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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to

DEPARTMENT OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI

GUWAHATI – 781039, INDIA

[Jul-Nov 2023]

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

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Nov 2023

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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ACKNOWLEDGMENT

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Keerthana S

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 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a kind of deep learning neural network that is designed for image and video analysis. CNNs work by utilizing a chain of convolution and pooling layers to extract features from images and videos. These features, are then used to classify or detect objects and scenes.

Convolutional Neural Networks (CNNs), are a type of deep learning algorithm that is mainly employed in the domain of pattern recognition.

Here are the most significant advantages of convolutional neural networks (CNNs):

1. Good at detecting patterns and features in images, videos, and audio signals
2. Automatic feature extraction
3. Highly accurate at image recognition & classification
4. Robust to translation, rotation and scaling invariance
5. Minimizes computation
6. End-to-end training, no need for manual feature extraction
7. Can handle large amounts of data and achieve high accuracy

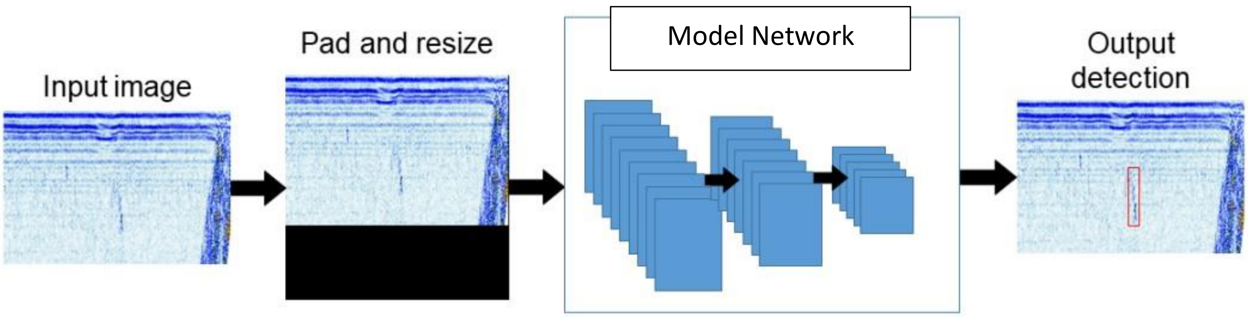


Figure 1.2.1 – Convolutional Network (Taken from [4])

CNN Architecture

A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice.

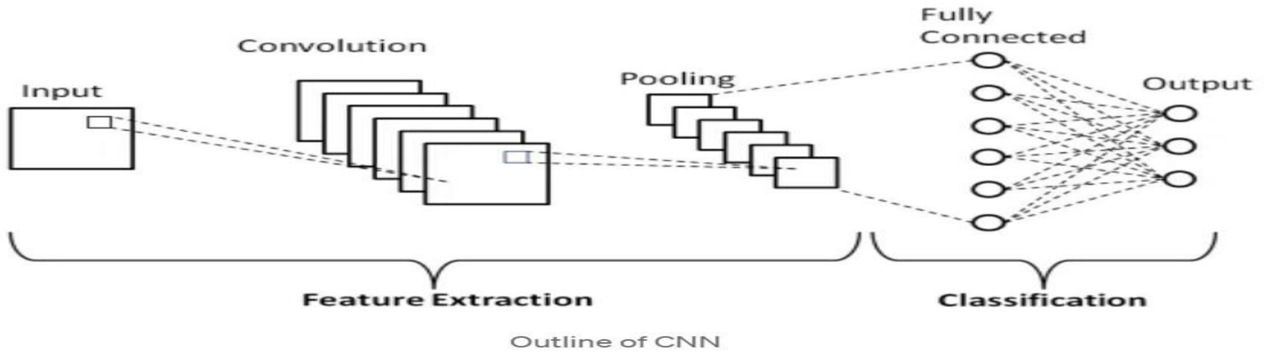


Figure 1.2.2 – Outline of CNN

Convolutional Layers: This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM).

The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

The convolution layer in CNN passes the result to the next layer once applying the convolution operation in the input. Convolutional layers in CNN benefit a lot as they ensure the spatial relationship between the pixels is intact.

Pooling Layer: In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. It basically summarises the features generated by a convolution layer.

In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

This CNN model generalises the features extracted by the convolution layer, and helps the networks to recognise the features independently. With the help of this, the computations are also reduced in a network.

