

2020  
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**VISION**  
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# Image Based Deep Learning for Manufacturing Fault Condition Detection

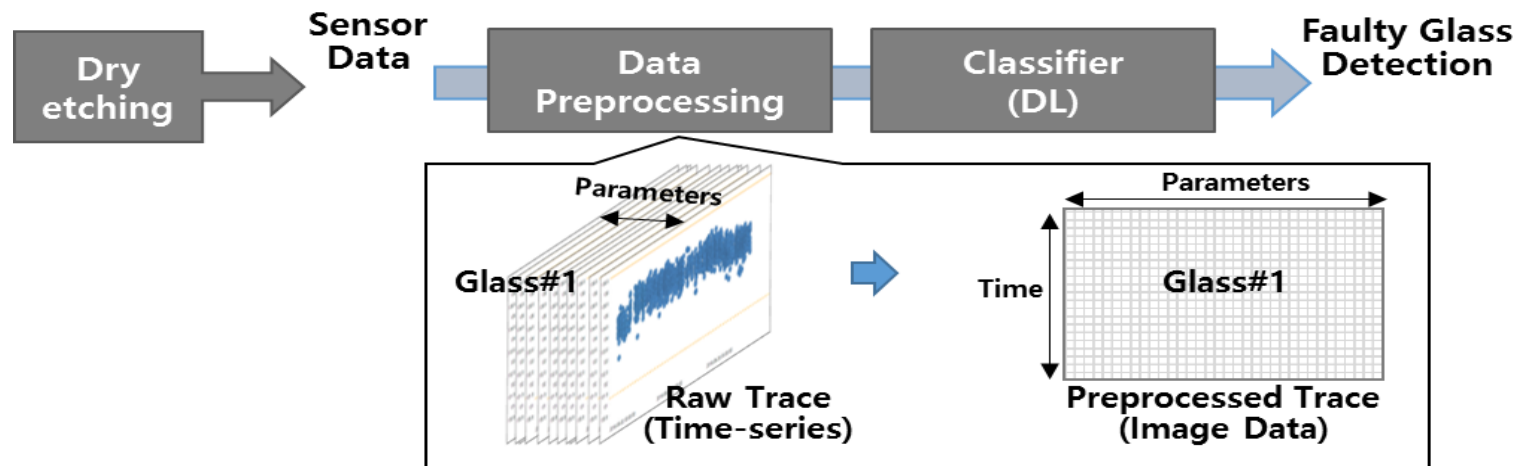
Janghwan Lee, Wei Xiong, Wonhyouk Jang  
Samsung Display America Lab and Display Research Center  
September 2020

**SAMSUNG**

- Introduction
- Challenges for the dataset
- Data processing & baseline solution
- Issue Analysis and Solutions
- Experiments and Result
- Conclusion

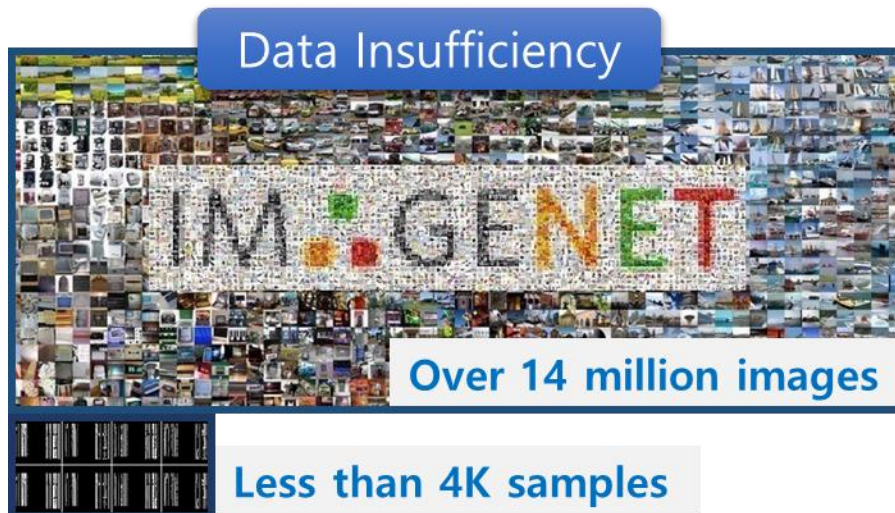
## Trace Data Analytics:

- To understand **the nature of fault conditions** in display panel manufacturing process using multivariate time series sensor signals
- **Digital trace data** is defined as **records of activity undertaken** through an information system. A trace is a mark left as a sign of passage; it is recorded evidence that something has occurred in the past. For trace data, the system acts as a data collection tool\*



# Challenges for the Dataset

- **Trace data from multivariate numerical data**
  - multiple time series input from sensors
- **Generalized ML model generation**
  - **Dataset insufficiency:** too sparse to train deep neural network
  - **Class imbalance:** lack of fault data samples



