I-Form

Advanced Manufacturing Research Centre

A World Leading SFI Research Centre

Science Foundation Ireland For what's next

Approaches and Datasets

Xiao Liu

HOST INSTITUTION

PARTNER INSTITUTIONS

FUNDED BY:

I-Form is an SFI Research Centre funded under the Science Foundation Ireland Research Centres Programme and co-funded under the European Regional Development Fund.

Datasets

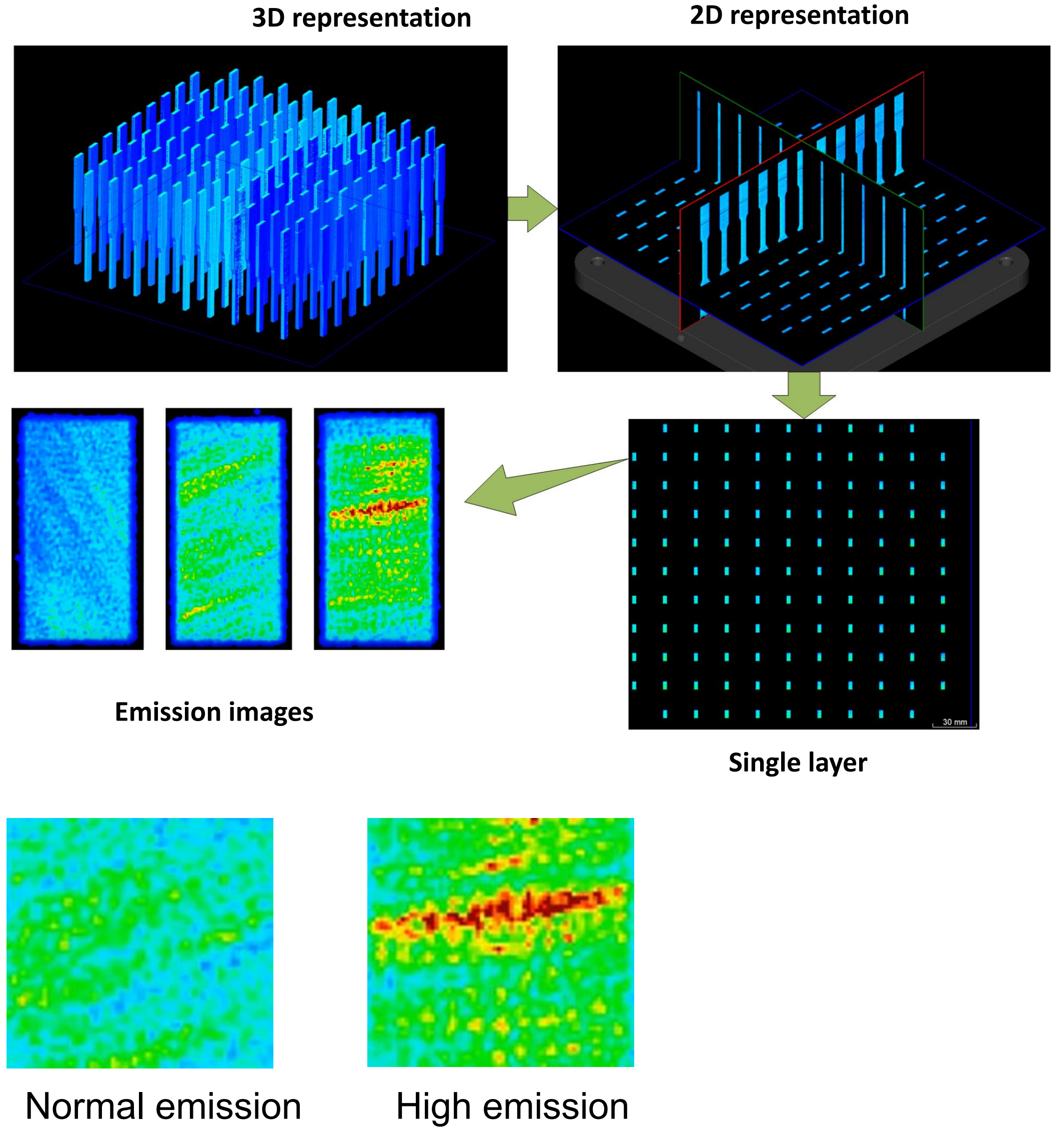
The emission images:

The in-situ monitoring system facilitates the collection of large amounts of data during the build process.

