Machine Learning Engineer Nanodegree

Capstone Proposal

Automated Optical Inspection using Deep Learning

Sai Tai

June 22nd, 2019

Domain Background

Automated Optical Inspection (AOI) is commonly used in the electronics and manufacturing industry to detect defects in products or its components. The traditional process takes place at regular intervals of time, usually a few months to tune the right parameters for building an ideal product model. It mainly uses the learning-based or rule-based method for defect classification, involving the whole production line for the purpose of quality control.

Since electronics and surface mount devices (SMD) are getting smaller nowadays, the accuracy of AOI is declining, thus an increasing need for manual inspections to prevent unidentified defect products. According to research, visual inspection errors typically range from 20% to 30% [1].

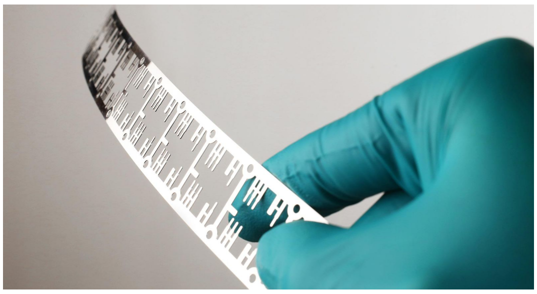

Fig 1: SMD component example [7]

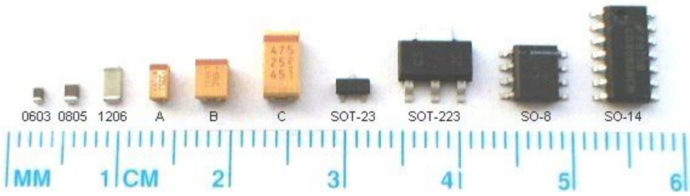

Fig 2: SMD component example [8]

Problem Statement

At present, electronics parts manufacturers are still widely using traditional manual inspection methods using the human eye. This however poses a few disadvantages, for example a high false detection rate, low detection efficiency and inflexible object adjustments . Since each of the inspectors may have his own subjective judgment of the product, it is hard to reach a high accuracy and with standard consistency.

Especially with a large and continuous production stream line, manual inspection cannot meet the testing requirements of today's industry standards. In addition, manual inspection remains a costly venture due to the appointment of (multiple) trained individuals. Cost-wise, manual inspection operators may be earning a yearly salary of $50,000 to $60,000. [2]

In our solution, we will only focus on the surface quality part to detect if there is any defect on the material sheet.

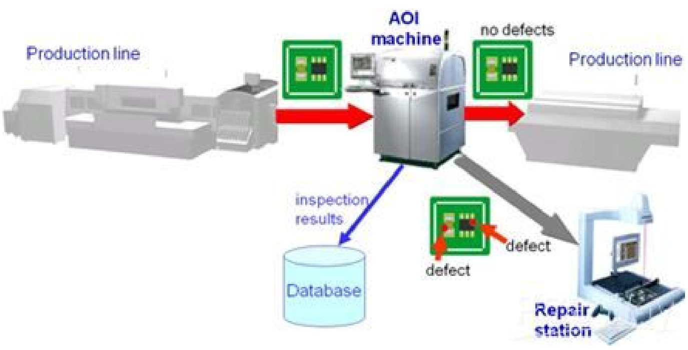

Fig 3: Post-Reflow Automated Optical Inspection [9]

Datasets and Inputs

For this project, I will train the deep learning model according to the order of the approaches listed below.

- If the current approach yields a successful performance, i.e. different defects can be identified correctly with an accuracy of above 50% (higher success rate than random guessing), I will adopt that approach as my model.
- If not, I will continue down the list of approaches to find one that results in a successful performance.

Approaches:
1: Directly using NEU surface defect dataset [5] to train the model.
2: Using transfer learning based on RestNet as our pre-trained model on a ImageNet dataset, then on top of it to use NEU surface defect database [5] to train a model.

In the Northeastern University (NEU) surface defect database, six kinds of typical surface defects of the hot-rolled steel strip are collected, i.e., rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In) and scratches (Sc). The database includes 1,800 grayscale images: 300 samples each of six different kinds of typical surface defects. The original resolution of each image is 200x200 pixels.