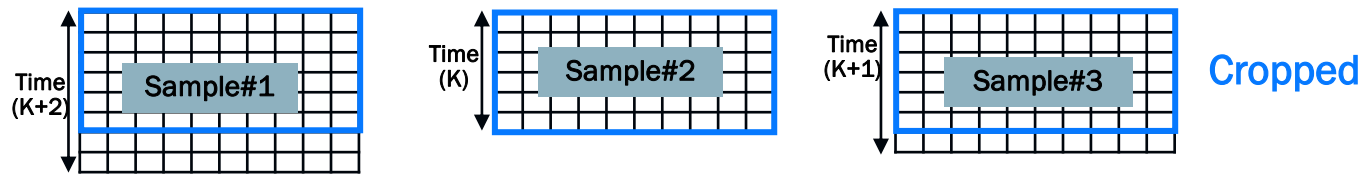


# Data Processing, Baseline Model, and Issue Analysis and Solutions

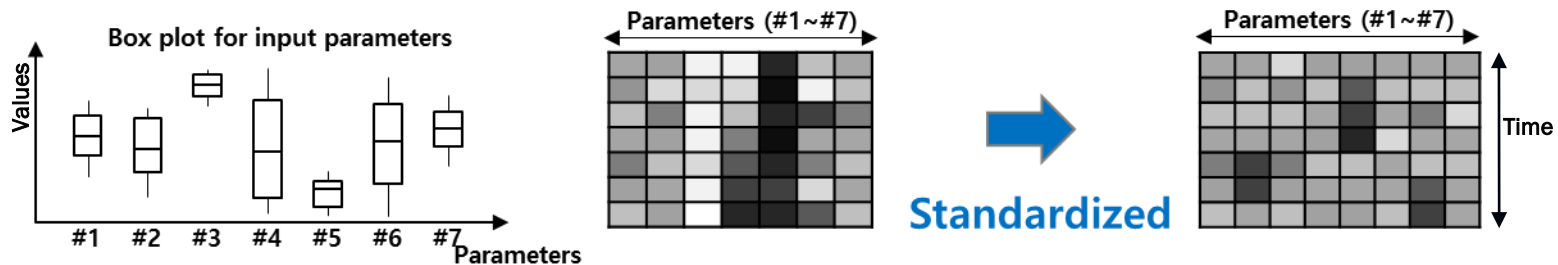
2D trace data generation from multiple time series input signals from sensors:

⇒ *empirical approach*

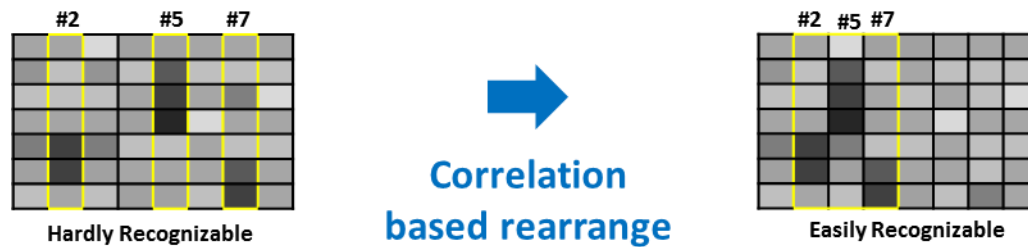
- Sample size alignment for unit task



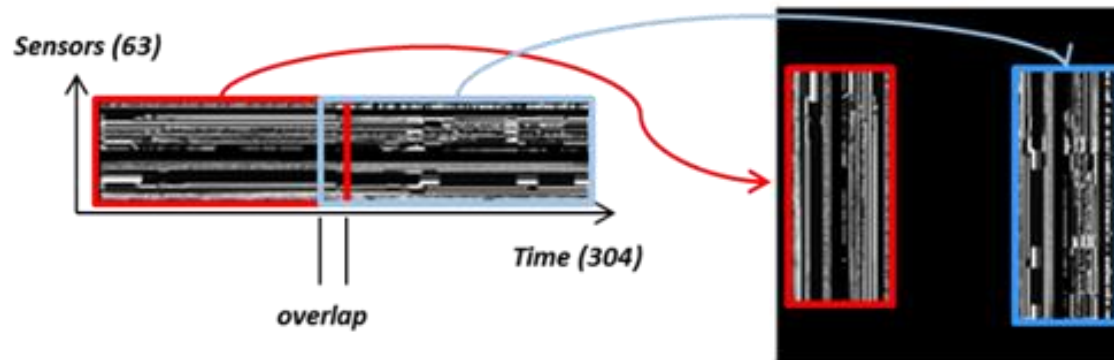
- Merge parameters



- Parameters order rearrangement



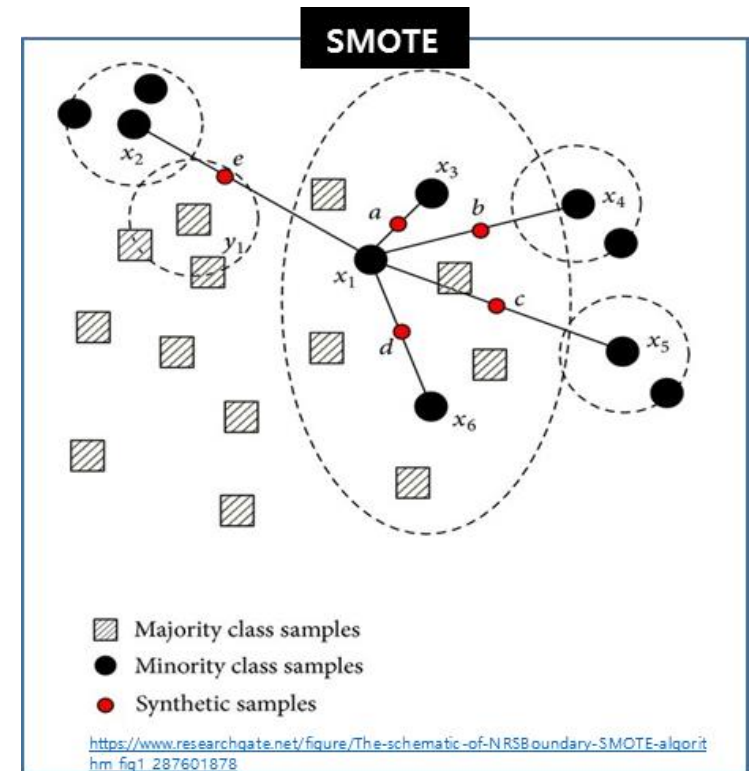
- Data conversion for CNN model



224x224 image to  
use transfer learning  
with SqueezeNet\*

- **Evaluate** that if **2D trace data** has enough information to identify fault conditions
- Input data processing
  - To overcome the **class imbalance** in input dataset:  
**oversampling** minority class (SMOTE and ADASYN)
- Dataset construction