The formation of defects in parts is typically related to the stability of the meltpool.

With increased instability and size of the meltpool comes an increase in the level of emissions generated as the laser processes the material.

It is still a manual process to do analysis and characterization of emissions, that involves looking at the 2D & 3D representations of the parts.

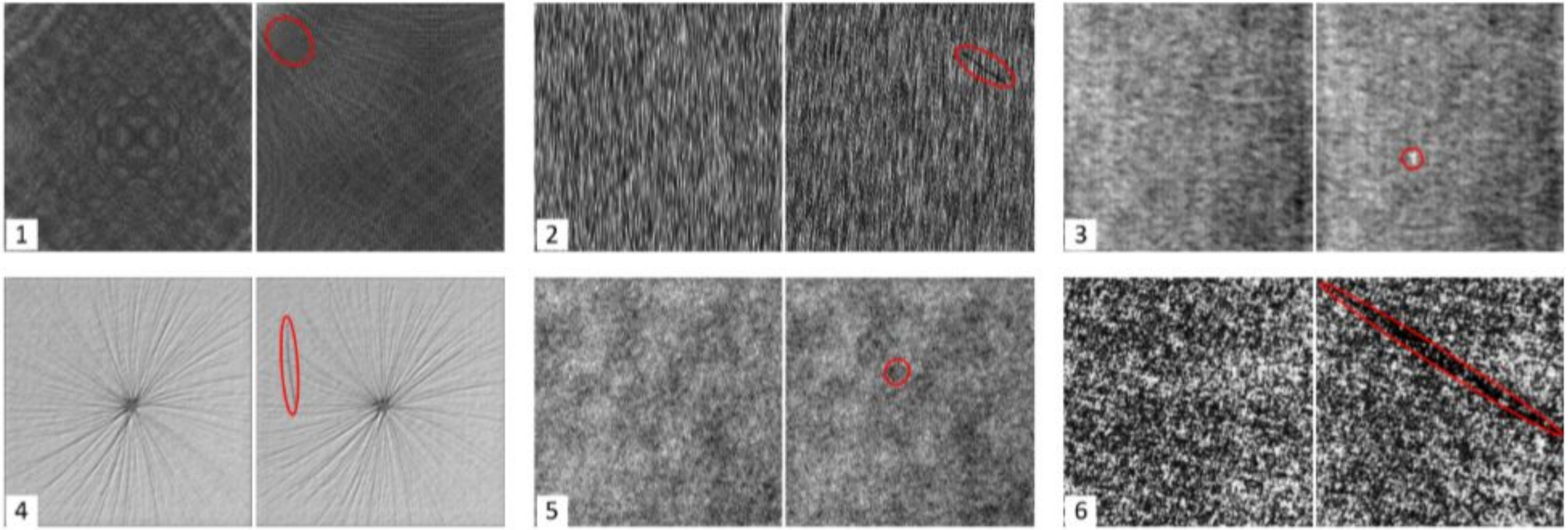


The dataset:

- 11,000 emission images have been manually examined to create a balanced labelled dataset

- The dataset contains 150 positive and 150 negative samples for the initial training and validation.

Comparative analysis on an open dataset



The DAGM datasets:

A public industrial dataset used as side support for testing purposes

- German Association for Pattern Recognition
- Contains 6 patterns with and without Defects
- 1000 normal and 150 defect for each pattern for total 6900 images

Data storage:

- GitHub, good for collaboration and version control
- Google drive, can be mounted with Colab and supports large size uploading
- There will be a tutorial for Transfer learning/Fine-tuning based on Keras (https://keras.io) and Google Colab

