

A fast and robust CNN-based defect detection model using Image Processing techniques

Project Report

ME 714 - Computer Integrated Manufacturing

By

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Chapter 1

Motivation

Being familiar with Deep Learning and Computer Vision, we were looking to apply my skills in some Mechanical Engineering discipline for so long. This is a perfect opportunity for us and we want to achieve practical results on the things we've learned in theory about Quality Control in Manufacturing processes. We got an understanding of various quality control methods implemented in manufacturing industries through this course and decided to make an image processing-based model that can detect defects in a metal surface. This will go long way in future in dealing with defect-detection on an automation based system.

Objectives

- Exploring Quality Control in Manufacturing Processes like defect detection and how it works.
- Building a scientific framework for an image processing-based model for defect detection.
- Brushing up related CV-DL libraries required such as OpenCV and Pytorch .
- Using DAGM Texture Database having 1000 images per class for training the model.
- Extracting patches from the images for the training of the model.
- Examining test results of model and consequent effectiveness of it.

Chapter 2

Problem Statement

2.1 What is Quality?

Quality of a product can be described as it's fitness to use. It is dependent of the features and characteristics of a product or service that in turn affect its ability to satisfy a given need.



Figure 1 Quality Metrics of general product [1]

2.2 Quality Control

Quality control is a process carried out by manufacturing firms to make sure that their product or service is governed by certain quality standards or guidelines. This activity enables firms to have a minimum threshold for its products, processes & services in terms of quality.



Figure 2 Part of Quality Control [ii]

2.2.1 Benefits of robust Quality Control system

- Desire for rapid prototyping
- It becomes critical for companies to deliver high performance goods.
- Analysing variances between set controls and actual quality.
- Customers always seek high value & good quality in the products & services that they pay for.

2.3 Surface defect detection

Surface defect detection is an essential task in the manufacturing process to ensure that the end product meets the quality standards and works in the way it is intended. A common property of these surface defects is that their visual texture is inherently different from the defect-free surface.

2.3.1 Conventional Method and it's Disadvantages

Visual inspection systems are used for detecting these defects.

- The manual task of looking at objects and finding those anomalies is difficult and tedious.
- The appearances of these defects such as cracks, dents, smudges, and impurities can differ in terms of pixel intensities, geometrical constraints, and visual appearance as a whole.
- Traditional handcrafted or engineered features work on specific textures; however, they are challenging to create and don't generalize to other tasks.



Figure 3 Visual inspection in industries [iii]

Chapter 3

Solution Proposed

3.1 Neural Networks

A neural network is a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so, the network generates the best possible result without needing to redesign the output criteria.

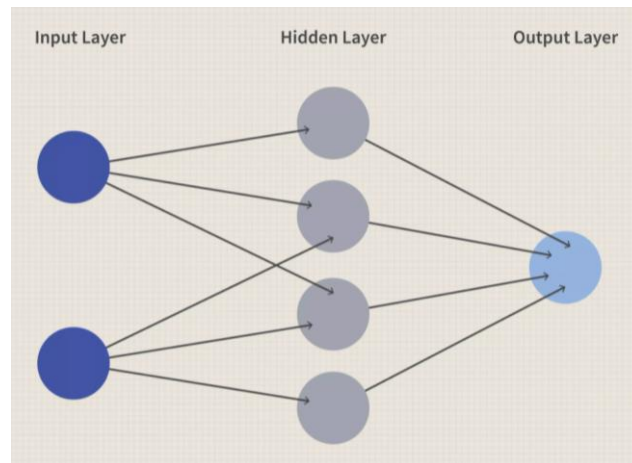


Figure 4 A Simple Neural Network [iv]

3.2 Drawbacks of traditional Neural Networks

The number of parameters in the state-of-the-art methods is generally in the order of tens to hundreds of millions. This forces the requirement of having a large GPU or a cluster of GPUs for training these models.