Type	Train set	Test set
Pass	3149	787
Fault	500(OVS)	22





- Results (with SqueezeNet)

Type	Train set	Test set	Train Acc.	Test Acc.
Pass	3149	787	0.9546	<b>0.9111</b>
Fault	500(OVS)	22	1.0000	<b>0.8182</b>

- Verified that it is possible to generate fault condition classifier using 2D trace data
- Remaining Issues for model generalization
  - Insufficient data and class imbalance
  - Solve with Model Instance Distillation

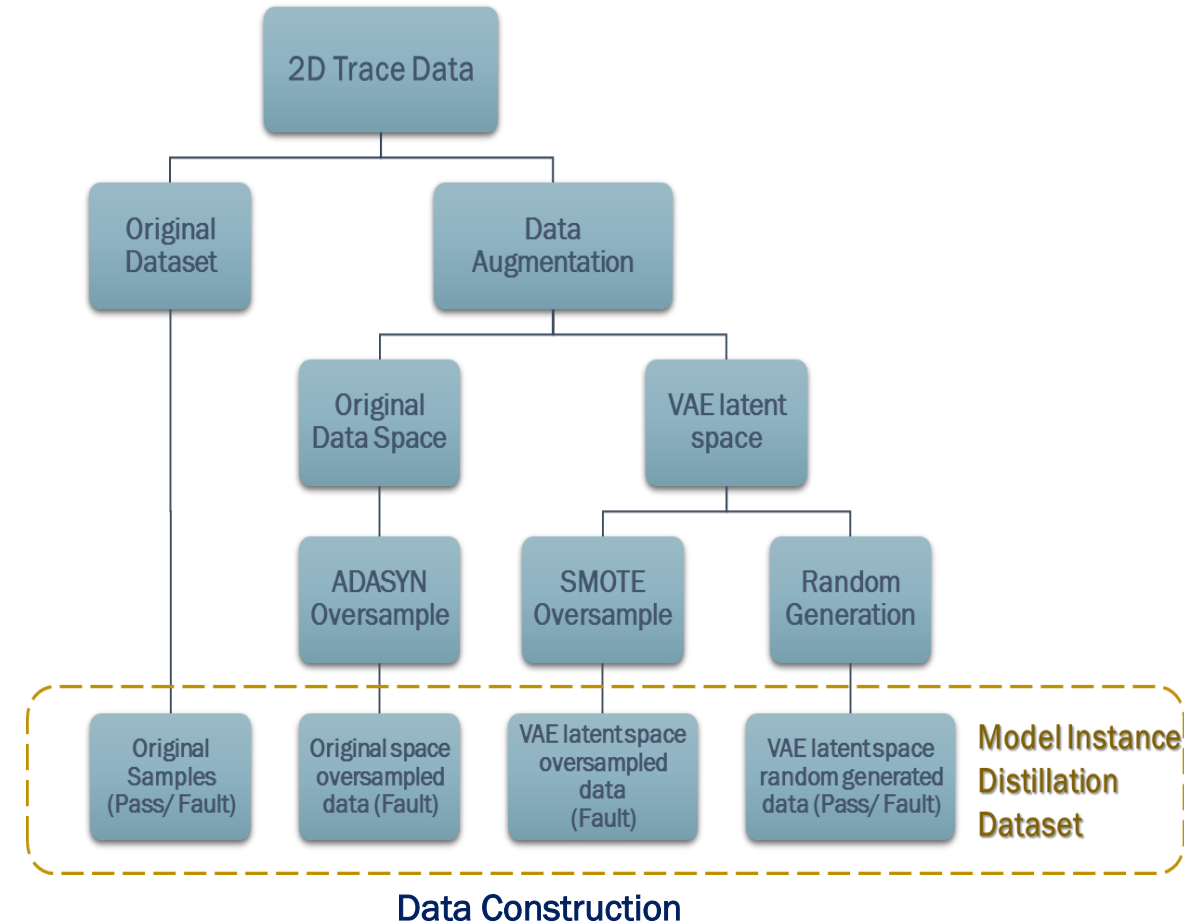
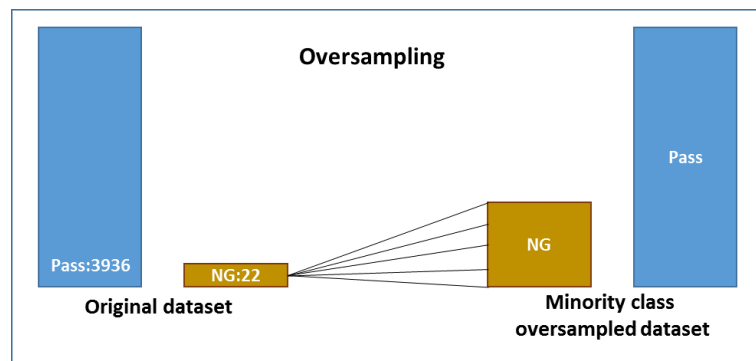
Comparison with other works	
ImageNet	Our Research
14,197,122 images	3,958 samples
1000 classes	Binary classes
<b>14K images/class</b>	<b>2K images/class</b>
Class balanced	Class imbalance (3936 : 22 (+500))
Fully trained	Transfer learning
97% / 86.4%	<b>91% / 82%</b>

