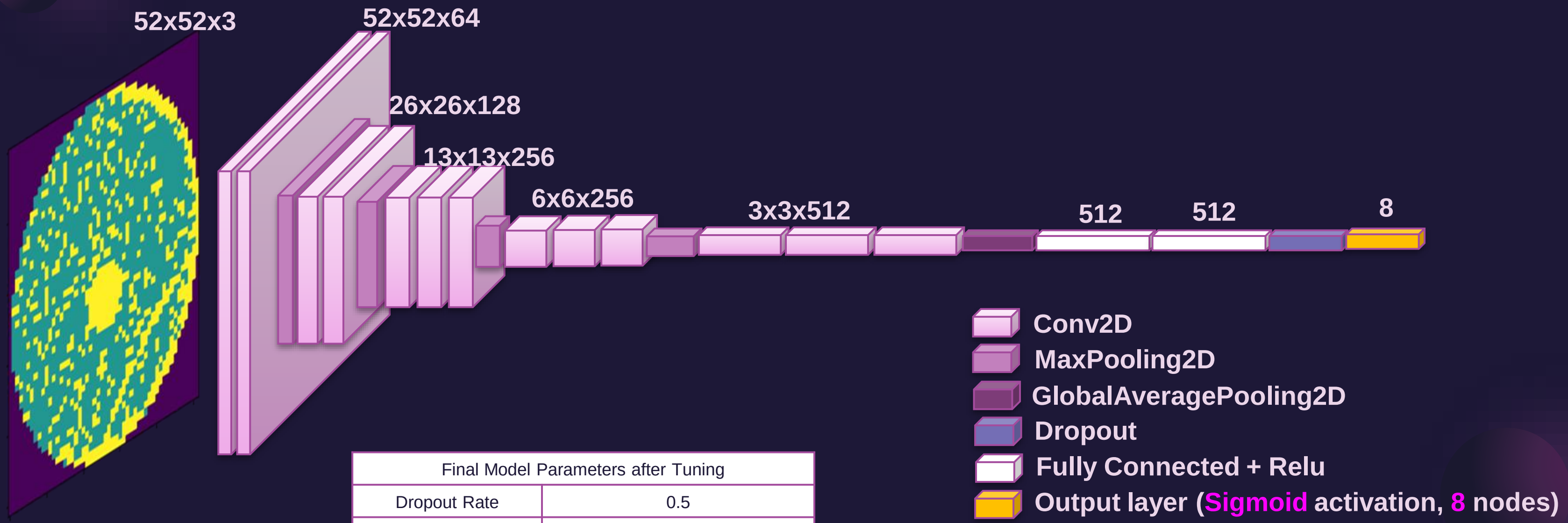


NearFull(NF) and Random(R) defects are much lower in count & Loc(L) and Scratch(S) are higher in count

Class Weights are calculated for each individual defects to address this Class Imbalance

Model

VGG16 base model + 2 Fully connected Layer + 1 Output Layer



Final Model Parameters after Tuning	
Dropout Rate	0.5
Learning Rate	0.0001
Kernel Regularizer	L2
Trainable Layers	All
Loss type	BinaryCrossentropy
Metric	BinaryAccuracy
Optimizer	Adam
Training Time	<20mins

