# Monitoring of Manufacturing process using Deep Learning

Project report submitted in partial fulfilment of the

requirements for the degree of

**BACHELOR OF TECHNOLOGY**

*in*

**Mechanical Engineering**

*by*


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*Under the supervision of*

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*to*


**DEPARTMENT OF MECHANICAL ENGINEERING**

**INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI**

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# CERTIFICATE

This is to certify that the work contained in this project report entitled **“Monitoring of Manufacturing process using Deep Learning”** submitted by **Keerthana S (210103065)** to the Indian Institute of Technology Guwahati towards the partial requirement of **Bachelor of Technology** in **Mechanical Engineering** is a bona fide work carried out by them under my supervision and that it has not been submitted elsewhere for the award of any degree.

**(Dr. Sukhomay Pal)**

**Mechanical Engineering**

**IIT GUWAHATI**

**Apr 2024**

# DECLARATION

We declare that this written submission represents our ideas in our own words, and where others' ideas or words have been included, we have adequately cited and referenced the sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated, or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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IIT Guwahati

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# Chapter 1

# Introduction

## 1.1 Motivation

Accurately detecting manufacturing defects is essential in many fields, including the automotive industry, electronics manufacturing, aerospace, and mechanical engineering. Early detection of manufacturing defects is particularly crucial, as it can prevent the production of faulty items, reduce the number of defective products, and result in significant cost savings and improved profitability. However, accurately predicting manufacturing defects is a challenging task that requires the use of advanced techniques and models. This project aims to develop a state-of-the-art deep-learning model for detecting manufacturing defects using ultrasonic images. By improving our ability to predict manufacturing defects, we can enhance safety in the automotive and aerospace industries, increase the reliability of electronic devices, improve efficiency in manufacturing processes, and prevent system failures in the aerospace and mechanical industries.

## 1.2 Estimation of NDT performance and probability of detection(POD)

NDE is most valuable when used in area, where its expected reliability is very high. Consequently, measuring the performance of an NDE system and its reliability, in particular is demanding. Demonstrating this high reliability requires high number of evaluation results on relevant targets and thus, high number of test samples with representative flaws. Providing these flawed test samples is costly and thus different methodologies have evolved to optimize the use of the available rest blocks.

Currently, the standard way to measure NDE performance is to define a probability of detection (POD) curve and, in particular the smallest crack that can be found at level of sufficient confidence, typically 90% POD at 95% confidence ($a_{90/95}$). Experimentally, the POD curve is determined with test block trials and a set of standardized statistical tools.

# Chapter 2

# Materials & Methods

## 2.1 NDT Data

Inspected specimen for data-acquisition was a butt-weld in an austenitic 316L stainless steel pipe. Three thermal fatigue cracks with depths 1.6, 4.0 and 8.6 mm were implemented in the inner diameter of the pipe near the weld root by Trueflaw ltd. and scanned with ultrasonic equipment. An austenitic weld has chosen as a test specimen due to being common in the industry. In addition, austenitic weld has increased inspection difficulty due to noise caused by the anisotropy of the weld structure. Inspection method used for data acquisition was Transmission Receive shear (TRS) phased array, one of the common methods used in inspecting of austenitic and dissimilar metal welds. The scan was carried out by using Zetec Dynaray 64/64PR-Lit flaw detector linked to a PC. The probes used were a Imasonic 1.5MHz 1.5M5x3E17.5-9 matrix probes with central frequency at 1.8MHz, element dimensions 3.35 x 2.85 mm and element arrangement as 5 x 3 elements. Used wedge was ADUX577A used to produce a shear wave efficiently. One linear scan with no skew angles was utilized. The ultrasonic wave was focused to the inner face of the pipe and the probe was positioned in a way that the beam would be focused directly to the manufactured cracks. Coupling was applied through a feed water system and the pipe was rotated underneath the probe to assure constant and even coupling between the probe and the pipe. Probe position was carefully monitored along the scan line by Zetec pipe scanner with 0.21 mm scan resolution. The specimen and the inspection procedure is described in more detail in Koskinen et al. (2018). The specimen and the scanner can be seen in Figure 1.