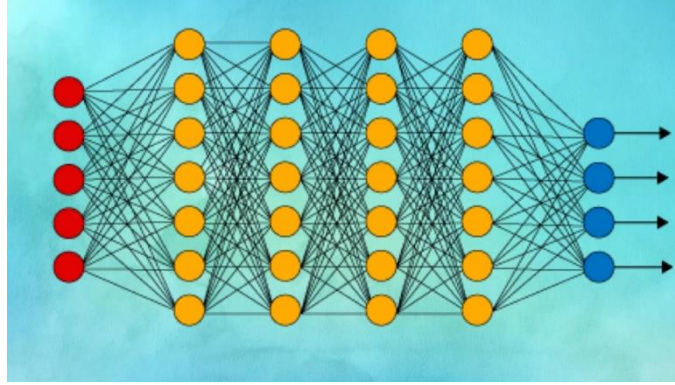


Figure 5 Deep Neural Network [^v]

3.3 Convolutional Neural Networks

CNNs are fully connected feed forward neural networks. CNNs are very effective in reducing the number of parameters without losing on the quality of models. Dimensionality reduction is achieved using a sliding window.

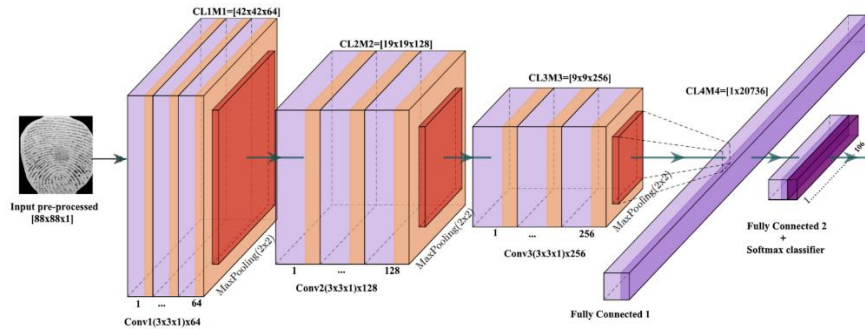


Figure 6 Convolutional Neural Network [^{vi}]

3.4 Dataset Used

In this work, a synthetic dataset for defect detection on textured surfaces. It was originally created for a competition at the 2007 symposium of the DAGM (the German chapter of the International Association for Pattern Recognition).

The data is artificially generated, but similar to real world problems. The first six out of ten datasets, denoted as development datasets, are supposed to be used for algorithm development. The remaining four datasets, which are referred to as competition datasets, can be used to evaluate the performance.

3.5 Salient features of dataset:

- Each development (competition) dataset consists of 1000 'non-defective' and of 150 'defective' images saved in grayscale 8-bit PNG format.
- Each dataset is generated by a different texture model and defect model.
- 'Non-defective' images show the background texture without defects, 'defective' images have exactly one labelled defect on the background texture.
- All datasets have been randomly split into a training and testing sub-dataset of equal size.
- Weak labels are provided as ellipses roughly indicating the defective area.

3.6 Preview of Data

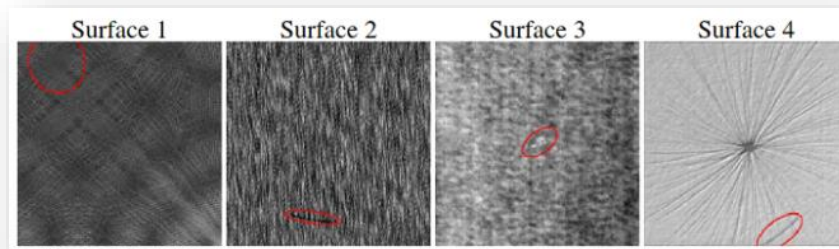


Figure 7 Labelled defective samples of surfaces [^{vii}]

Surface	Train examples		Test examples	
	Positive	Negative	Positive	Negative
1	79	496	71	504
2	66	509	84	491
3	66	509	85	490
4	82	493	68	507

Figure 8 Number of datapoints in dataset [^{viii}]

Chapter 4

Experimental Methodology

4.1 Network Architecture

The authors proposed the following network architecture for anomaly detection. The network comprises of two stages namely, Segmentation and Classification.

The classification score is a value between 0 to 1 and represents the confidence score of the network that the input sample has a defect or not.

The segmentation network outputs a heatmap mask for the anomalous regions.