Results & Conclusions

Model Metrics

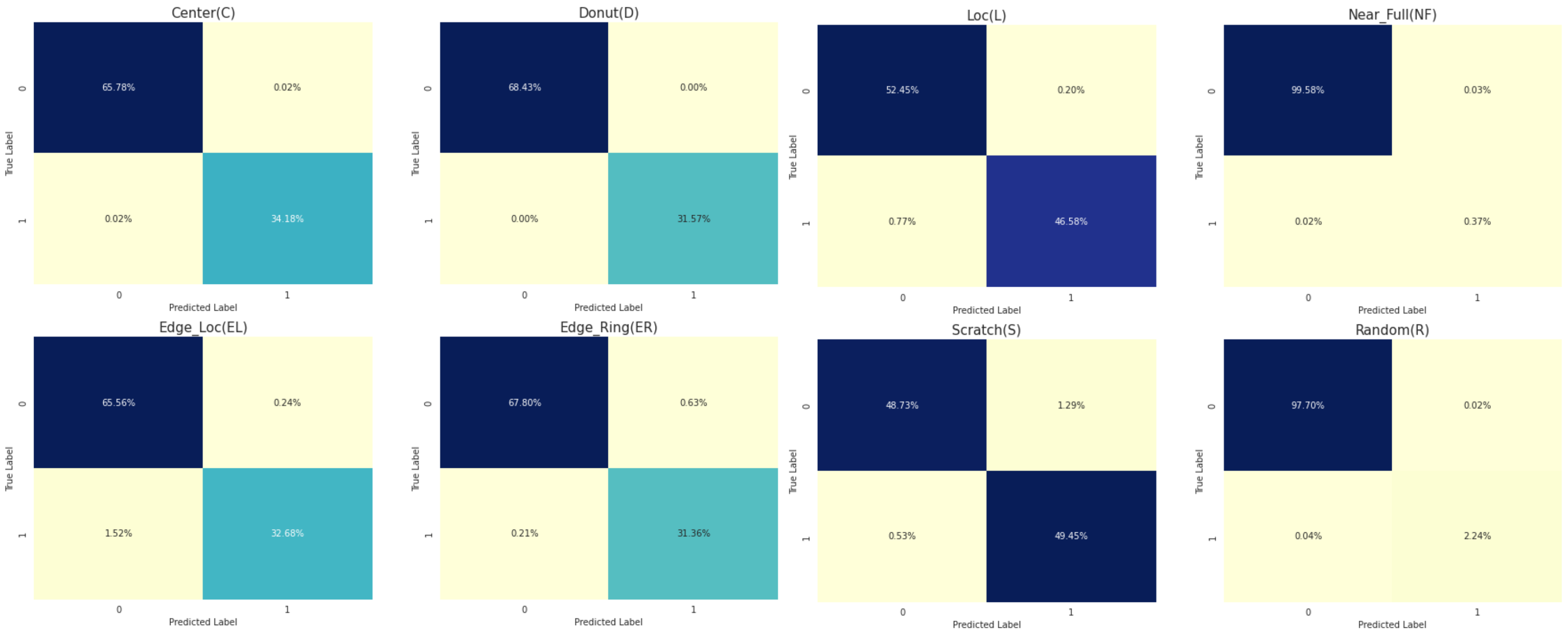
Evaluation Metric	Exact Match Ratio/ Accuracy Score	Hamming Loss
Train Set	0.957	0.007
Val Set	0.953	0.007
Test Set	0.954	0.007

	precision	recall	f1-score	support
Center(C)	1.000000	0.999692	0.999846	3250.0
Donut(D)	1.000000	1.000000	1.000000	3000.0
Edge_Loc(EL)	0.997504	0.983692	0.990550	3250.0
Edge_Ring(ER)	0.990089	0.999000	0.994525	3000.0
Loc(L)	0.999776	0.991778	0.995761	4500.0
Near_Full(NF)	0.972973	0.972973	0.972973	37.0
Scratch(S)	0.993909	0.996211	0.995058	4750.0
Random(R)	0.995392	0.995392	0.995392	217.0
micro avg	0.996812	0.994819	0.995815	22004.0
macro avg	0.993705	0.992342	0.993013	22004.0
weighted avg	0.996828	0.994819	0.995810	22004.0
samples avg	0.970320	0.968768	0.969099	22004.0

- High Exact Match Ratio and Low Hamming Loss for all the 3 data sets
- No Signs of overfitting