Approaches

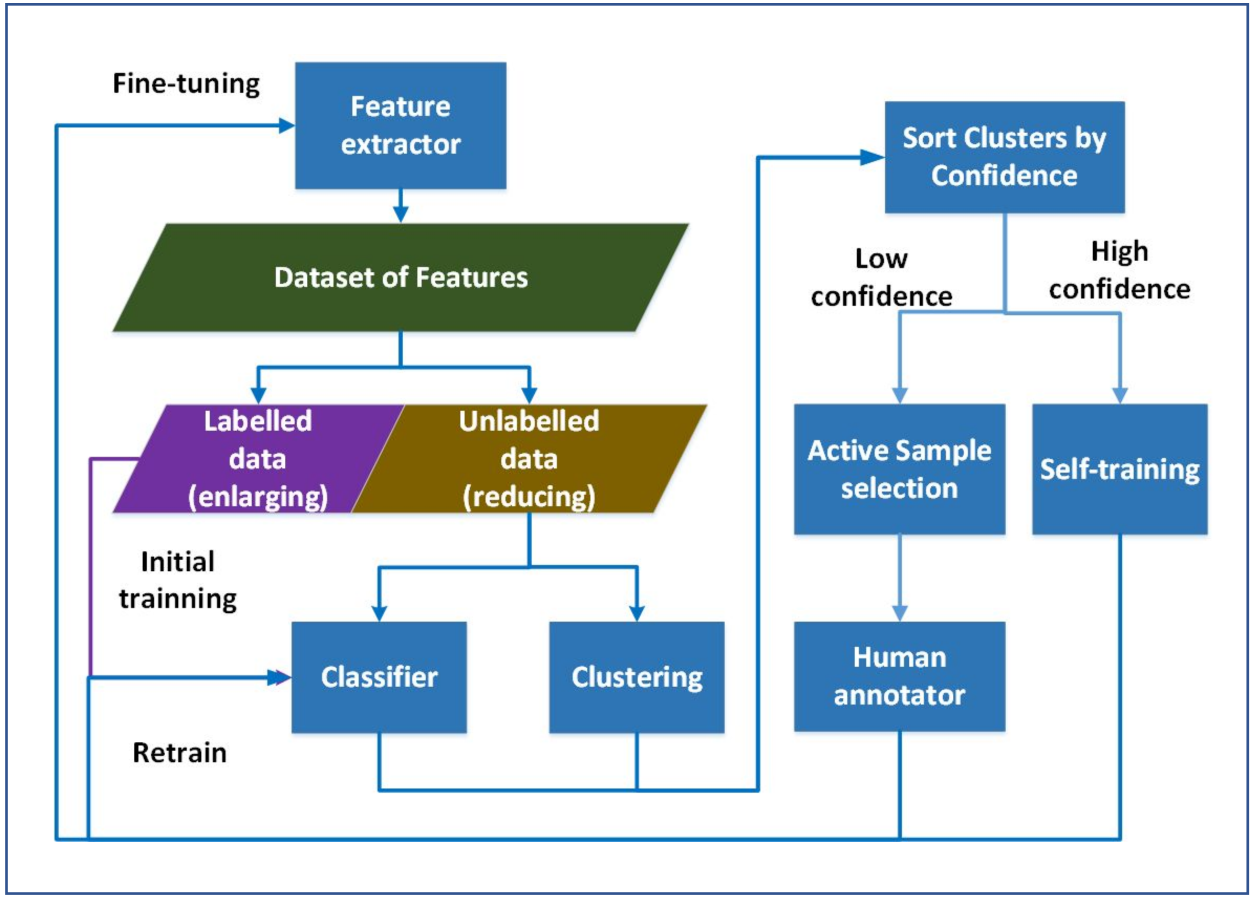
Aim of the project:

The project aims to apply neural network (NN) models to automated optical inspection of the data streams collected from an In-situ monitoring system and continuously improve the NN models while accelerating the data labelling process and gaining understanding about the manufactured object from the data

Labeling Framework:

Using a combination of Active learning and Semi-supervised learning, a framework has been designed to overcome the challenge of labelling large amount of emission image data in a data driven style.