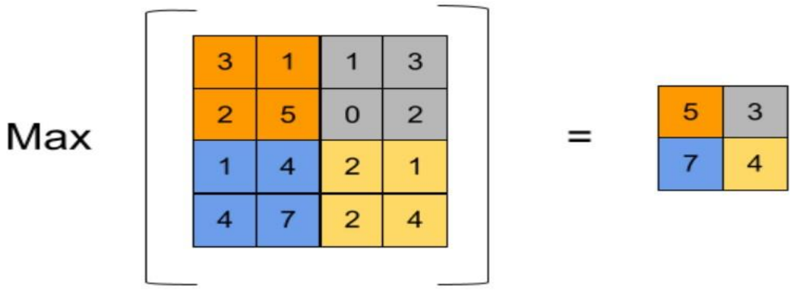


Figure 1.2.3 – MaxPooling

Fully Connected Layer: The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture.

In this, the input image from the previous layers are flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place. The reason two layers are connected is that two fully connected layers will perform better than a single connected layer. These layers in CNN reduce the human supervision.

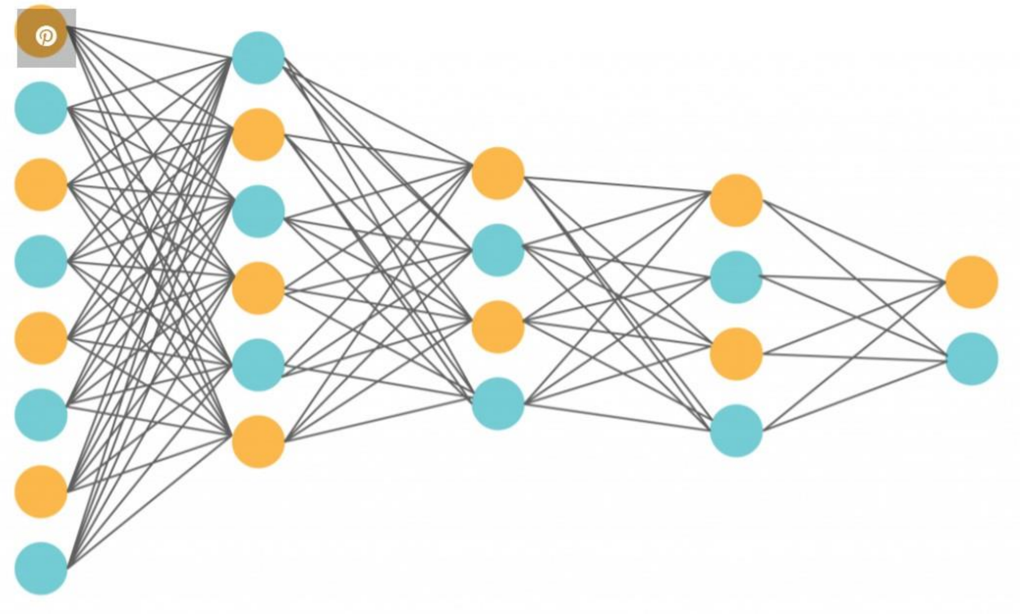


Figure 1.2.4 – Fully Connected Layer

Dropout: Usually, when all the features are connected to the FC layer, it can cause overfitting in the training dataset. Overfitting occurs when a particular model works so well on the training data causing a negative impact in the model's performance when used on a new data.

To overcome this problem, a dropout layer is utilised wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model. On passing a dropout of 0.3, 30% of the nodes are dropped out randomly from the neural network.

Dropout results in improving the performance of a machine learning model as it prevents overfitting by making the network simpler. It drops neurons from the neural networks during training.

