# MATH 6380o Final Project: Defects Recognition on Nexperia's Semi-Conductors

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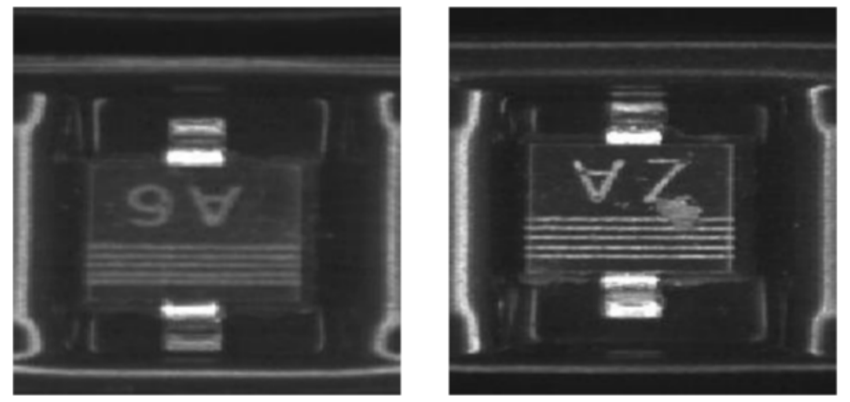
## Introduction

Nexperia is the world's leading producer of semi-conductors, which will produce billions of semi-conductors every year. Due to its tiny size of products and large production, quality assurance emerges as a tough issue. Thanks to the development of Deep Learning techniques, the defects in semi-conductor devices can be detected more accurately and efficiently than the current human-based anomaly detection methods.



In this project, we transfer pretrained CNN model to this binary classification task, where the one class is semi-conductors in good quality and the other in bad quality. Then the fine-tuned feature selection and classification procedure have been visualized for better understanding and interpreting the classification results.

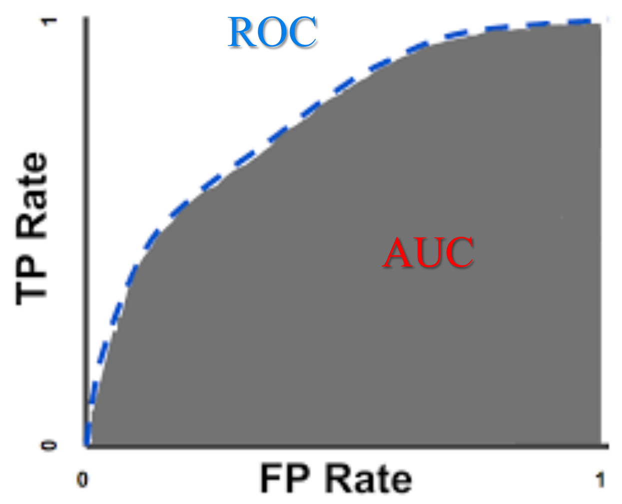
## Data Description

The labelled data are provided by Nexperia, which contain 3,000 bad product images and 27,000 good ones, 1,000 of the images are randomly chosen to be validation data and the rest are used as training data in our experiments.

Finally, the classification performance will be evaluated by additionally 3,000 images as test data and its Area Under Curve (AUC) will be computed.

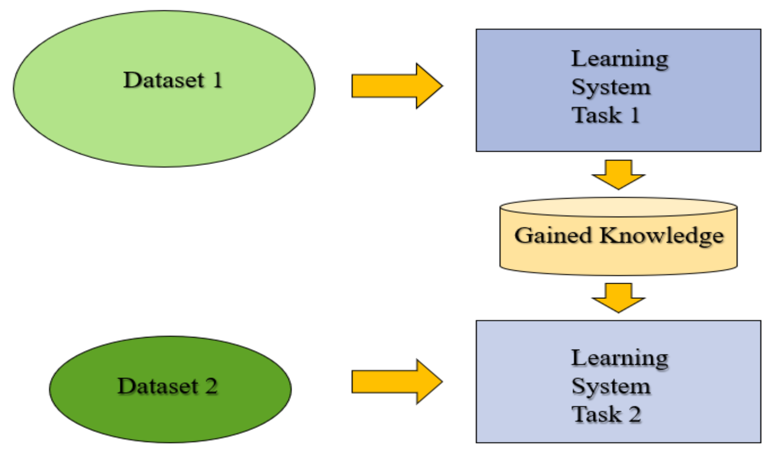
## ROC Curve and AUC Score

ROC Curve measures the relationship between False Positive Rate (FPR) versus True Positive Rate (TPR), where with a fixed FPR we expect a higher TPR. Running through all the classification criteria, we measure the area under ROC Curve (normally between 0.5 and 1) as the performance measure of classification results. We expect a higher AUC score for better models.

