DEVELOPMENT OF FEATURE EXTRACTION TECHNIQUES USING CNN FOR WELD RADIOGRAPHY INTERPRETATION

PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering Degree in Electronics and Communication Engineering

by

KONDA RAKESWAR REDDY (40130116)

INDUKURI KARTHIK VARMA (40130081)

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

SCHOOL OF ELECTRICAL AND ELECTRONICS

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **KONDA RAKESWAR REDDY (40130116)** and **INDUKURI KARTHIK VARMA (40130081)** who carried out the project entitled "**DEVELOPMENT OF FEATURE EXTRACTION TECHNIQUES USING CNN FOR WELD RADIOGRAPHY INTERPRETATION**" under my supervision from November 2023 to April 2024.

Internal Guide
Dr. N. M. NANDHITHA, M.E., Ph.D.,

Head of the Department
Dr. T. RAVI, M.E., Ph.D.,

Submitted for Viva voce Examination held on ___________________

Internal Examiner **External Examiner**

DECLARATION

We, **KONDA RAKESWAR REDDY (40130116)** and **INDUKURI KARTHIK VARMA (40130081)** hereby declare that the Project Report entitled "**DEVELOPMENT OF FEATURE EXTRACTION TECHNIQUES USING CNN FOR WELD RADIOGRAPHY INTERPRETATION**" done by us under the guidance of **Dr. N. M. NANDHITHA,** Professor and Dean, School of Electrical and Electronics, Sathyabama Institute of Science of Technology, Chennai, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

DATE:

PLACE: Chennai **SIGNATURE OF THE CANDIDATES**

1.

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We convey our thanks to **Dr. N. M. NANDHITHA, M.E., Ph.D., Dean, School of Electrical and Electronics** and **Dr. T. RAVI, M.E., Ph.D., Head of the Department, Department of Electronics and Communication Engineering** for providing us necessary support and details at the right time during the progressive reviews.

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ABSTRACT

Welding is the most commonly used technique for joining metals. In spite of technological advances, defects do occur in welds. So before delivering the weld pieces, Quality Assurance department ensures the quality of the weld piece. i.e., to check if the weld adheres to the ASME standards. In order to assess the quality of weld, various diagnostic techniques are already available in literature. Digital radiography is regarded as the golden standard for post quality assurance. Radiographs are acquired and are digitized using an appropriate scanner. Having digitized the radiographs, these radiographs are interpreted for assessing the presence or absence of the defect. If defect occurs, then the severity of the defect is also obtained. Though various computer aided techniques are already available, complete automation of radiograph interpretation is yet to be developed. Hence the proposed research work aims at developing completely automated techniques for weld defect detection. In this work, radiographs of AISI Stainless steel welds are considered and the defects are deliberately introduced. Convolutional Neural Networks are used for extracting the features and thereby identifying the defect. Initially the feasibility of conventional CNNs such as SQUEEZENET, ALEXNET for weld defect detection is studied. Having studied the performance of these networks, these networks are modified to reduce the computational complexity without affecting the performance of the network.

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ABBREVIATIONS	EXPANSIONS
CNN	Convolutional Neural Network
WRIR	Welding Radiographic Image Recognition
SSL	Self-Supervised Learning
IPT	Image Processing Techniques
DNN	Deep Neural Network
ILSVRC	Imagenet Large Scale Visual Recognition Challenge
ReLU	Rectified Linear Unit
LRN	Local Response Normalization
ASME	American Society of Mechanical Engineers
BPVC	Boiler and Pressure Vessel Code
AWS	American Welding Society
ISO	International Organization for Standardization
JIS	Japanese Industrial Standards
JISC	Japanese Industrial Standards Committee
JSA	Japanese Standards Association

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CHAPTER 1
INTRODUCTION

Weld radiography is often referred as radiographic testing or radiographic inspection of the weld rods this critically known as non-destructive testing method used in many industries for checking the quality. The weld radiography interpretation plays a crucial role in various industries where welding is much important, such as construction, manufacturing, and automotive sectors. By examine these images, experts can identify defects like lack of penetration, porosity and cracks within the weld joints. These weld radiography interpretation aids in quality control and assurance process, enabling companies to meet regulatory requirements and maintain high standards of production.