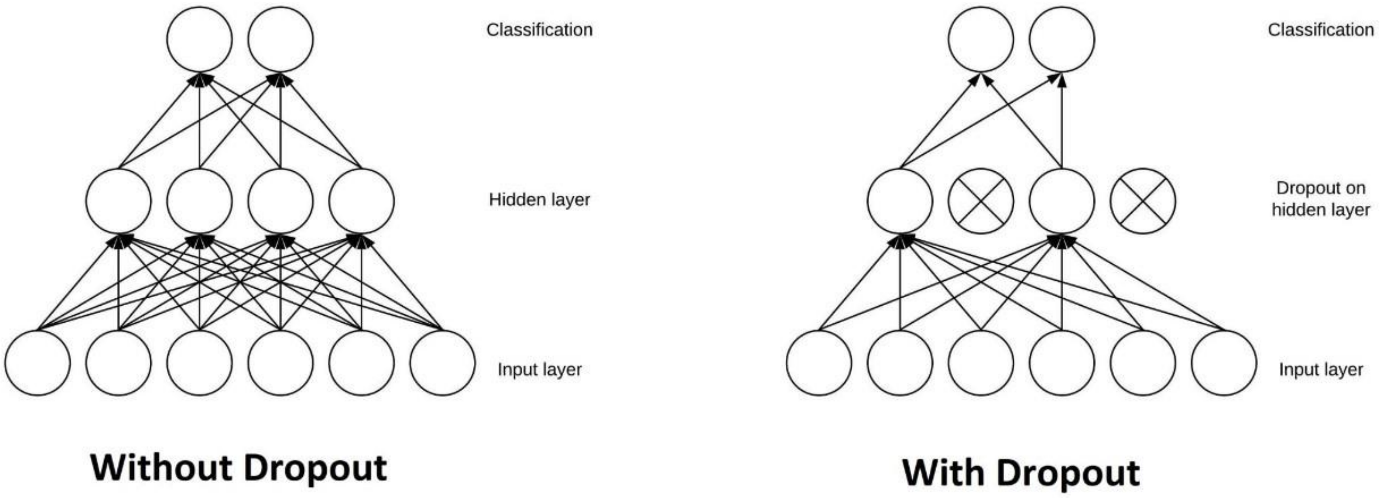


Figure 1.2.5 – Dropout Layer

Activation Functions: Finally, one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network.

It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and softmax functions are preferred an for a multi-class classification, generally softmax us used. In simple terms, activation functions in a CNN model determine whether a neuron should be activated or not. It decides whether the input to the work is important or not to predict using mathematical operations.

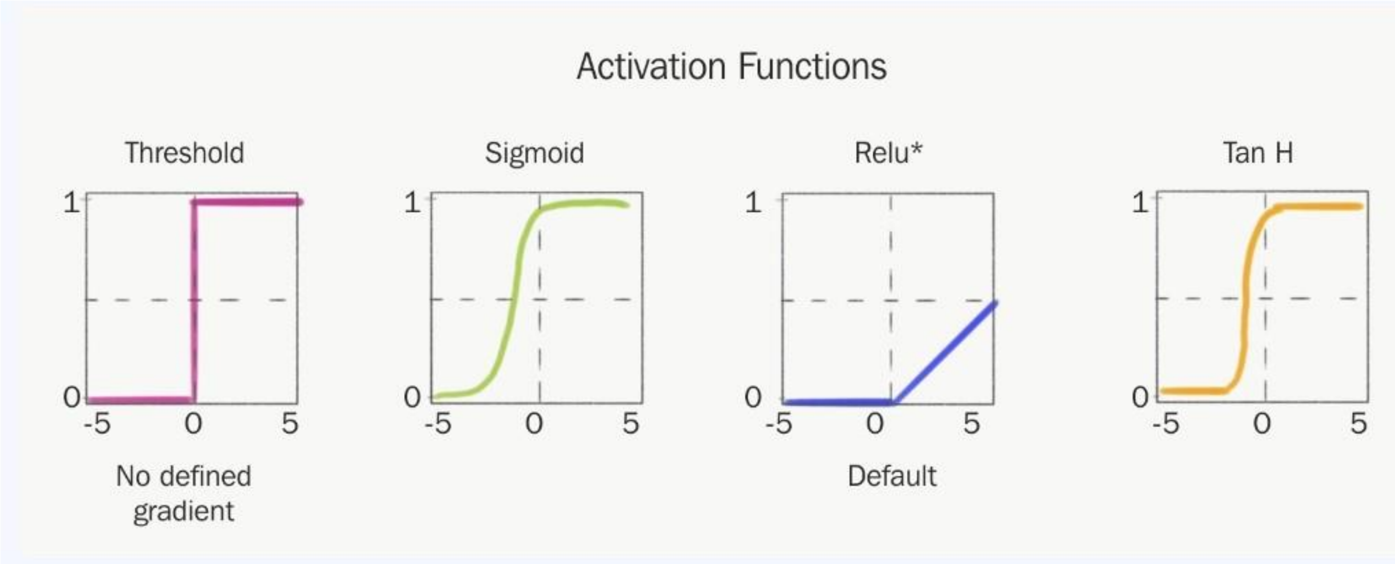


Figure 1.2.6 – Activation Functions

1.3 Literature Review

This study[1] discusses the role of deep learning models for sustainable production and presents a framework for achieving it. The review shows that research in deep learning for manufacturing is limited, and industries lack knowledge of its benefits. The study demonstrates how deep learning can improve quality management, predictive maintenance, reliability analysis, and fault diagnosis in sustainable production. The proposed framework can help manufacturing organizations achieve sustainable production in Industry 4.0-based business models, with benefits such as reduced machine downtime and improved fault diagnosis. Future studies can empirically test the proposed framework across various industry sectors.