## Minority Class Data Oversampling

- Original data space
- Latent space

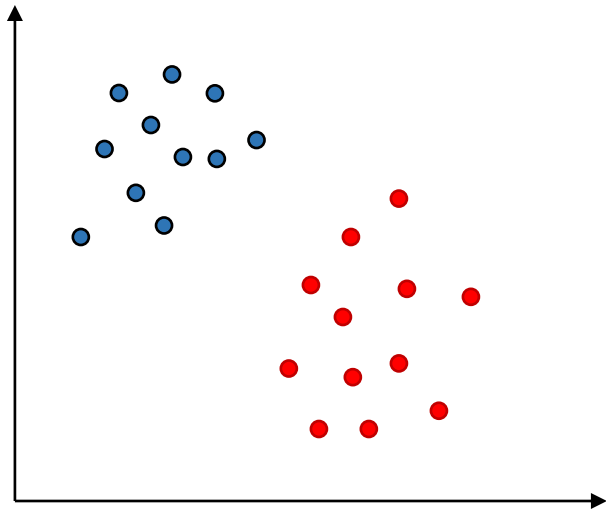
## Synthetic Data Generation

- Random data generation using deep generative model



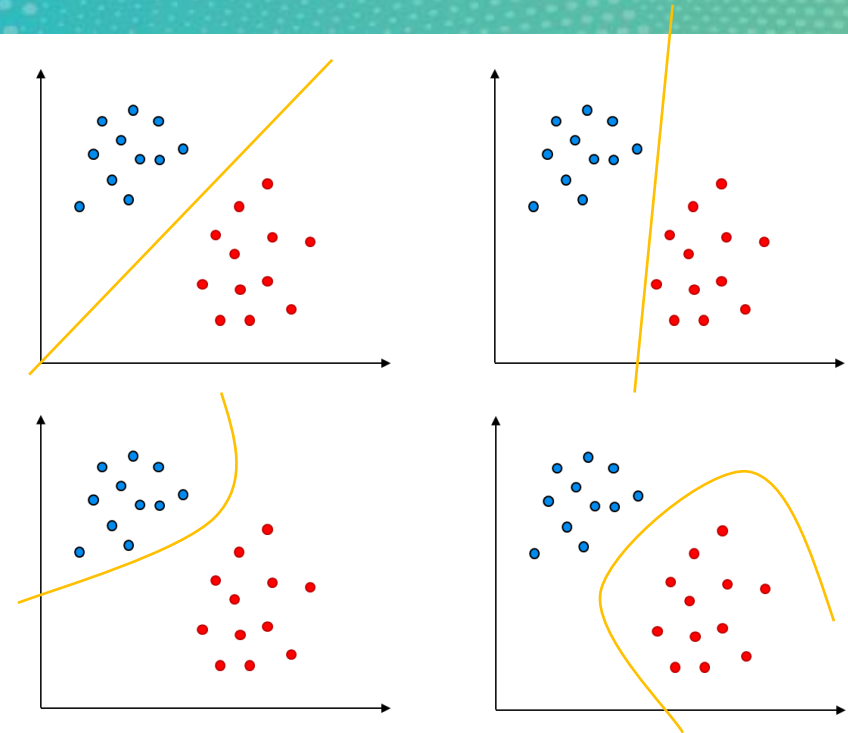
# Issue for Data Insufficiency: Generalization

- **Lack of generality**



*Small dataset to train a deep Learning model*

*With a given dataset, all ML/AI models make same classification*



*Multiple decision boundary from multiple instantiation of ML models*

*These ML/AI models will make different decisions for future data*

# Issue for Data Insufficiency: Explanation

- To train complex DNN model with limited amount of data samples is a challenging task.
- The curse of dimensionality:

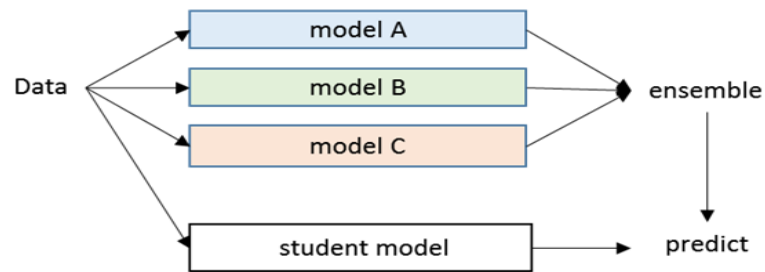


## Hypothesis

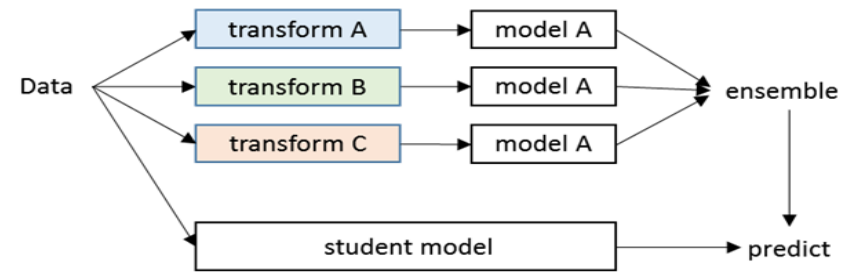
The major issue for generating a generalized model with limited dataset is the **sparsity** of input dataset and this issue could be improved by **augmenting dataset with enough variance**