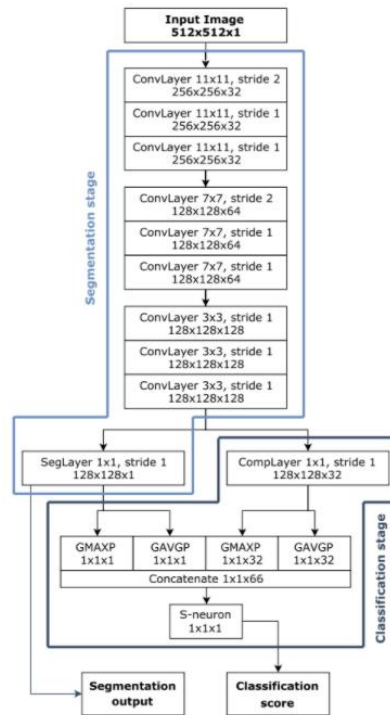


Figure 9 The network architecture consisting of the segmentation and classification subnetworks [19]

4.2 Segmentation Network

It has three convolutional blocks consisting of three convolutional layers each. The number of features increases by a factor of two in each convolutional block.

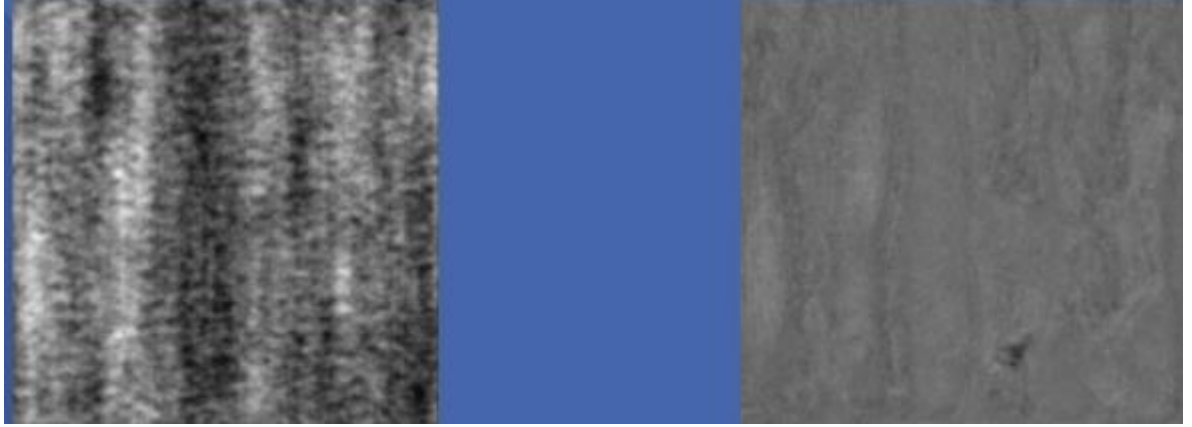


Figure 10 Input image and Segmentation heatmap [x]

4.3 Classification Network

This part heavily relies on the segmentation network to perform properly in terms of finding the hotspots related to the anomalous regions. Then global statistics are calculated using max and average pooling operations. These features are concatenated and passed through S-neuron that outputs a single channel.

4.4 Loss Function

4.4.1 Segmentation stage

Mean squared error is used in segmentation network:

$$\mathcal{L}_S = \frac{1}{np} \sum_{i=1}^n \sum_{j=1}^p \|x_i^{(j)} - \hat{x}_i^{(j)}\|^2$$

where n denotes the number of examples, p is the number of pixels, x_i the annotated pixel value and \hat{x}_i the predicted pixel value.

4.4.2 Classification stage

Binary cross-entropy loss:

$$\mathcal{L}_C = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

where n denotes the number of examples, y_i the ground truth and \hat{y}_i the regression output.

4.5 Experimental Setup

- Platform for training - Google Colab (GPU enabled).
- Adadelta optimizer is used, it adapts learning rates based on a moving window of gradient updates.
- Segmentation stage training: In this stage, only the segmentation network is trained for 25 epochs. All the classification network layer weights are frozen during this stage.
- Classification stage training: In this stage, only the classification network is trained for 10 epochs. This is performed after the segmentation stage training.