This research[2] introduces an innovative method leveraging big data and an AI decision-making tool to optimize manufacturing processes, a significant contribution to Industry 4.0 initiatives. The model, trained with images of acceptable and defective products, achieves up to 97% accuracy in detecting defects, showcasing its potential impact in real-world production settings. The implementation of Industry 4.0 enablers, including machine learning, Cyber-Physical Systems (CPS), and the Internet of Things (IoT), is a key objective for enhancing efficiency at the iFactory facility. The proposed model comprises three phases, involving dataset retrieval from a supercomputer, pre-training using ResNet-50 for model weight initialization, and end-to-end training for capturing fine details and discriminative features. The model structure, illustrated in Fig. 9, utilizes a convolution layer, max-pooling layer, ReLU activation function, and SoftMax nonlinearity activation function with binary cross-entropy loss. The ADAM optimization method further refines the model's performance.

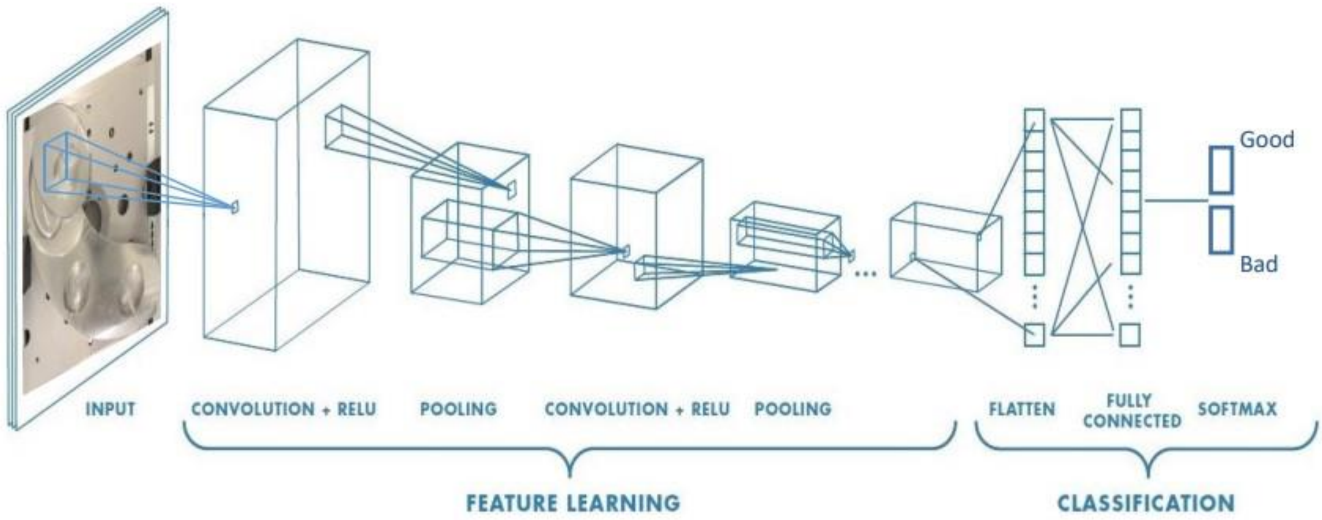


Figure 1.3.1 – Convolutional Network (Taken from [2])

In this study[3], three state-of-the-art methods for anomaly detection in images were tested on an eight-fold real-world ultrasonic NDT dataset. Proposed improvements included cropping-out patches from images for Ganomaly and using a faster MobileNet network for PaDiM. PaDiM outperformed the other two methods by detecting all defects in the dataset and performing better than classifiers when the proportion of positive samples in the training set was very small. The study highlights the importance of testing anomaly detection methods on real-world datasets before using them in production.