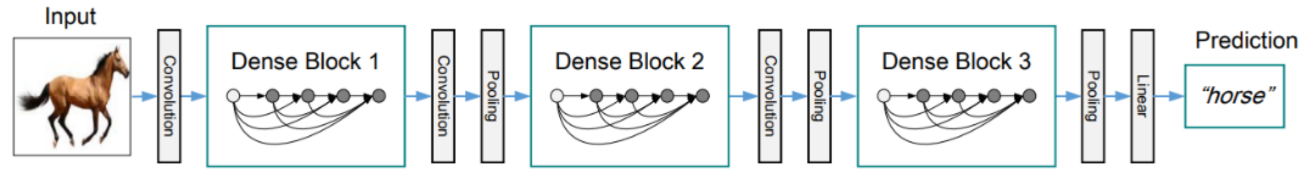



## Transfer Learning

Transfer Learning is a new research area which aims to store the pre-learned knowledge to one specific problem and applies it to the other related problem. The transferred related knowledge can help with improving the training efficiency in most problems, and the number of parameters to train can be largely reduced.




In this project, we use pre-trained DenseNet-121. DenseNet is also known as Densely Connected Convolutional Networks, which builds shorter connections between layers in a feed-forward fashion [1]. While the traditional Convolutional Neural Network (CNN) with L layers has L connections, DenseNet has L(L+1)/2 connections with direction. DenseNet achieved significant improvement in highly competitive object recognition or image classification tasks like: CIFAR-10, CIFAR-100, SVHN, and ImageNet.




Advantages of DenseNet are demonstrated as follows:

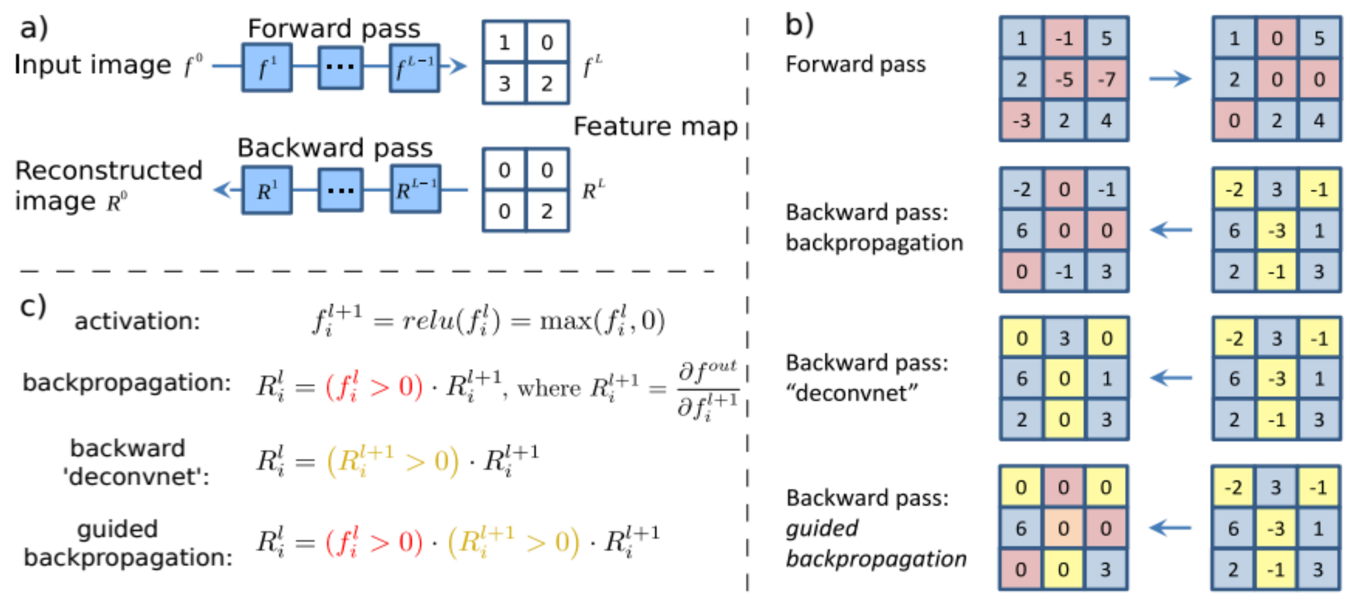
1) DenseNet can alleviate the vanishing-gradient problem;
2) Feature propagation can be strengthened;
3) DenseNet encourages feature reuse;
4) Significantly reduces the number of parameters.

## Deconvolution network approach

We first want visualize the features by a python visualization toolkit "FlashTorch", which is built with Pytorch for neural networks. In this step, the feature visualization aims to understand how our convolutional neural networks perceive images. It is a new variant of the "deconvolution approach" for visualizing features learned by CNNs.