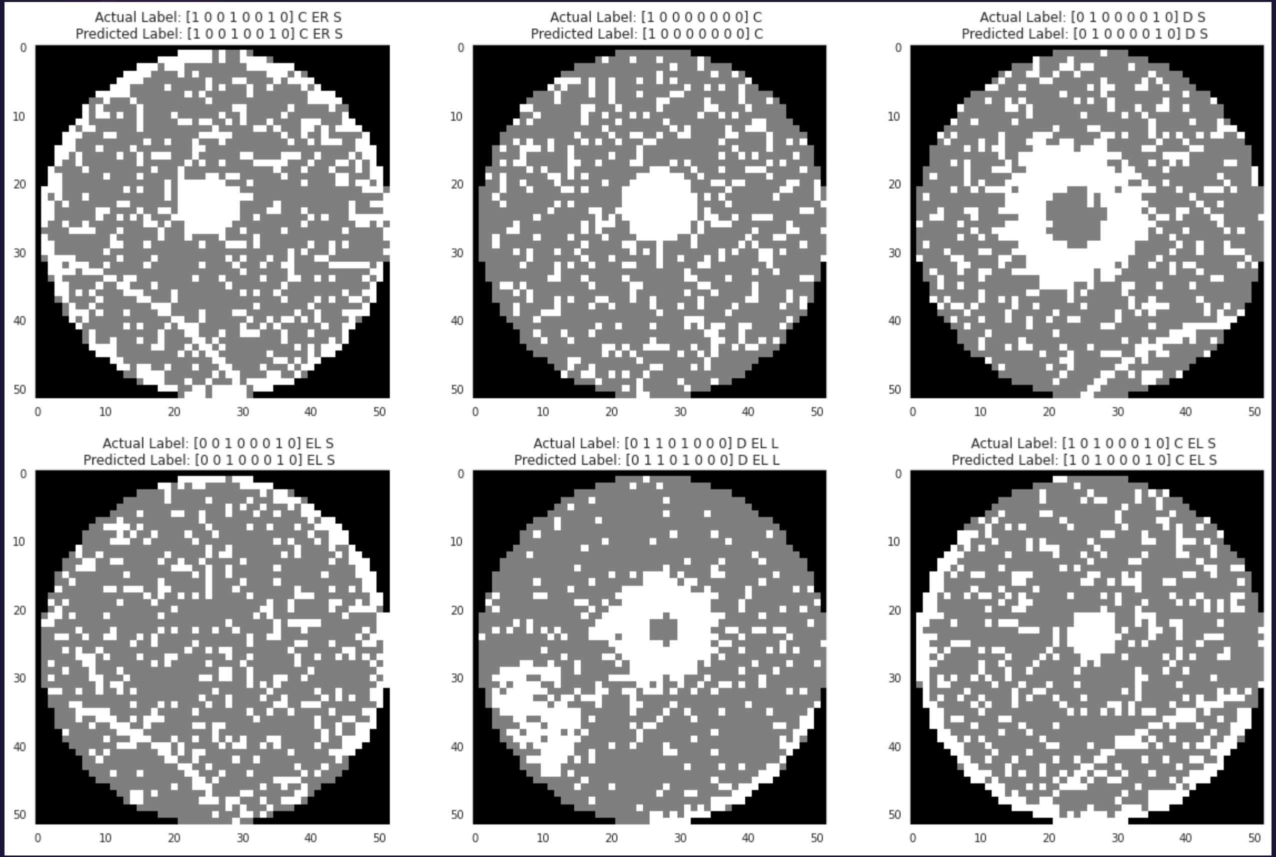
- Precision/F1-score/Recall > 95% for all the individual defects in test data

Confusion Matrix



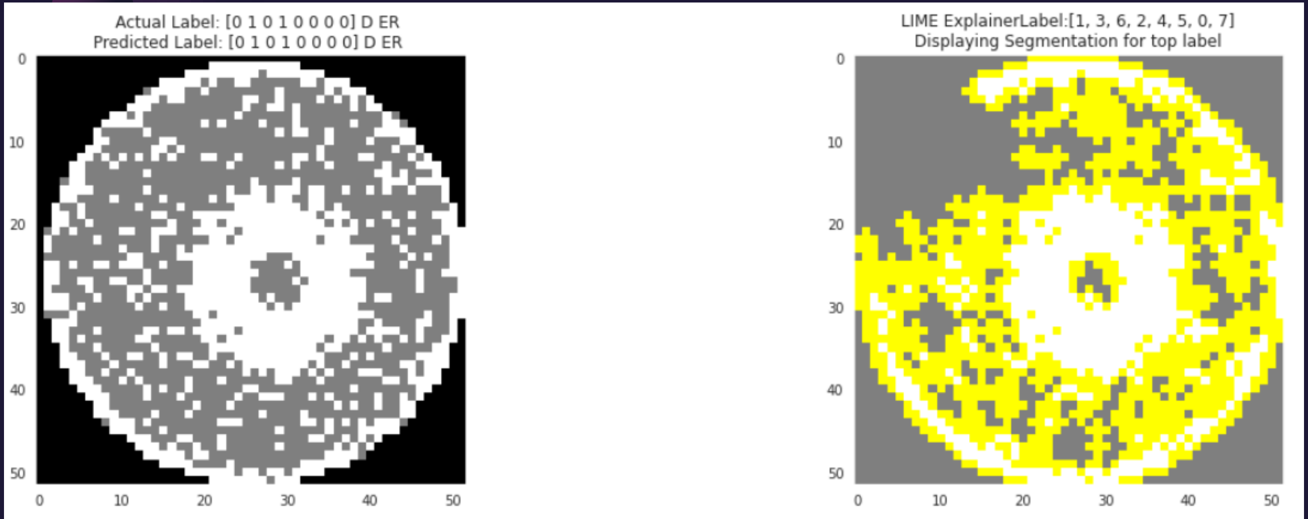
- False Positive/False Negatives < 1% for all the individual defects