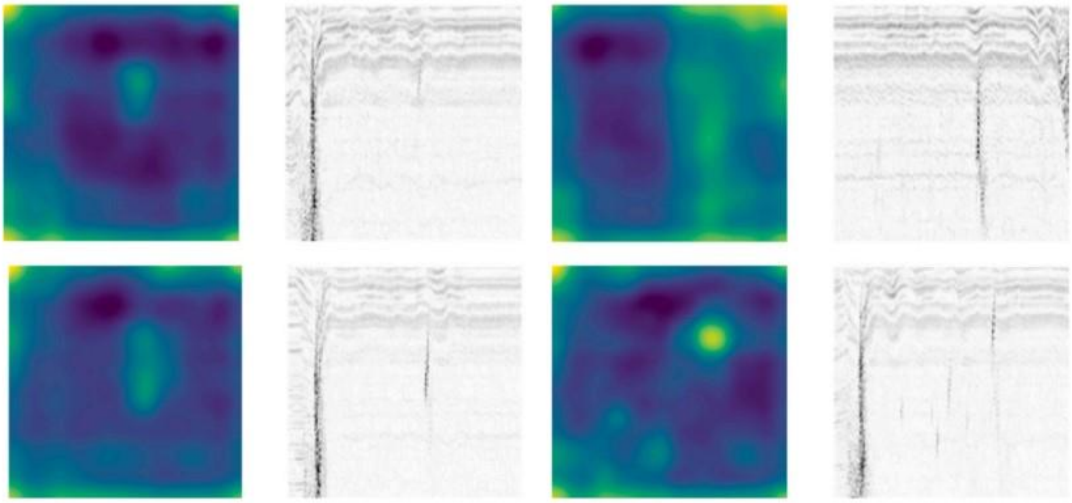


Figure 1.3.2 – Examples of anomalous images and attention from the PaDiM model(taken from [3])

The study[4] demonstrates that the EfficientDet-D0 architecture can detect defects from images taken with a phased-array probe. The researchers improved the network's performance by introducing a new approach to compute anchors' hyperparameters. The proposed EfficientDet-D0 model achieved an mAP of 89.6%, surpassing YOLOv3 by 9%. However, to validate its performance, it would be valuable to compare it to that of human inspectors.

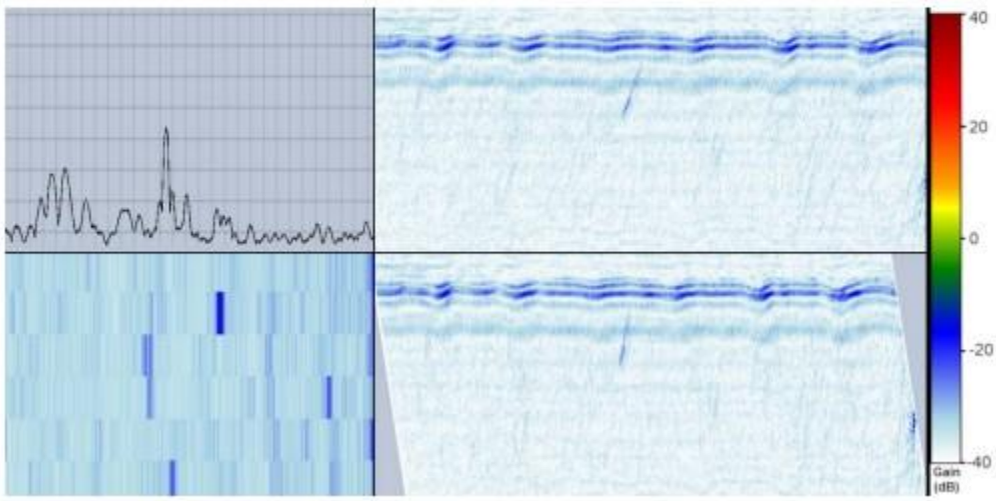


Figure 1.3.3 – Examples of different ultrasonic data representations. Top left: A-scan. Beneath it is the C-scan representation. Right: B-scan (top) and volume corrected B-scan (bottom) (taken from [4]).