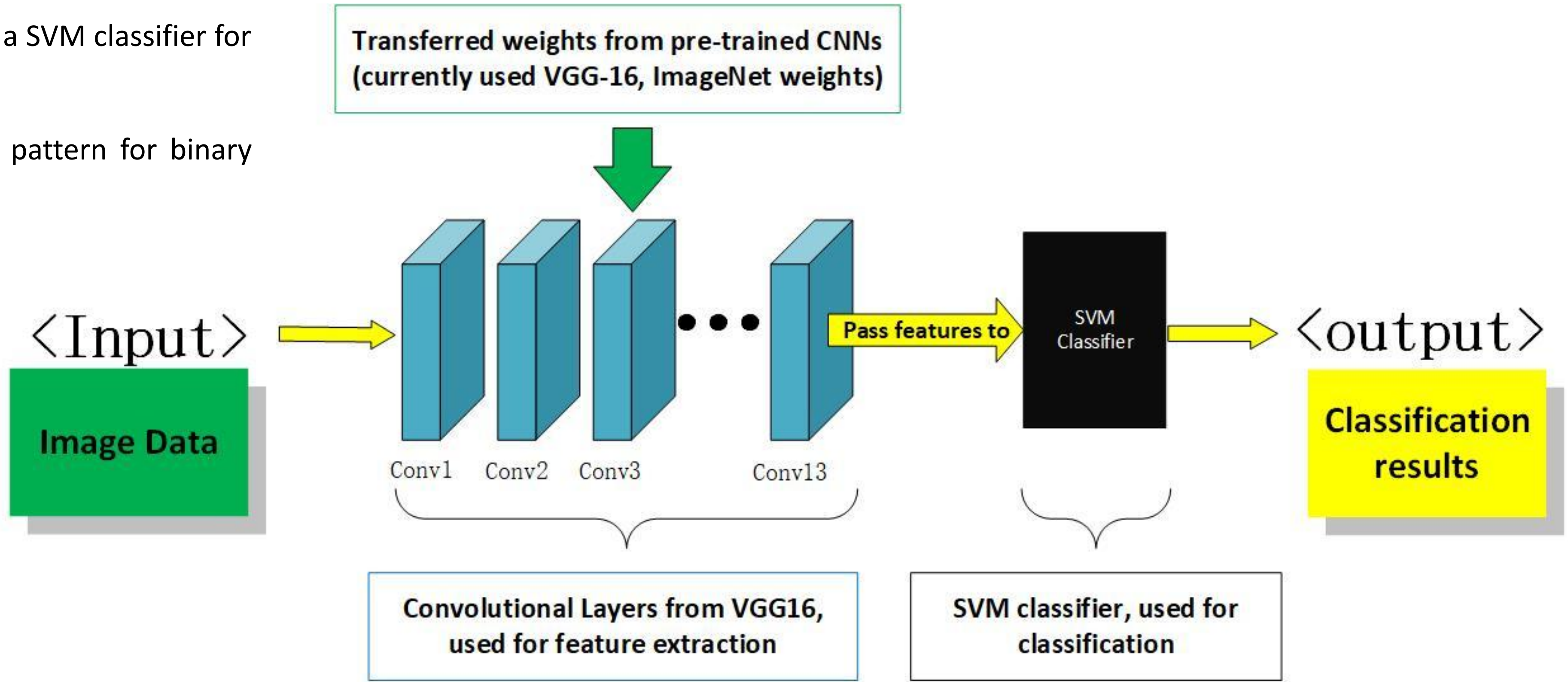
- Samples in the clusters with high confidence pass to self-training
- Samples in the cluster with low confidence pass to active learning/human annotator
- Retrain/further fine-tuning and next iteration to improve NN models



Transfer Learning approach (without fine-tuning)

Transfer Learning (VGG16+SVM) :

- Directly use a VGG16 CNN model which has been trained using the image data from ImageNet
- The VGG16 model is used to extract features from the images in the dataset show in the previous slides.
- These features are further pass to a SVM classifier for classification.
- This approach is applied to each pattern for binary classification.

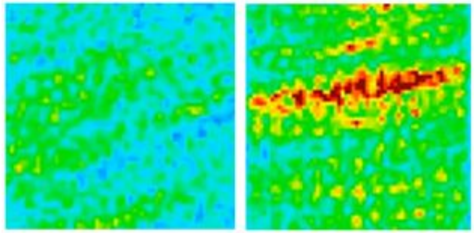


Transfer Learning approach (without fine-tuning)

Output:

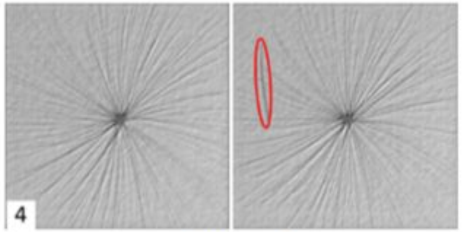
- This is a testing on the performance for image dataset
- works well for some patterns, but not all of them
- For the low performance patterns, **Fine-tuning** can improve

good performance:



Class 7

Low performance:



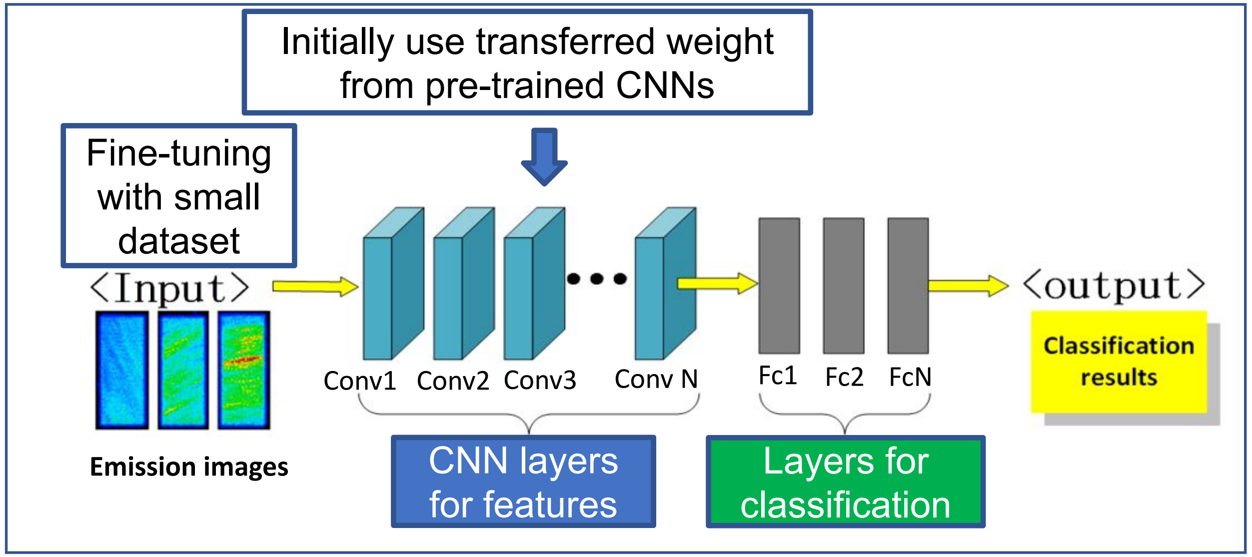
Class 4

Class	Precision	Recall	F1-score	Support
Class1_Def	0.88	0.15	0.25	42
Class1	0.50	0.98	0.66	48
Class2_Def	0.50	0.52	0.51	42
Class2	0.57	0.54	0.55	48
Class3_Def	0.47	1.00	0.64	42
Class3	0.00	0.00	0.00	48
Class4_Def	0.47	1.00	0.64	42
Class4	0.00	0.00	0.00	48
Class5_Def	1.00	0.79	0.88	42
Class5	0.84	1.00	0.91	48
Class6_Def	0.57	0.92	0.72	42
Class6	0.94	0.35	0.52	48
Class7_Def	0.91	0.98	0.94	42
Class7	0.98	0.92	0.95	48

Our approach

CNN models:

Use pre-trained Convolutional Neural Networks (CNN) with transfer learning and fine-tuning to do classification on the images from the manufacturing process.



Advantages

- Only require relatively small amount of labelled data for the initial training
- The training of such a model requires relatively low Computational power
- Show relatively good general performance and have potential to be further improved

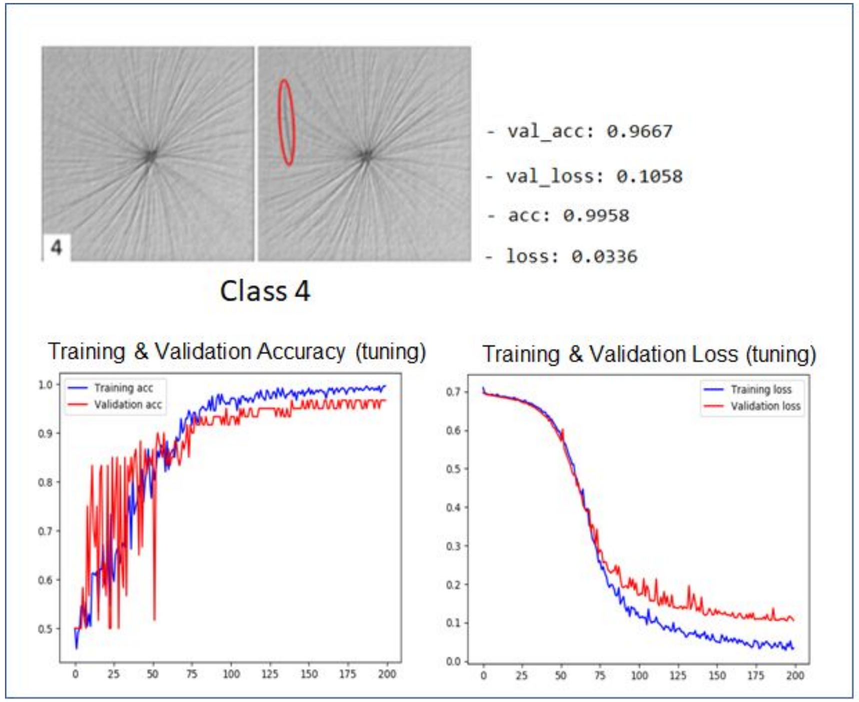
Transfer Learning approach (with fine-tuning)