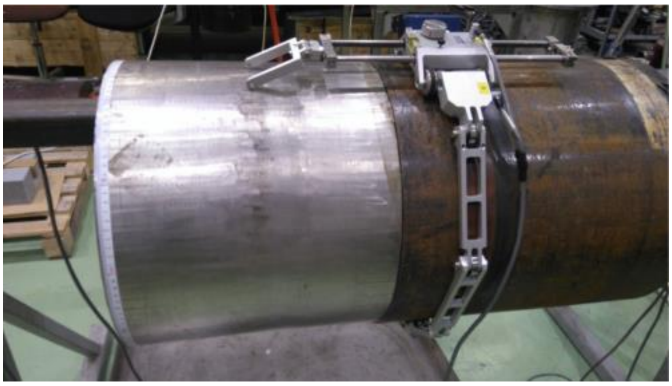
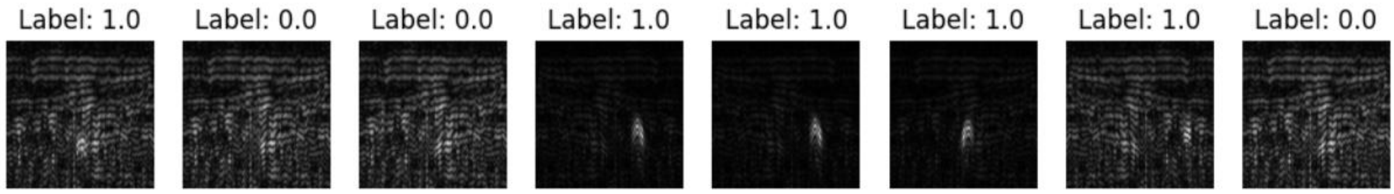


Figure 1: Scan set-up with Zetec pipe scanner, extension fixed to the right side for scanner mounting.

## 2.2 Training and Validating Data

An ultrasonic dataset comprising manufacturing flaw data was utilized for developing and validating a deep learning model. The dataset consists of 796 training files and 8 validation files, each identified by a unique UUID. Each file in the dataset is associated with several components: a .bins file containing raw data in uint16 format with dimensions of 256 x 256 x

100, a .meta file documenting the raw data format, a .jsons file containing metadata such as flaw locations, source flaw size, and "equivalent size," and a .labels file providing tab-separated data indicating flaw existence (0 or 1) and equivalent flaw size. This comprehensive dataset structure facilitated the training and evaluation of the deep learning model for accurate detection and characterization of manufacturing flaws using ultrasonic imaging data.




## 2.3 ML Architecture

The architecture starts with an input layer defined by a 256x256 matrix representing the ultrasonic image data. The initial processing step involves a 2D max-pooling operation along the width dimension to capture localized features within the ultrasound data. The subsequent layers of the model comprise a series of convolutional (Conv2D) and separable convolutional (SeparableConv2D) layers, interspersed with batch normalization and rectified linear unit (ReLU) activation functions to enhance feature extraction and promote model stability.

Specifically, the model architecture includes multiple layers of Conv2D and SeparableConv2D operations with increasing numbers of filters (128, 94, 64, 32) and varying kernel sizes (3x3). Each convolutional layer is followed by batch normalization to standardize the input to the next layer and activation functions to introduce non-linearity.

To reduce spatial dimensions and extract dominant features, max-pooling layers with a stride of (2,2) are applied at strategic points in the network. After the convolutional layers, the model employs global average pooling to aggregate feature maps into a vector representation suitable for classification. This is followed by fully connected (Dense) layers with ReLU activation and dropout regularization to prevent overfitting.