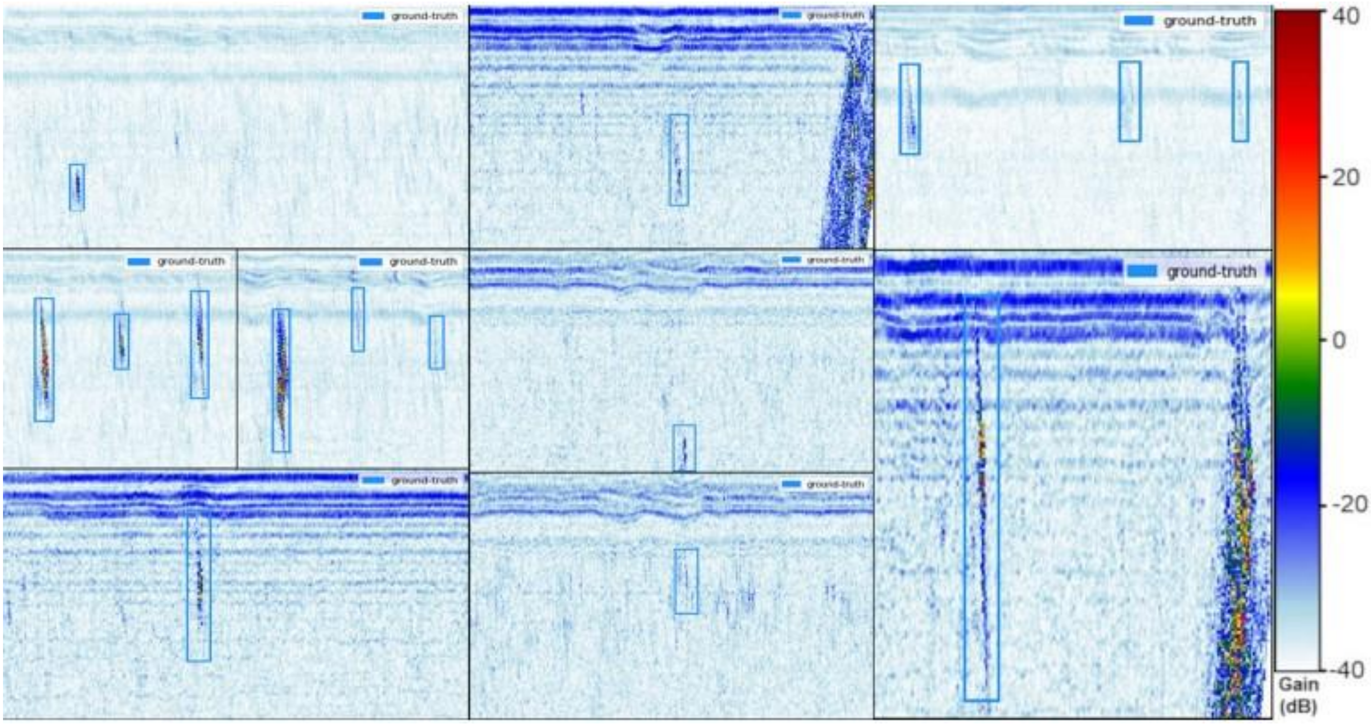


Figure 1.3.4 – Examples of the used VC-B-scans with ground-truth labels (taken from [4]).

In this study[5], a computerized system for ultrasonic image investigation was developed that performs with comparable accuracy to humans. The researchers began by creating an ultrasonic inspection image dataset and conducting a comparative evaluation of computer vision techniques. The proposed USresNet with deep neural networks outperformed all conventional approaches in both detection accuracy and model stability. Future research will focus on subtle defect pattern detection from ultrasonic images, and expanding the ultrasonic image dataset to improve analysis precision.