Chapter 5

Results and Conclusions

5.1 Training progress

Figure illustrates the impact of the temperature profiles of the voxels immediately surrounding the target

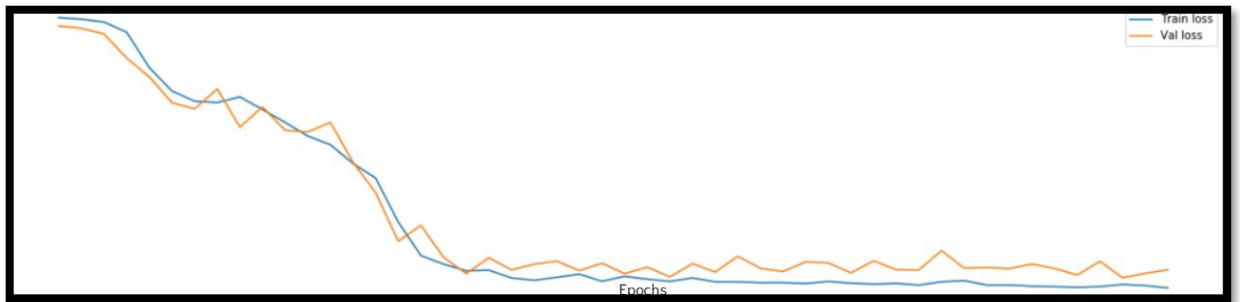


Figure 11 Training and validation loss with Epochs ^[xi]

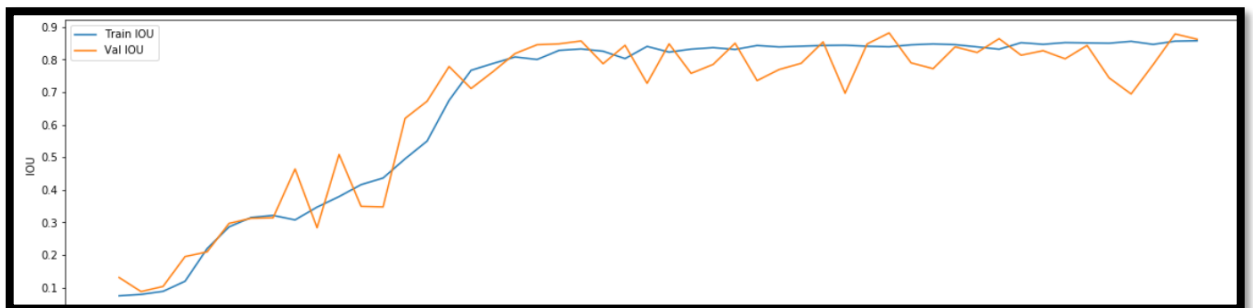


Figure 12 Training and validation IOU values with Epochs ^[xii]

5.2 Qualitative results

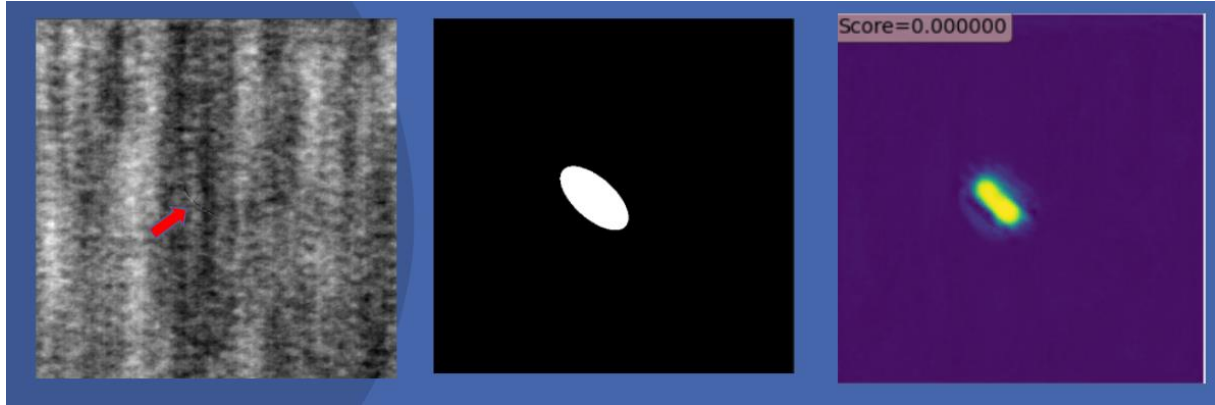


Figure 13 Sample data for defective sample, Ground truth label and Prediction heatmap with defective score [0=Defective, 1=Non-Defective] ^[xiii]