# Knowledge Distillation: Model Instance Distillation

- Existing models

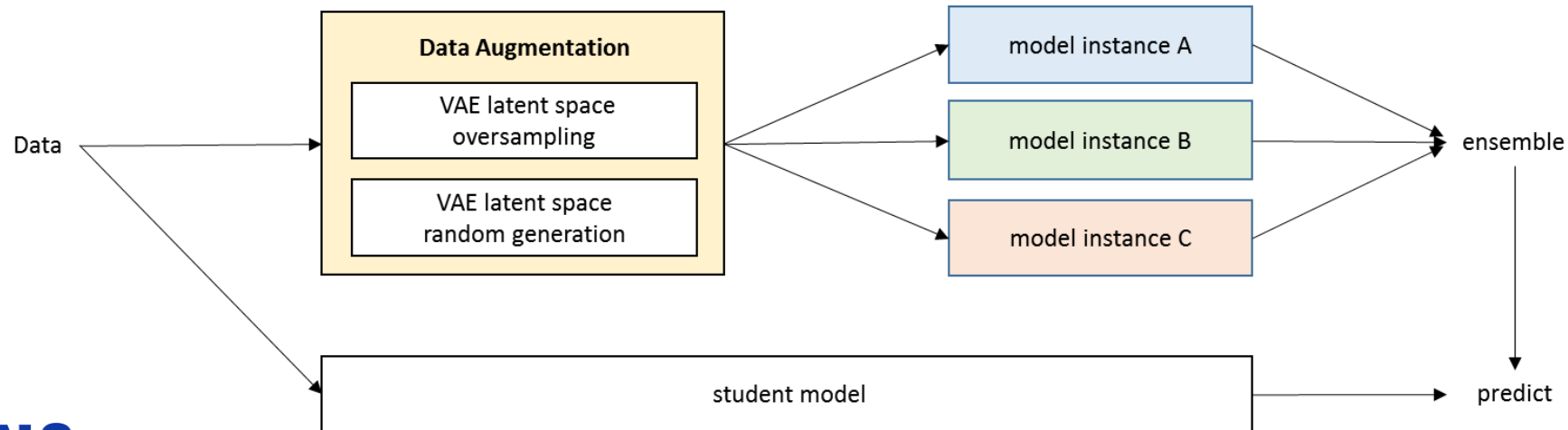


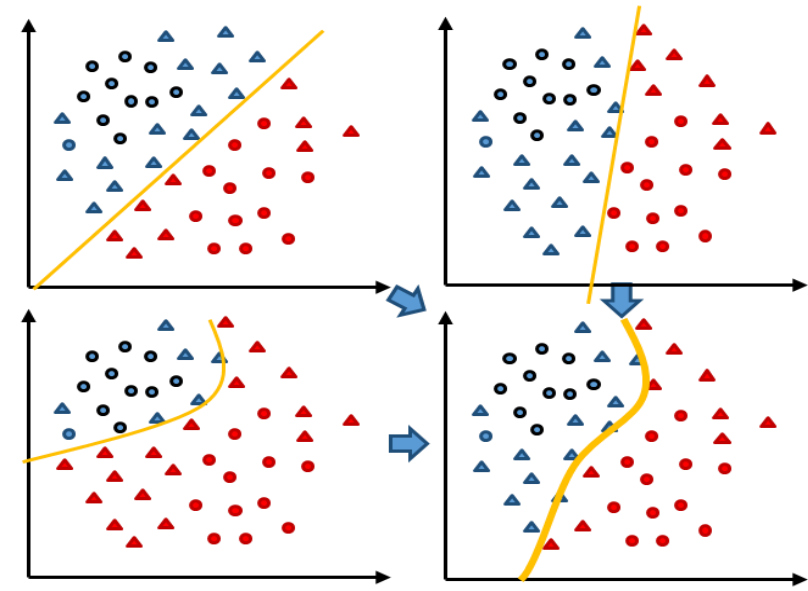
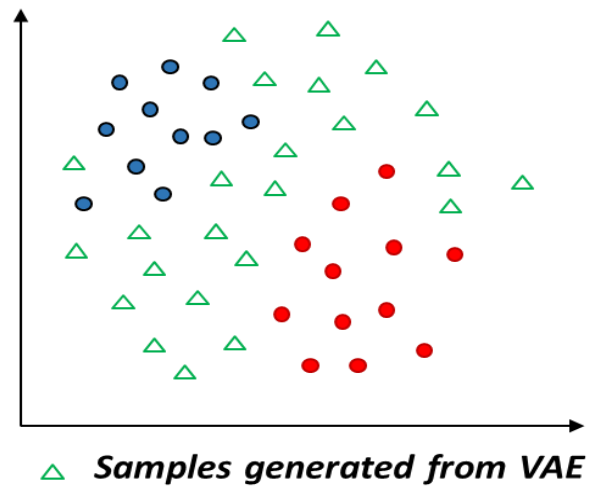
(a) Model distillation



(b) Data distillation

- Model Instance Distillation (MID)





- Searching for a method to augment variability in input data
  - (a) Spatial transform (b) Obtain unlabeled dataset (c) **Generative model**

Could we generate data points to clarify the decision boundary?  
⇒ Deep Generative Models (VAE)

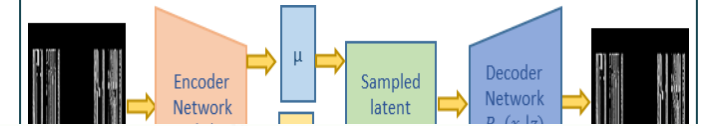
Knowledge distillation from multiple instances of AI/ML models into a dataset  
⇒ Generate a new dataset annotated with a new decision boundary