1.1 Weld Radiography Interpretation

The CNN is majorly known as Convolutional Neural Network this have become indispensable in various due to their remarkable capabilities in pattern recognition and feature extraction from visual data. In MATLAB, CNNs are extensively utilized in image processing and computer vision tasks. Beyond the computer vision, CNNs find the applications in natural language processing for tasks like sentiment analysis and text classification. Their ability to learn hierarchical representation from raw data makes them versatile tools across numerous domains, driving advancements in technology and innovation.

Weld radiography interpretation in MATLAB CNNs enhances manufacturing and construction quality control by automating defect detection like lack of penetration, cracks and porosities. This technology streamlines inspection processes, saving time and effort while ensuring accuracy. Real-time analysis enables timely decision-making, improving safety and structural integrity. Integrating weld radiography with CNNs in MATLAB empowers industries to achieve higher reliability and efficiency in welding processes, fostering quality assurance and productivity. Feasibility of conventional CNNs for the classification of weld defects from weld radiographs is studied.

Shelly soffer, Avi Ben Colen (2019) proposed a CNN for radiological images in which application of Convolutional Neural Networks is studied. The survey of the studies is followed by a discussion about current challenges and future trends and their potential implications for radiology. This article may be used as a guide for radiologists planning research in the field of radiologic image analysis using convolutional neural networks.

Dalila Say, Salah Zidi (2023) proposed the automated categorization of multiclass welding defects using CNN. This article defines the detection of weld defects by using X-rays is an important task in the industry. It requires trained specialists with the expertise to conduct a timely inspection, which is costly and cumbersome. Moreover, the process can be erroneous due to fatigue and lack of concentration. In this context, this study proposes an automated approach to identify multi-class welding defects by processing the X-ray images. It is realized by an intelligent hybridization of the data augmentation techniques and Convolutional Neural Network (CNN).

Yasheng Chang, Weiku Wang (2021) have proposed Deep Learning-Based Radiographic Weld Inspection which shows welding defect detection based on radiographic images plays a vital role in industrial non-destructive testing. It provides an effective guarantee with respect to welding quality in shipbuilding, chemical industry, and aerospace applications. A variety of related computer-based image processing technologies have been designed for the detection of weld defects. However, this is a challenging task because weld defects can exhibit different shapes, sizes, positions, and contrasts in radiographic images.

Tianyuan Liu, Hangbin Zheng (2023) have proposed Empowered CNN approach for welding radiographic image recognition that shows Non-destructive testing of welds based on the radiographic image is crucial for improving the reliability of aerospace structural components. The deep learning method represented by the Convolutional Neural Network (CNN) has received extensive attention in Welding Radiographic Image Recognition (WRIR) owing to its powerful feature adaptive extraction ability. However, CNN-based WRIR faces key challenges of small sample size and poor explanation. Inspired by the process of interpreting radiographic film by experts, expert knowledge-empowered CNN for WRIR is proposed. Two Self-Supervised Learning (SSL) tasks for radiographic image deblurring and brightness adjustment are designed to model expert experience. The expert knowledge learned from the SSL process is used to guide the CNN to identify the weld defects.

Ang-jin, Min-jae Jung (2020) have proposed Automatic Detection of Welding Defects Using Faster R-CNN shows that for welding quality inspection is mainly used for the permanent storage of the testing results and the radio-graphic testing which can visually inspect the interior of the welded part. Experts are required to properly detect the test results and it takes a lot of time and cost to manually Interpret the radio-graphic testing image of the structure over 500 blocks. The algorithms that automatically interpret the existing radio-graphic testing images to extract features through image pre-processing and classify the defects using neural networks, and only partial automation is performed. In order to implement the feature extraction and classification in one algorithm and to implement the overall automation, this paper proposes a method of automatically detecting welding defect using Faster R-CNN.