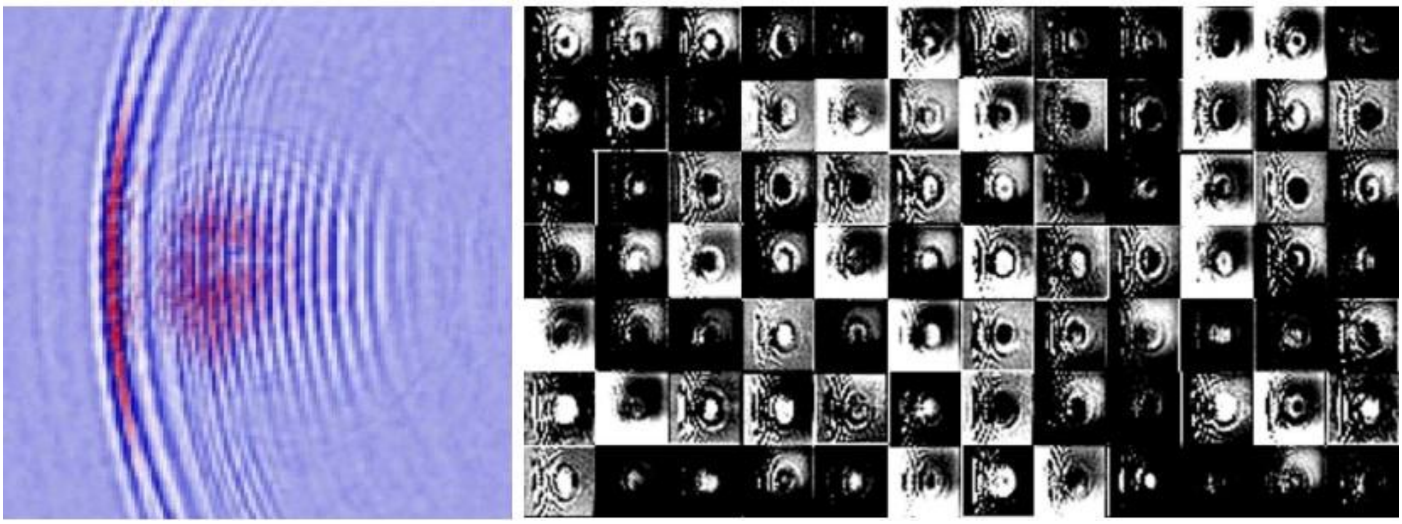
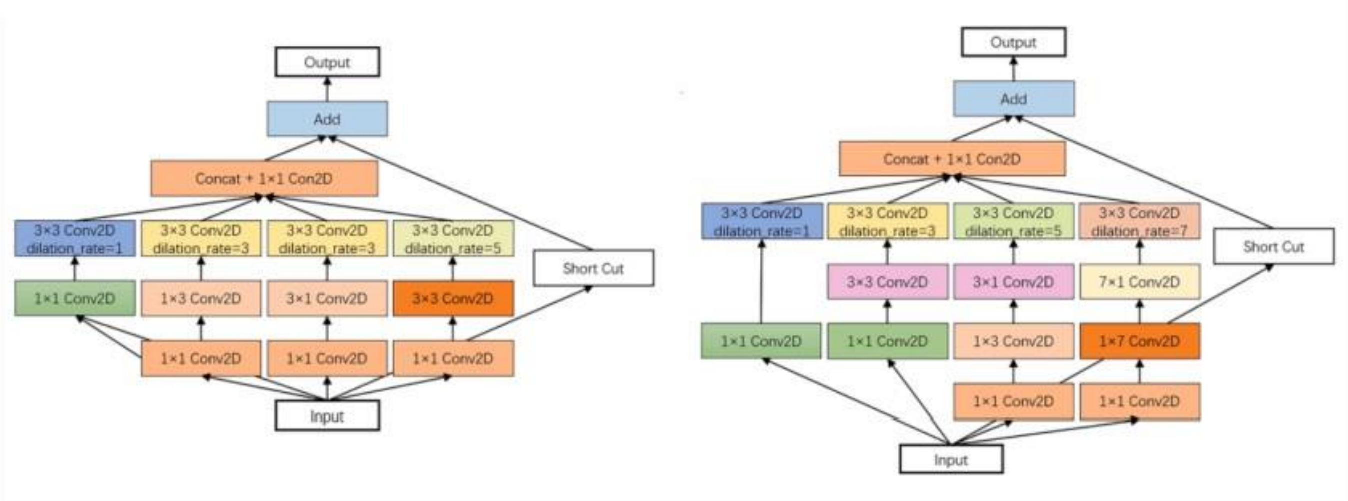


Figure 1.3.5 – Visualization of USresNet B4 layer activation generated by an ultrasonic image with defect (taken from [5])

A new algorithm based on improved YOLOv4[6] has been proposed to detect defects in steel strips. The algorithm utilizes CBAM and RFB structure to achieve better detection accuracy. The model outperforms most current detection networks, achieving a 3.87% improvement in mAP. However, the inclusion and patch detection ability needs improvement due to a smaller dataset. The researchers plan to increase the sample size to enhance detection accuracy.



(a) (b)

Figure 1.3.6 – Receptive field block(RFB) modifications: (a) RFB for small structures (RFB-S) and (b) our custom RFB. The Customised RFB structure readjusts parameters while deepening the network layer to enhance network generalizability (taken from [6]).

This work[7] proposes an automatic pattern recognition system for detecting flaws in steel welded joints using various feature extraction and classification methods. The system includes two classification methodologies based on MLP neural networks, and the most important input features are selected using PCA and WMW test. Results show that the system efficiently identifies the regions of defects. With the first type of classifier, only 20 coefficients are required out of the original 2500 A-scan time-samples. Using the second methodology, high efficiency in detecting defect signatures can be achieved by using only 5 input features.