# Deep Generative Models

## Variational Autoencoder (VAE)

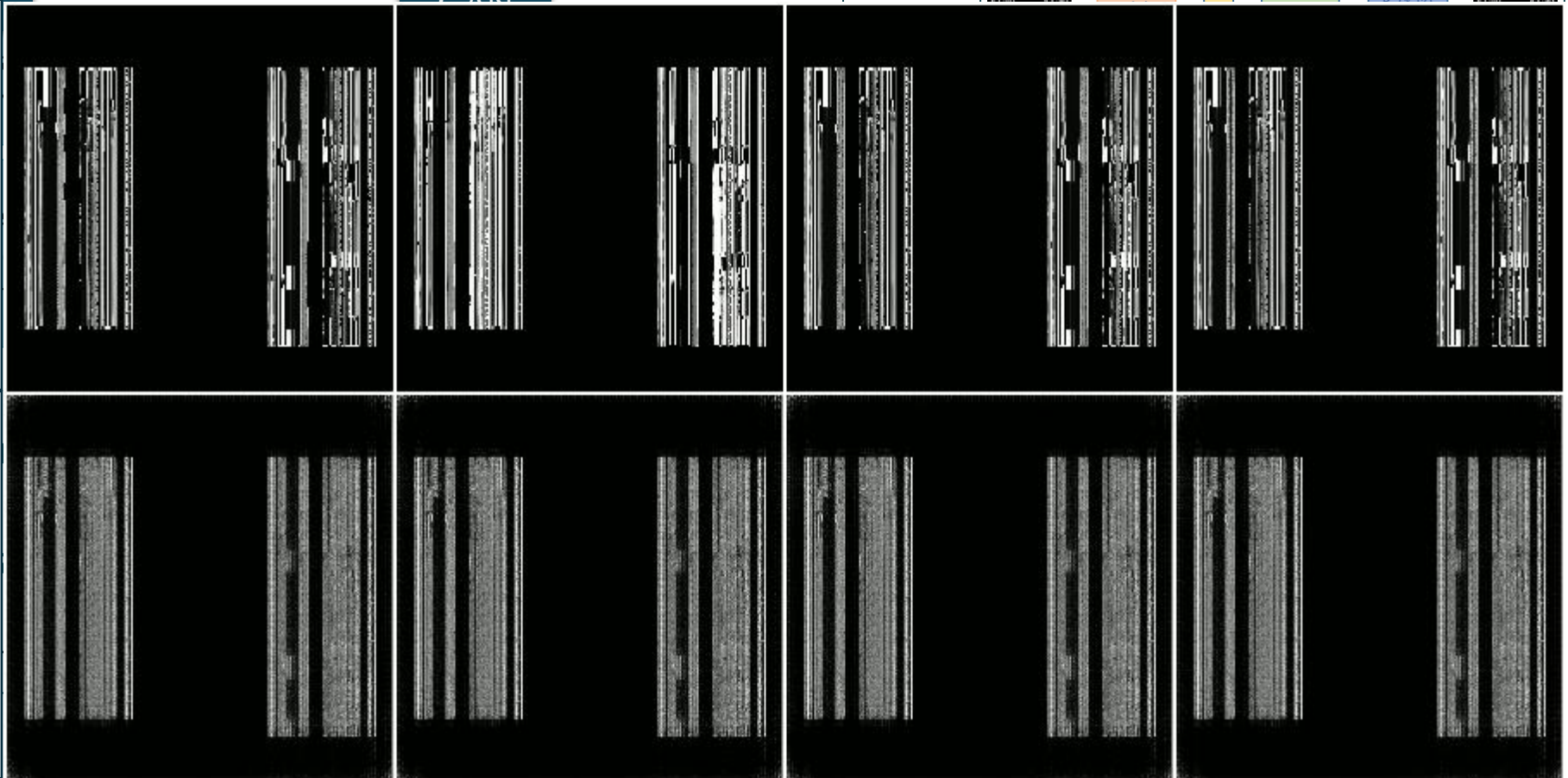
- Generative model comparison

## Architecture



Original  
Data

Reconstructed  
Data





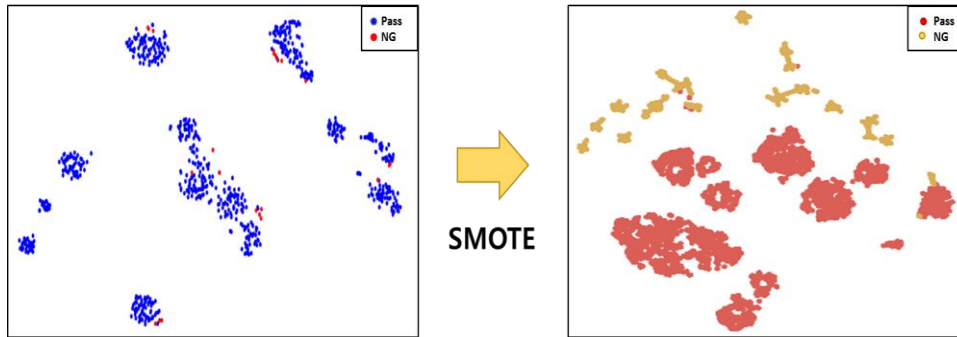
# Experiments and Results

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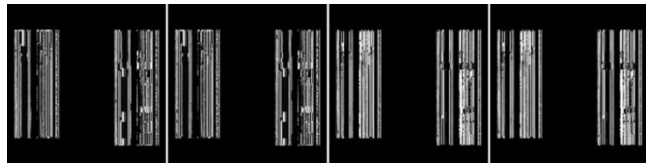


# Dataset : Data Augmentation for MID

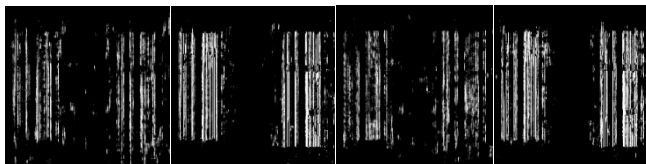
## VAE Latent Space Oversampling



- *Generate samples with label in latent space*
- *Cluster analysis and classification in latent space*