Bharath Chandra (2019) proposed Defect Classification from Weld Radiography Images Using VGG-19 based Convolutional Neural Network that shows Weld Radiography Images are traditionally analysed by the experts. The accuracy of this inspection process is more dependent on various external factors and is also time consuming. Due to these reasons, there is a need to perform automatic weld defect detection by analysing the images obtained directly from the digital radiographic systems. A VGG-19 based Convolutional Neural Network is trained by using transfer learning technique over a sample of 3000 weld radiography images of size 128X128 pixels belonging to three different classes.

Li Yaping, Gao Weixin (2019) proposed Research on X-ray welding image defect detection based on CNN which demonstrates that in order to improve the efficiency of X-ray welding image defect recognition, it is proposed to use the deep learning network to identify welding defects. Based on the analysis of X-ray weld defect image characteristics, the convolutional neural network template and the number of layers is determined. By constructing a deep learning network structure that simulates the principle of visual perception, the steps of feature extraction of weld defect images are avoided. Also, the deep learning network can directly determine whether the suspected defect image is a linear defect, circular defect or noise. The designed system can automatically learn the complex depth features in the X-ray weld defect image.

Jiawei Huang, Caixia BI (2020) proposed that CNN-based intelligent recognition method for negative images of weld defects shows that the existing technology of automatic classification and recognition of welding negative images by computer is difficult to achieve a multiple classification defect recognition while maintaining a high recognition accuracy, and the developed automatic recognition model of negative image defect cannot meet the actual needs of the field. Therefore, the Convolutional Neural Network (CNN)-based intelligent recognition algorithm for negative image of weld defects is proposed architecture of weld defect feature image database combined with CNN.

Samuel Kumaresan, K. S. Jai Aultrin (2021) proposed that Transfer Learning with CNN for Classification of Weld Defect which shows that Traditional Image Processing Techniques (IPT), used for automating the detection and classification of weld defects from radiography images, have their own limitations, which can be overcome by Deep Neural Networks (DNN). DNN produces considerably good results in fields which offer big dataset for it to train. DNN trained with small datasets by conventional methods produces less accurate results. This limits the use of DNN in many fields. This study focuses to overcome this limitation, by adopting transfer learning using pre-trained deep convolutional neural networks.

Wenhui Hou, Dashan Zhang (2020) proposed that Review on Computer Aided Weld Defect Detection from Radiography Images which shows that the weld defects inspection from radiography films is critical for assuring the serviceability and safety of weld joints. The various limitations of human interpretation made the development of innovative computer-aided techniques for automatic detection from radiography images an interest point of recent studies. The studies of automatic defect inspection are synthetically concluded from three aspects: pre-processing, defect segmentation and defect classification.

M-Mahdi Naddaf-Sh a, Sadra Naddaf-Sh a, Hassan Zargarzadeh., (2021) proposed that Defect detection and classification in welding using deep learning and digital radiography Continuous and digitized monitoring and automated inspection are key parts of modern manufacturing and sustainment of aging infrastructure. The growing demand for these needs and shortage of required skill sets can slow down the global economy by increasing the risk or costs associated with catastrophic events. The diversity of requirements and specialized standards and codes around the world, along with the time-sensitive aspect of such inspections, makes automated fault detection.

Roman Sizyakina, Viacheslav Voronin (2018) have proposed the automatic detection of welding defects using CNN this article shows the quality control of welded joints is an important step before commissioning of various types of metal structures. The main obstacles to the commissioning of such facilities are the areas where the welded joint deviates from acceptable defective standards. The defects of welded joints include non-welded, foreign inclusions, cracks, pores, etc. The article describes an approach to the detection of the main types of defects of welded joints using a combination of convolutional neural networks and support vector machine methods. Convolutional neural networks are used for primary classification.