Prediction



- Model predicts Well for all type of defects and Mixed defect Patterns

LIME explainer segmentation mask

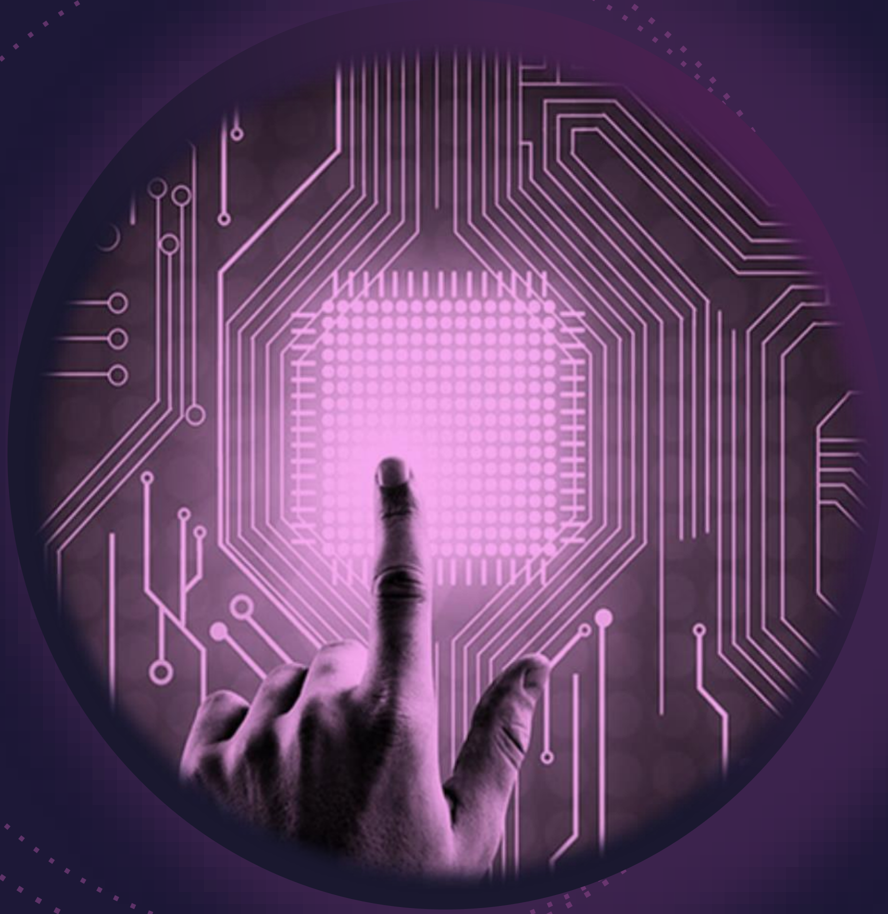


- In this Image top label is the Donut(D)
- LIME Segmentation Image on the right clearly shows that the model is able to identify the shape of the Donut(D) well and so can predict it correctly

Conclusions

- The Multi-label Classification model that have been built can successfully predict the Mixed-type defects with overall Accuracy score > 90% and Precision/Recall/F1 score >90% of for individual defects

Future Work



Future Work

- As the complexity of the semiconductor process keep increasing constantly with the advancement in technology, there are high possibility to encounter new defect patterns.
  - As the Future work, plan to develop Image Segmentation model to detect New patterns and integrate with Multi-Label Classification Model

References
[1] Takeshi Nakazawa, Deepak V. Kulkarni "Anomaly Detection and Segmentation for Wafer Defect Patterns Using Deep Convolutional Encoder–Decoder Neural Network Architectures in Semiconductor Manufacturing"

Q & A

Thank You!

APPENDIX

- **GlobalAveragePooling2D** convert multi dimensional object to one dimensional
- **Sigmoid** activation squashes a vector of range (0,1) for each of the 8 outputs
- **BinaryCrossentrophy** - Loss computed for every vector is not affected by other component values
- **Class weights** would provide a weight or bias for each output class
- **Exact Match Ratio**: Percentage of samples that have all their labels classified correctly
- **Hamming-Loss**: Fraction of labels that are incorrectly predicted

Glossary