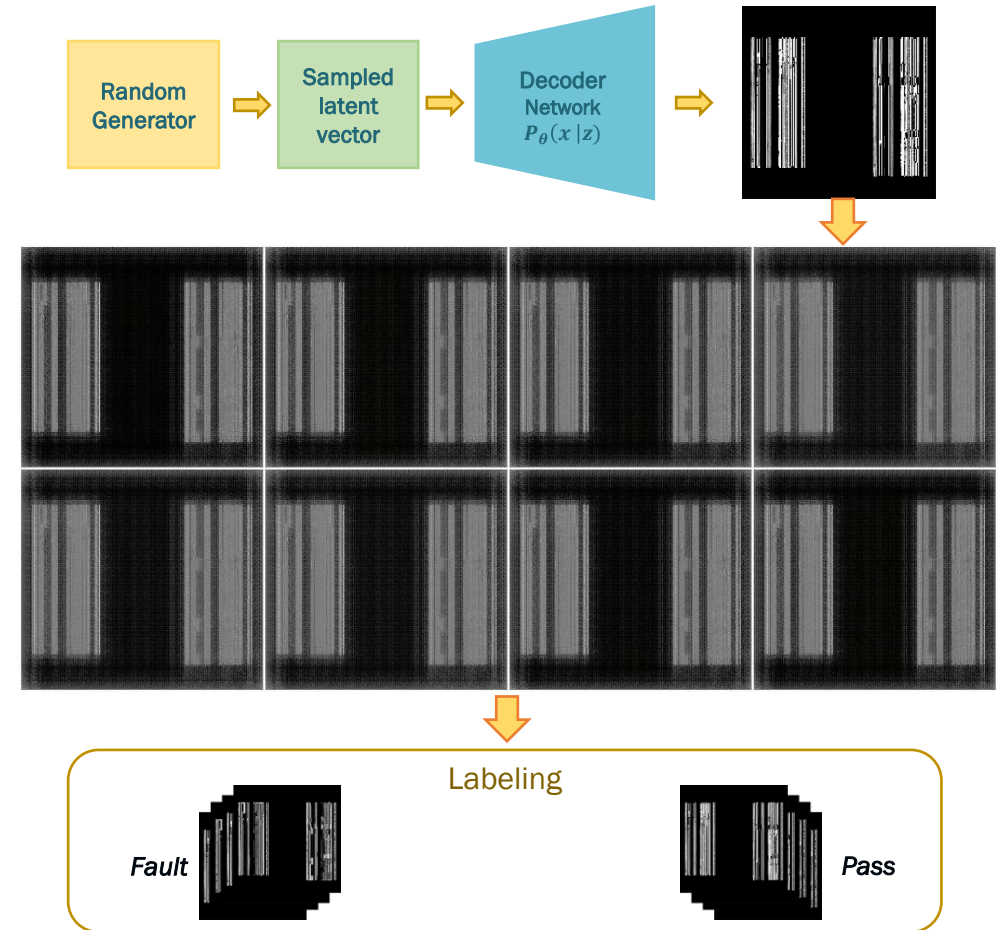


VAE latent space oversampling

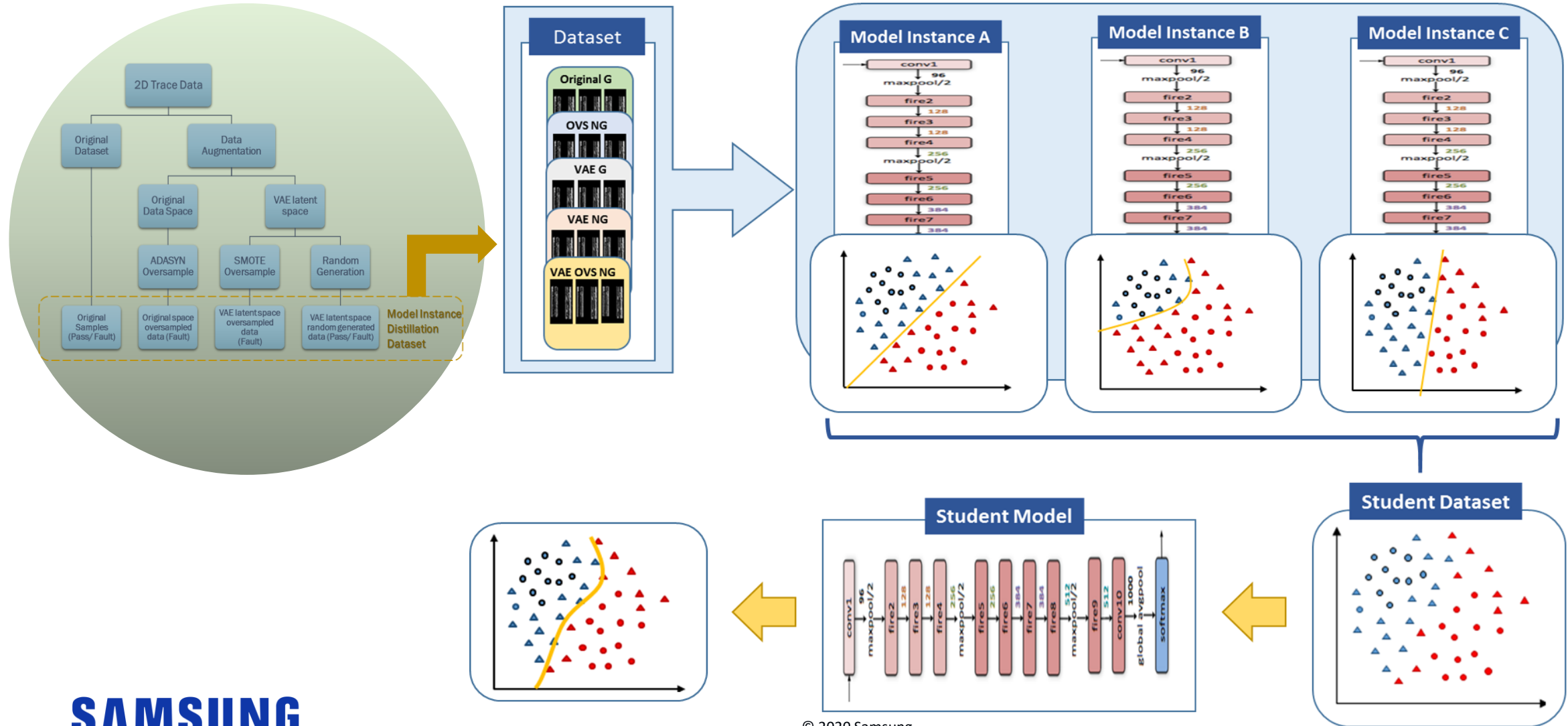


Bad case of oversampling

## VAE Latent Space Random Generation



# Model Instance Distillation (MID)

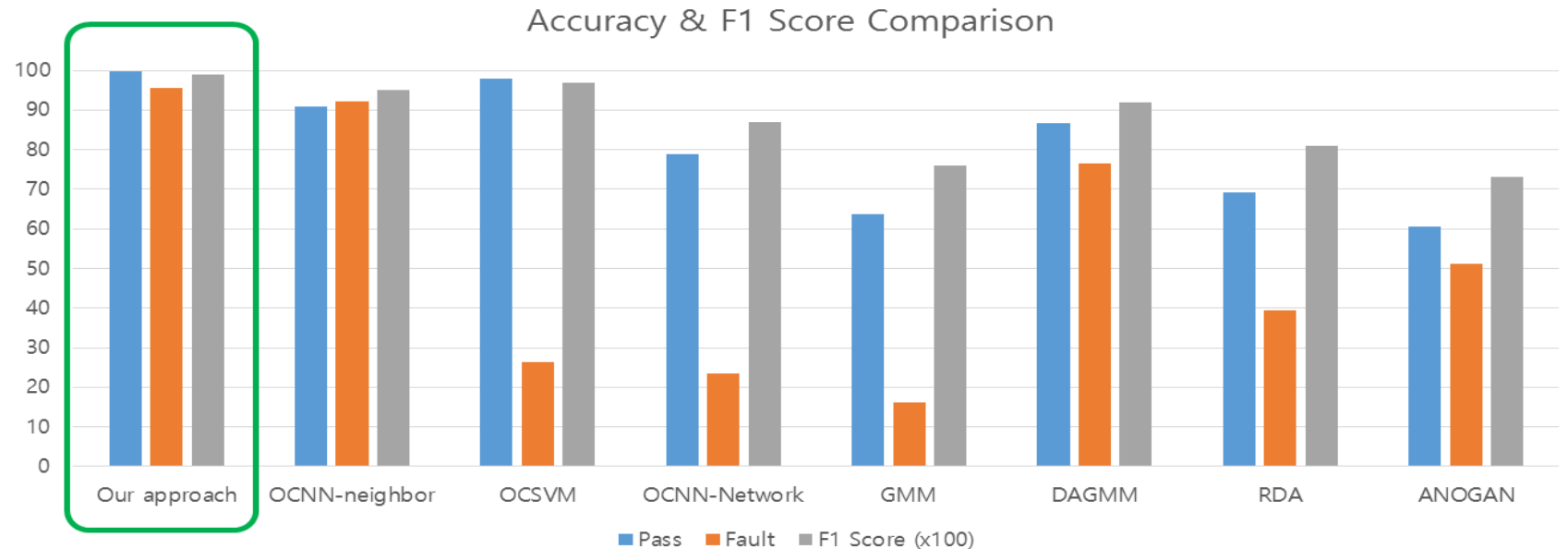


- Fault condition classification results
- Comparison with other approaches
  - High Accuracy
  - Model Consistency
  - Light weight comparing to ensemble models

Classification Results		
Type	Training Accuracy	Test Accuracy
Pass	1.000	0.9975
Fault	0.9997	0.9545

Classification Results w/o VAE OVS		
Type	Training Accuracy	Test Accuracy
Pass	1.000	0.9988
Fault	0.9997	0.9091

## Comparison with other methods



- **High accuracy fault condition classification** using supervised trace data together with large amount of synthetically generated data in VAE latent space.
- **Knowledge distillation from model instances** over augmented dataset to overcome class imbalance and data insufficiency.
- Proposed a method to **generate 2D trace data** from multivariate manufacturing sensor signals.

## Future works

- Deploy to monitor manufacturing processes
- Extend to other display manufacturing datasets
- Cluster analysis in latent space

## References

### 1. Trace Data Analytics with Knowledge Distillation

J. Lee, W. Xiong, and W. Jang, ASMC (2020 )

### 2. Auto-Encoding Variational Bayes

D. Kingma and W. Welling, Proc. ICLR (2015)

### 3. Data Distillation: Toward Omni-Supervised Learning

I. Radosavovic, P. Dollar, R. Girshick, G. Gkioxari, K. He, CVPR (2018)

### 4. SqueezeNet: Alexnet-level accuracy with 50x fewer parameters and <0.5MB model size

F.N. Iandola, S. Han, M.W. Moskewicz, K. Ashraf, W. J. Dally, K. Keutzer, arXiv (2017)