Monitoring of Manufacturing process using Deep Learning

Project report submitted in partial fulfilment of the

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BACHELOR OF TECHNOLOGY

in

Mechanical Engineering

by

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to

DEPARTMENT OF MECHANICAL ENGINEERING

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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

Nov 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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CONTENTS

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 increase the 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.

1.3 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.

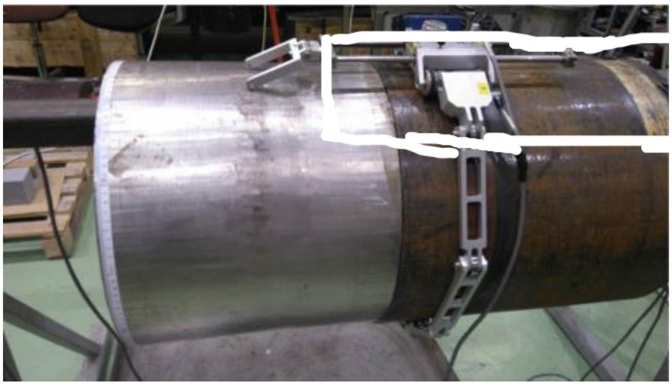
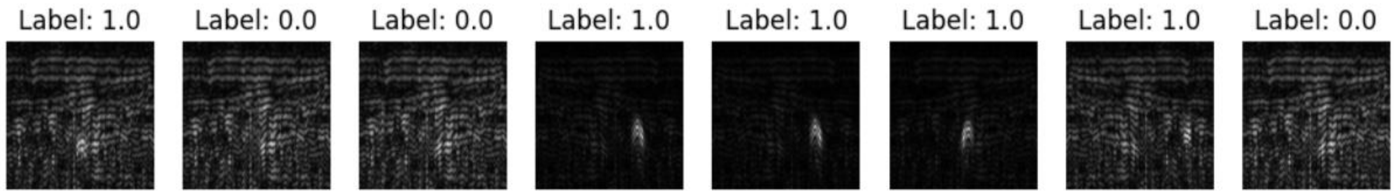


Figure 1: Scan set-up with Zetec pipe scanner, extension fixed to the right side for scanner mounting.

1.4 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.



Chapter 2

Model Implementation

2.1 Custom 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.

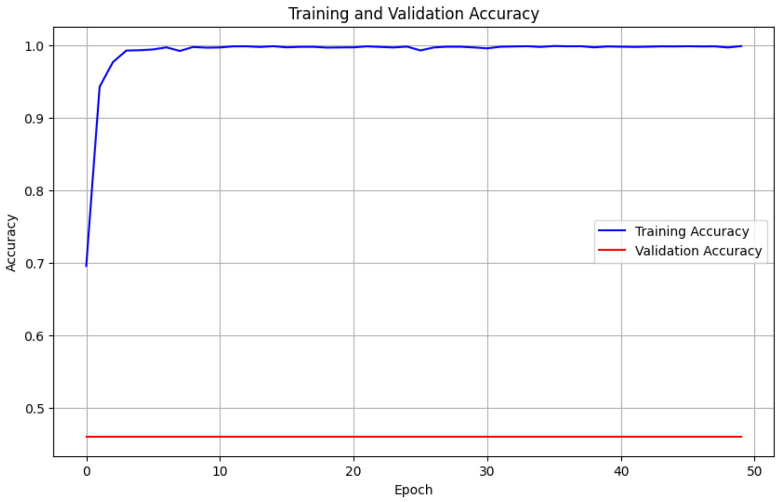
The final layer of the model utilizes a sigmoid activation function to produce a binary classification output, indicating the presence or absence of defects in the ultrasonic image. The model is compiled using the Adam optimizer with a learning rate of 0.0001 and clipnorm regularization. The overall 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.

2.2 ResNet50

The ResNet50 model is a convolutional neural network (CNN) architecture widely known for its effectiveness and efficiency in image classification tasks. ResNet50 refers to the fact that it has 50 layers, making it a deeper model compared to ResNet18 and ResNet34 but lighter than ResNet101 and ResNet152. This specific architecture employs residual learning, where shortcut connections (or "skip connections") allow the model to bypass certain layers. This design addresses the problem of vanishing gradients and allows the model to train effectively even with a large number of layers.

Compared to other ResNet variants, ResNet50 strikes a balance between computational efficiency and model complexity. ResNet18 and ResNet34 are relatively shallow and may struggle with complex datasets, while ResNet101 and ResNet152 are deeper and can capture more intricate patterns, but they require more computational power and may lead to overfitting on smaller datasets. ResNet50 is a good compromise, capturing sufficient detail while being computationally feasible for most applications, making it a popular choice in many image classification tasks.

The plot shows the training and validation accuracy over 50 epochs with the ResNet50 model. Training accuracy improves quickly and reaches nearly 100%, indicating that the model learns the training data well. However, the validation accuracy remains flat at around 50%, which strongly suggests overfitting. This gap between training and validation performance indicates that the model may have memorized the training data without generalizing to unseen data. Possible reasons for this could include insufficient regularization, lack of data augmentation, or an inadequate validation dataset.