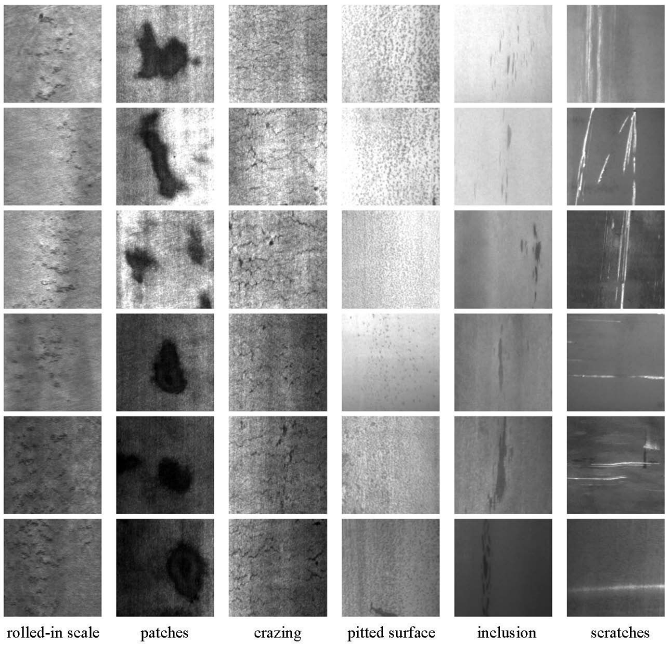

Fig 4: NEU surface defect database [5]

Solution Statement

We will use convolution neural network (CNN) to overcome the limitations of AOI and cater to varying sizes and orientation of objects. It will also make the whole inspection procedure independent of any human involvement. That said, minimal preprocessing such as image acquisition, rescaling, feature extraction and classification are still needed.

There are some experiments that may help to find the optimal architecture, such as data augmentation, initialization strategy, loss function and optimizer.

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$

Fig 6: Loss function: Cross-Entropy [3]
Source: superdatascience [3]

$$V_t = \beta V_{t-1} + (1-\beta) \nabla_w L(W, X, y)$$
$$W = W - \alpha V_t$$

Fig7: Optimizer: Stochastic Gradient Descent (SGD)
Source: towardsdatascience [4]

Benchmark Model

We can take reference to the investigations others have done with the NEU surface defect dataset. According to SAURABH G [6], his KNN algorithm can accurately classify the defect surface up to 75.27%.

Evaluation Metrics

The evaluation is done using accuracy metrics. The following formula shows the accuracy of the model given:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ Images}{Total\ number\ of input\ images}.$$

As the goal is to classify the defects, accuracy is an appropriate metric to evaluate the project. The accuracy tells us how well the algorithm is classifying the defects.

Project Design

Data preprocessing and augmentation

First I will try to organize the dataset into different categories, then split it into a training and testing set.

Prepare pretrained model

Using pretrained ResNet to see if such experience will help to recognise defects of my problem.

CNN model construction

I will use 2 approaches here to see which one is better:

1. Using the NEU dataset to train it from scratch.
2. Using pretrained model then adding new images to see if that helps.

Model training and evaluation

I will be tuning different parameters of data augmentation, initialization strategy, loss function and optimizer to find the optimal architecture. Then I will iterate this process to reach an accuracy score I am satisfied with.

Reference

[1] Drury C.G., Sinclair M.A., *Human and machine performance in an inspection task. Human Factors*, 25, 391–399, 1983.

[2] Glassdoor - *Quality Inspector Salaries*
https://www.glassdoor.co.in/Salaries/quality-control-inspector-salary-SRCH_KO0,25.htm

[3] Superdatascience - *Convolutional Neural Networks (CNN): Softmax & Cross-Entropy*
https://www.superdatascience.com/blogs/convolutional-neural-networks-cnn-softmax-crossentropy

[4] Vitaly Bushaev. *towardsdatascience - Stochastic Gradient Descent with momentum*
https://towardsdatascience.com/stochastic-gradient-descent-with-momentum-a84097641a5d

[5] Kechen Song and Yunhui Yan - *NEU surface defect database*
http://faculty.neu.edu.cn/yunhyan/NEU_surface_defect_database.html

[6] SAURABH G., *Use Machine Learning to Detect Defects on the Steel Surface, Benchmark*, 2018.
https://software.intel.com/en-us/articles/use-machine-learning-to-detect-defects-on-the-steel-surface

[7] image source: http://wallsviews.co/smd-led-lead-frame/

[8] image source: https://www.fpga4fun.com/SMD.html

[9] image source: https://www.pcbway.com/blog/PCB_Assembly/The_PCB_Assembly_Process.html