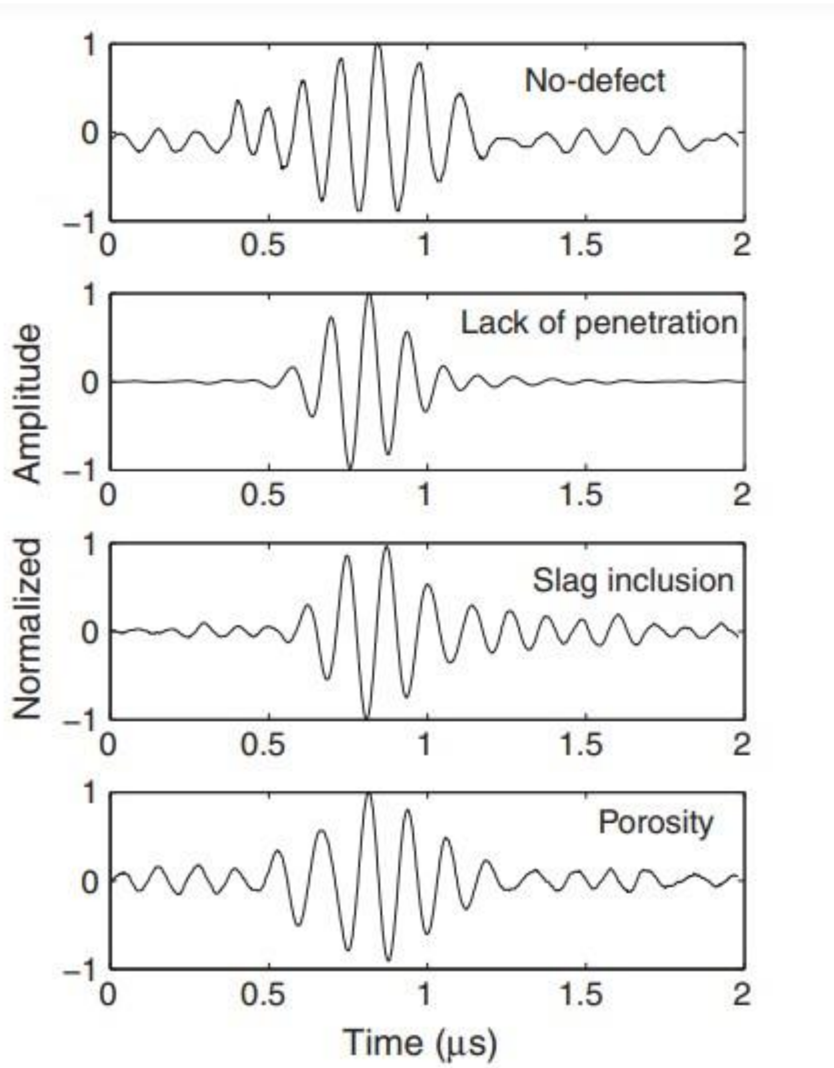


Figure 1.3.6 – Typical A-scan signals from the four classes of interest (taken from [5]).

1.4 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.

1.5 Conclusion

During the analysis of seven research papers that used various methods to build accurate models for defect analysis, a key observation was made. The observation was that pre-trained models failed to produce more than 95% accuracy. The research findings suggest that the techniques used, such as HOG, LBP, and Gabor filters, did not significantly impact the accuracy levels. Instead, these techniques helped to reveal more about the features they extract. The papers did not utilized pre-trained models directly but rather added some layers to enhance accuracy.

1.6 Future Work

I am planning to create a custom model for the upcoming semester that will be tailored specifically to the task at hand. By developing a bespoke model, I will have maximum control over the architecture and ensure it aligns perfectly with the requirements of the problem domain. This personalized approach will allow for a more finely tuned solution, potentially surpassing the performance of generic, pre-existing models.

References

[1] https://www.sciencedirect.com/science/article/pii/S2667096822000507

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[3] https://www.sciencedirect.com/science/article/pii/S0041624X2200049X

[4] https://ieeexplore.ieee.org/document/9435411

[5]https://www.researchgate.net/publication/328800138_Computerized_Ultrasonic_Imaging_Inspection_From_Shallow_to_Deep_Learning**Regress**

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