The final layer of the model utilizes a sigmoid activation function to produce a binary classification output, indicating the presence or absence of defects in the ultrasonic image. The model is compiled using the Adam optimizer with a learning rate of 0.0001 and clipnorm regularization. The overall architecture is designed to efficiently process and classify ultrasonic image data for defect detection tasks, leveraging the capabilities of deep learning and convolutional neural networks (CNNs) to achieve accurate and robust performance.

```
input_1 (InputLayer)              [(None, 256, 256, 1)]     0

 max_pooling2d (MaxPooling2D       (None, 36, 256, 1)       0
 )

 conv2d (Conv2D)                  (None, 36, 256, 128)      256

 batch_normalization (BatchN      (None, 36, 256, 128)     512
 ormalization)

 activation (Activation)          (None, 36, 256, 128)      0

 conv2d_1 (Conv2D)                (None, 34, 254, 128)      147584

 batch_normalization_1 (Batc      (None, 34, 254, 128)     512
 hNormalization)

 activation_1 (Activation)        (None, 34, 254, 128)      0

 separable_conv2d (Separable      (None, 34, 254, 94)      13278
 Conv2D)

 batch_normalization_2 (Batc      (None, 34, 254, 94)      376
 hNormalization)

 activation_2 (Activation)        (None, 34, 254, 94)       0

 max_pooling2d_1 (MaxPooling      (None, 17, 127, 94)      0
 2D)

 separable_conv2d_1 (Separab      (None, 17, 127, 94)      9776
 leConv2D)

 batch_normalization_3 (Batc      (None, 17, 127, 94)      376
 hNormalization)

 activation_3 (Activation)        (None, 17, 127, 94)       0

 separable_conv2d_2 (Separab      (None, 17, 127, 64)      6926
 leConv2D)

 batch_normalization_4 (Batc      (None, 17, 127, 64)      256
 hNormalization)

 activation_4 (Activation)        (None, 17, 127, 64)       0
```

```
max_pooling2d_2 (MaxPooling     (None, 8, 63, 64)       0
2D)

separable_conv2d_3 (Separab     (None, 8, 63, 64)       4736
leConv2D)

batch_normalization_5 (Batc     (None, 8, 63, 64)       256
hNormalization)

activation_5 (Activation)       (None, 8, 63, 64)        0

separable_conv2d_4 (Separab     (None, 8, 63, 32)       2656
leConv2D)

batch_normalization_6 (Batc     (None, 8, 63, 32)       128
hNormalization)

activation_6 (Activation)       (None, 8, 63, 32)        0

separable_conv2d_5 (Separab     (None, 8, 63, 32)       1344
leConv2D)

batch_normalization_7 (Batc     (None, 8, 63, 32)       128
hNormalization)

activation_7 (Activation)       (None, 8, 63, 32)        0

global_average_pooling2d (G     (None, 32)              0
lobalAveragePooling2D)

dense (Dense)                   (None, 16)               528

dropout (Dropout)               (None, 16)               0

RNN (Dense)                     (None, 16)               272

dropout_1 (Dropout)             (None, 16)               0

dense_1 (Dense)                 (None, 1)                17
```

## 2.4 Results

After training the deep learning model for 50 epochs on the ultrasonic defect detection task, a remarkable performance was achieved. The final model exhibited a minimal training loss of 0.0216 and a high training accuracy of 99.53%. This outcome demonstrates the efficacy of the model in accurately identifying and classifying manufacturing defects in ultrasonic images. The achieved accuracy and low loss values highlight the effectiveness of utilizing deep learning architectures for automated defect detection in industrial settings, showcasing potential advancements in quality control and process optimization.

## 2.5 Objective

Develop a precise defect analysis model that efficiently identifies and categorizes manufacturing defects. Leverage advanced technology and methodologies to improve quality control and manufacturing excellence.

## 2.5 Conclusion

The development and evaluation of a deep learning model for manufacturing defect detection using ultrasonic images have yielded promising results. The utilization of a comprehensive dataset comprising 796 training files and 8 validation files, each containing essential components such as raw data (.bins), metadata (.meta and .jsons), and label information (.labels), facilitated the training and validation of the model. The designed deep learning architecture, consisting of convolutional and separable convolutional layers with batch normalization and dropout regularization, effectively captured intricate features from the ultrasonic images. The trained model demonstrated outstanding performance with a training loss of 0.0216 and a training accuracy of 99.53% after 50 epochs.

## 2.5 Future Work

I intend to incorporate data augmentation techniques to enhance the quality of results obtained. Additionally, I aim to leverage pre-trained models to compare and analyze the performance of the model I am developing against these established benchmarks. This comparative analysis will provide valuable insights into the effectiveness and potential advancements of my model.

# References

[1] **Anbesh Jamwal, Rajeev Agarwal, Monica Sharma (2022)**: Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications, Vol. 2, Issue 2

[2] **Ashraf Abou Tabl, Abedalrhmaan Alkhateeb, W. H. Elmaragraphy** : Deep Learning Method based on Big Data for Defects Detection in Manufacturing Systems Industry 4.0, Vol. 2, 1-14

[3] **Luka Posilovic, Duje Medak, Fran Milkovic, Marko Subasic, Marko Budimir, Sven Loncaric**: Deep learning-based anomaly detection from ultrasonic images, Vol. 124,

[4] **Jiaxing Ye, Shunya Ito, Nobuyuki Toyama**: Computerized Image Inspection: From shallow to deep learning.

[5] **Virkkunen, I., Haapalainen, J., Papula, S., Sarikka, T., Kotamies, J., and Hanninen, H. (2017).** ¨Effect of feedback and variation on inspection reliability. In 7th European-American Workshop on Reliability of NDE. German Society for Non-Destructive Testing