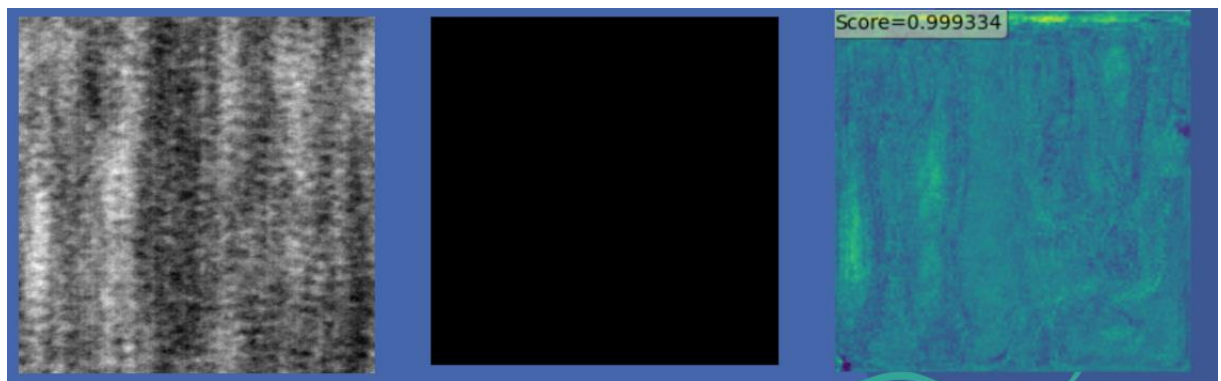


Figure 14 Sample data for non-defective sample, Ground truth label and Prediction heatmap with defective score [0=Defective, 1=Non-Defective] ^[xiv]

5.3 Future Work

We can combine object detection with this model as currently the input to model is required to be 512*512*1 dimensioned. With object detection we can identify the surface in our picture and extract a suitable 512*512 ROI (Regions of Interest) for classification.

Chapter 6 References:

- **Our Code:**

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?usp=sharing

- **Paper:**

<https://link.springer.com/article/10.1007/s00170-017-0882-0>

- **Code Repository:**

<https://github.com/Tandon-A/Quality-Control-using-Deep-Learning->

- **Dataset:**

<https://www.kaggle.com/mhskjelvareid/dagm-2007-competition-dataset-optical-inspection>

Figures Citations:

ⁱ <https://www.pharmaguideline.com/2019/01/quality-metrics-for-pharmaceuticals.html>

ⁱⁱ <https://www.mbaskool.com/business-concepts/operations-logistics-supply-chain-terms/8415-quality-control.html>

ⁱⁱⁱ <https://www.dbsva.com/professional/assembly-operators-production/>

^{iv} <https://www.investopedia.com/terms/n/neuralnetwork.asp>

^v <https://bdtechtalks.com/2021/01/28/deep-learning-explainer/>

^{vi} <https://towardsdatascience.com/covolutional-neural-network-cb0883dd6529>

^{vii} <https://conferences.mpi-inf.mpg.de/dagm/2007/prizes.html#industry>

^{viii} <https://conferences.mpi-inf.mpg.de/dagm/2007/prizes.html#industry>

^{ix} <https://link.springer.com/article/10.1007/s00170-017-0882-0>

^xOur Code

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?authuser=1

^{xi}Our Code

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?authuser=1

^{xii}Our Code

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?authuser=1

^{xiii}Our Code

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?authuser=1

^{xiv}Our Code

https://colab.research.google.com/drive/1t8nFJDV4KnhISz0ybYqKAXTjQuI_dUAP?authuser=1