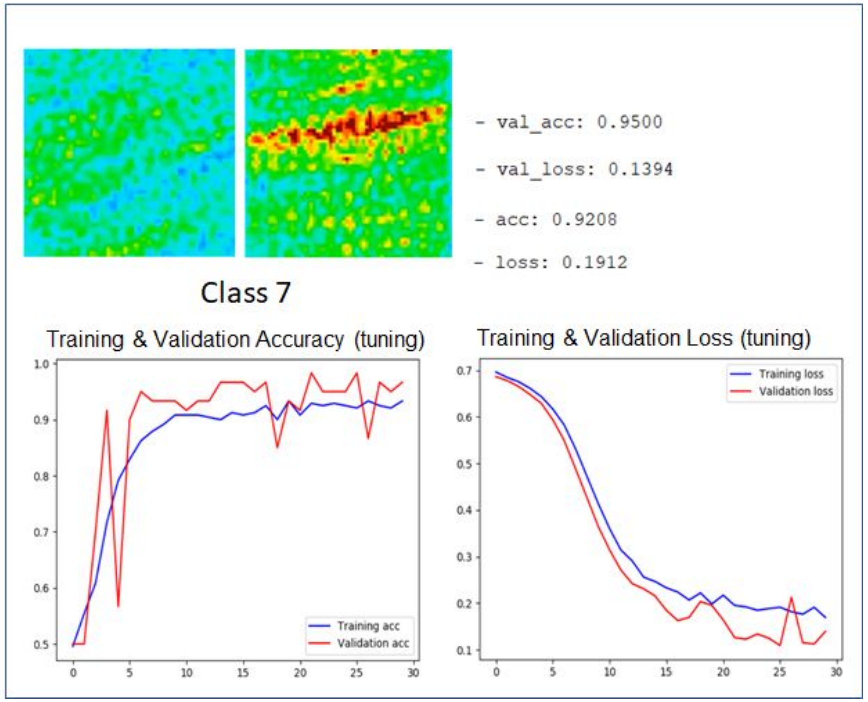
Fine-tuning (VGG16) :

- Still use a VGG16 CNN model which has been trained using the image data from ImageNet
- Still use the VGG16 model to extract features from the images in the dataset.
- Add fully connected layers after the VGG16 layers for classification
- Apply fine-tuning to further modify the weight in the model using some of the image data from the dataset

Output:

- Result shows significant improvement on previously low performance patterns
- classification accuracy for Class 4 increased to over 96%
- Still works well for Class 7 with 95% classification accuracy, in fact, this can be further improved





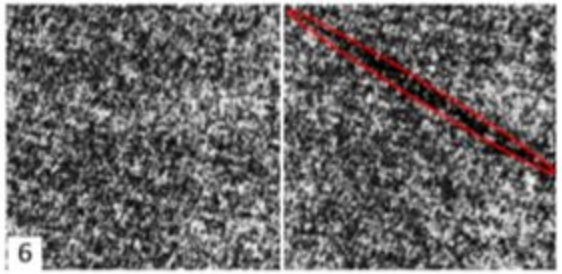
Freeze or fine-tune?

What if we don't fine-tune the model ?
More experiments show that:

- Using the pattern 6 dataset for testing for 200 epochs
- Same setting of the model (VGG16+fully connected layers)
- Classification test without fine-tuning
- Apply fine-tuning on the model and then do the Classificatio

Output:

- With tuning, there is a significant improvement in validation accuracy (from around 80% to 95%)
- Reduction in validation loss (from 0.6 to about 0.1)
- Classification with higher confidence, results more stable



Class 6

Lab:

- There will be a lab section on how to do transfer learning and fine-tuning using Keras Python package on Colab