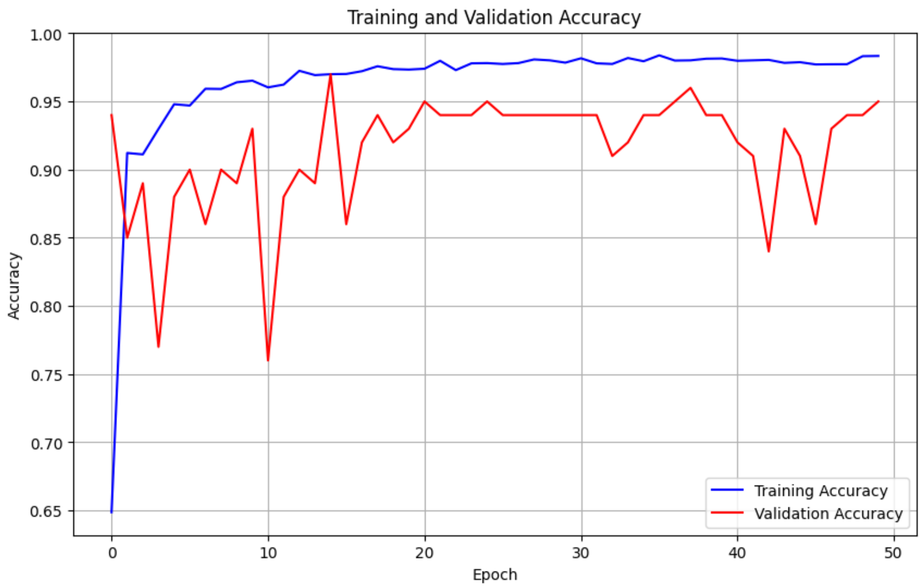


2.3 VGG-19

VGG19 consists of 19 layers with learnable weights, including 16 convolutional layers and three fully connected layers. The architecture uses small, fixed-size convolutional filters (3x3) and follows a consistent pattern of stacking convolutional layers followed by max-pooling layers. This design emphasizes depth and simplicity, allowing VGG19 to capture intricate patterns and complex features in images, making it a strong choice for a variety of image classification tasks.

According to the training and validation accuracy graph, VGG19 appears to yield better results than ResNet50 in this specific case. The training accuracy of VGG19 remains consistently high, with minimal fluctuations, suggesting that the model is effectively learning the patterns in the training data. Although the validation accuracy varies more, it still maintains a high level overall, indicating that the model generalizes well to unseen data. This stability could be attributed to VGG19’s structured convolutional layers, which allow it to capture features consistently across different samples.

Several factors might explain why VGG19 outperforms ResNet50 here. First, the dataset characteristics could favor a simpler architecture like VGG19 over the more complex residual connections in ResNet50. The specific patterns and structures in the images might be better suited to VGG19's straightforward, depth-based approach rather than ResNet50's skip connections, which excel in cases where the depth of the network might lead to diminishing gradients or the need for finer detail preservation. Additionally, VGG19's dense, fully connected layers at the end of the network could be particularly effective in the final stages of classification, enhancing its ability to distinguish between classes in the dataset. The variations in validation accuracy also suggest that while VGG19 may be slightly overfitting at times, its overall performance is still robust, potentially due to effective regularization techniques like dropout and batch normalization.



2.4 Results

Based on the results, it's evident that different model architectures significantly impact training and validation performance. The custom model and ResNet50 both achieved high training accuracy (99.88%) with low training losses (0.0216 and 0.1464, respectively), indicating that they effectively fit the training data. However, both models had a poor validation accuracy of 46%, suggesting they likely overfitted the training set and failed to generalize well to new data. In contrast, VGG19 reached a high validation accuracy of 95% while maintaining a strong training performance (98.34% training accuracy and 0.0175 training loss). This result indicates that VGG19 achieved a better balance between fitting the training data and generalizing to the validation set, making it a more suitable architecture for this task compared to the custom model and ResNet50.

2.5 Conclusion

The development and evaluation of a deep learning model for manufacturing defect detection using ultrasonic images have yielded promising results. Using a comprehensive dataset of 796 training files and 8 validation files, which included raw data, metadata, and label information, the model was trained and validated effectively. The custom architecture, incorporating convolutional and separable convolutional layers with batch normalization and dropout regularization, captured intricate features in the ultrasonic images, achieving a training loss of 0.0216 and a training accuracy of 99.53% after 50 epochs. Comparatively, the ResNet50 model achieved a similar high training accuracy of 99.88% but demonstrated limited generalization with a validation accuracy of only 46%. In contrast, VGG19 achieved both excellent training performance (98.34% training accuracy) and strong generalization, with a high validation accuracy of 95%. These results indicate that the VGG19 model offers a well-balanced approach, effectively handling both training and validation data for defect detection in ultrasonic images.

2.7 Future Work

To further enhance the performance and robustness of the defect detection model, several strategies will be explored. First, implementing advanced data augmentation techniques, such as random rotations, shifts, zooms, and flips, will be prioritized to improve model generalization and simulate various real-world conditions in ultrasonic imaging. Additionally, Generative Adversarial Networks (GANs) will be employed to generate synthetic defect samples, potentially addressing data imbalance issues and further expanding the dataset with diverse examples of manufacturing defects. This approach could enable the model to learn from a broader range of defect patterns, which may otherwise be underrepresented in the current dataset.

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