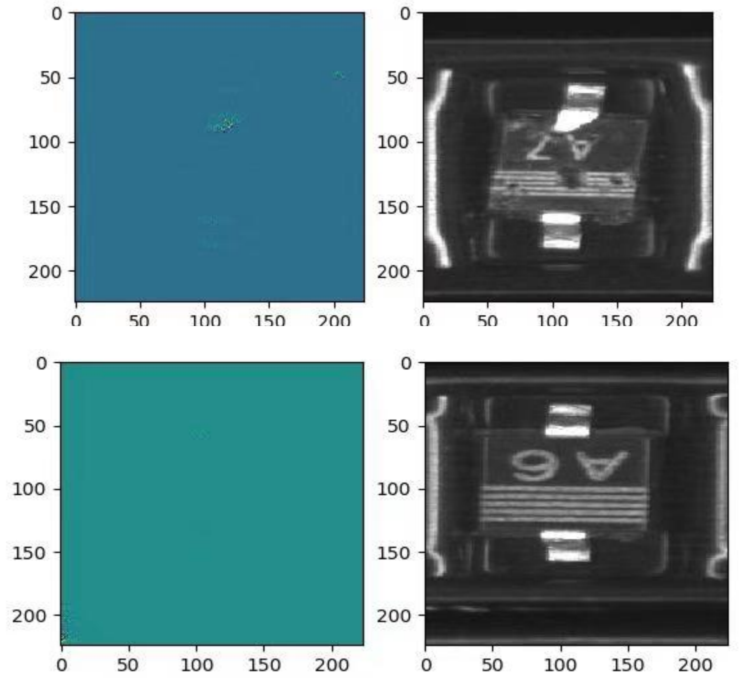
The deconvolutional network "deconvnet" approach to visualize concepts learned by neurons in higher layers of a CNN can be summarized as follows: Given a high-level feature map, the "deconvnet" inverts the data flow of a CNN, going from neuron activations in the given layer down to an image.

Typically, a single neuron is left non-zero in the high-level feature map. Then the resulting reconstructed image shows the part of the input image that is most strongly activating this neuron (and hence the part that is most discriminative to it). The figure below[2] is the schematic of visualizing the activations of high layer neurons.

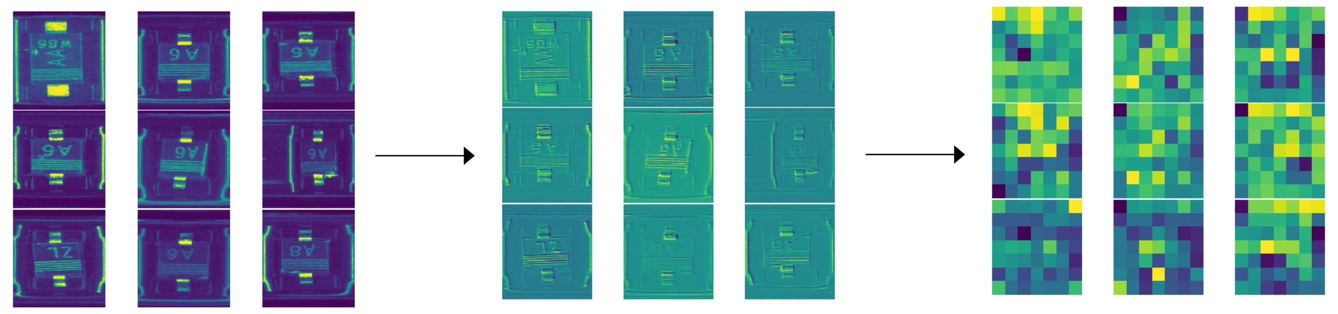



## Feature Visualization

The saliency maps for defective-(top) and good-(down) conditioned semi-conductors have been shown as follow. We can observe a spike signal on saliency map for defects at the injured position, which means the pre-trained DenseNet can find the defects for the semi-conductors well only through images. In this way, the labor cost can be reduced, and the efficiency can be improved.



For our semi-conductor images, the feature visualization is represented as below in viridis color scale, including the original greyscale images (left). The filter transformation are illustrated in the other two figures. The second figure (middle) is the illustration of post first convolution layer images, and the last one (right) is for post last convolution layer images. It is demonstrated that shallow layer feature map preserves low-level features (e.g. edges), while deeper ones contain more uninterpretable semantic information.



Original Images (viridis heatmap) | Post 1st convolution layer images, channel 5 | Post last convolution layer images, channel 5

## Results

In this semi-conductor defects identification task, we achieve good performance in training set and validation set.

| | Precision | Recall | Accuracy | F1 Score |
|---|---|---|---|---|
| Training Set | 1.0000 | 1.0000 | 0.9999 | 1.0000 |
| Validation Set | 0.9857 | 0.9933 | 0.9810 | 0.9895 |

We apply the model with best validation results to the test dataset, where we achieve AUC score = 0.92537, which can be interpreted as the probability to classify a random image into the right class. The AUC score shows the generality of our classification model.

## Contribution

- Mutian He: Transfer learning using DenseNet-121, Feature visualization using FlashTorch, Binary classification on testing datasets
- Yuxin Tong: Feature visualization using FlashTorch & Poster
- Qing Yang: Results analysis & Poster
- Ruoyang Hou: Transfer learning & Slides

## Reference

[1] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

[2] Springenberg, J., Dosovitskiy, A., Brox, T., & Riedmiller, M. (n.d.). STRIVING FOR SIMPLICITY: THE ALL CONVOLUTIONAL NET. Posted on Arxiv., 2015 https://arxiv.org/pdf/1412.6806.pdf