Li Yaping, Gao Weixin (2019) have proposed the X- rays welding images detection based on the CNN this article explains in order to improve the efficiency of X-ray welding image defect recognition, it is proposed to use the deep learning network to identify welding defects. Based on the analysis of X-ray weld defect image characteristics, the convolutional neural network template and the number of layers is determined. By constructing a deep learning network structure that simulates the principle of visual perception, the steps of feature extraction of weld defect images are avoided. Also, the deep learning network can directly determine whether the suspected defect image is a linear defect, circular defect or noise. The designed system can automatically learn the complex depth features in the X-ray weld defect image.

S. Ramesh Krishnan, T. V. Abhishek (2021) have proposed automatic detection and characterization of weld defects using CNN in ML this article helps to explains the Conventional radiographic technique uses visual inspection of scanned output for defect detection. This makes the inline testing of products time consuming and hectic. Convolutional Neural Network (CNN) algorithm in machine learning can be used for the automation of defect detection in radiography thereby reducing human intervention and associated delays. By the use of robotics, the welding parameters can be adjusted and the issue of welding defects can be resolved. By combining the two, the defect detection process can be modified into a digital manufacturing process. A dataset created from radiography test data is used for training the algorithm and for writing a program to train this dataset which can be used for defect detection and its characterization.

Benito Totino and Fanny Spagnolo (2018) proposed a novel approach using radiographic images for automatic weld defect classification. Despite advancements in computer vision, making automatic processes accessible in this domain remains challenging. Convolutional Neural Networks (CNNs) are acknowledged for their efficiency and accuracy in classification tasks, including weld defect classification. The application of CNNs has shown promising results in this area, indicating the potential for automated defect detection in welding. This research highlights the increasing interest and importance of automated defect detection in industry. However, further advancements are needed to make these processes more accessible and effective.

1.2 Convolutional Methods for Weld Radiography Interpretation

In this weld radiography interpretation using Convolutional Neural Networks majorly using the SqueezeNet, AlexNet and Modified AlexNet to improve the accuracy we are getting into these algorithms which helps us to achieve the maximum amount to accuracy with the training dataset and testing dataset. In the training data we had arranged nearly 200 images and we separated according to the type of defects such as lack of penetration, porosity, crack and no defect. And similarly arranged 80 images in testing for different kinds of defects and these convolution methods majorly for the better accuracy than making in traditional methods with less accuracy.

1.3 Motivation

The motivation behind developing feature extraction techniques using Convolutional Neural Networks (CNN) for Weld Radiography interpretation lies in the urgent need to enhance efficiency and accuracy in the assessment of welding defects. Traditional methods are prone to errors and time-consuming manual work. Employing CNNs allows for automated, precise defect detection, offering a transformative solution to streamline weld radiography interpretation, reduce human error, and optimize inspection processes in the shipbuilding and offshore industry.

1.4 OBJECTIVES

The objectives are detailed as follows:

- To acquire radiographs detecting weld defects.
- To study the feasibility of Convolutional Neural Networks for the classification of weld defects.
- To determine the performance of the classifiers through sensitivity, specificity and accuracy.
- To modify the convolutional CNN architecture and pretrained it.
- To study the feasibility of modified CNN for weld defect detection.
- To study the performance of modified Alexnet in terms of performance metrics.

1.5 Organization of the Report

The report will be organized into several sections to ensure clarity and coherence. Chapter 1 deals with the introduction provides an overview of the project goals and motivation, including a description of the project. This section should also include a brief review of the relevant literature and previous work in the field. Chapter 2 details the research database on different types of weld defects, Convolutional Neural Networks. Chapter 3 details about the feasibility of CNN for weld defect detection and overview of the Squeezenet and Alexnet with the architecture. Chapter 4 Proposed work in these there will be a detailed information about the standards, constraints, Trade off, The feasibility of modified CNN for weld defect detection and performances of the Squeezenet, Alexnet and Modified Alexnet with the comparison of these convolutional methods. Chapter 5 is about the final summary of the project called and conclusion along with the future work and finally ends up with the References.

CHAPTER 2
RESEARCH DATABASE

Radiographs acquired by deliberately introducing weld defects are discussed in this chapter. Also, nature of the defects is explained in this chapter. Intensity variation in radiographs indicate the defects in radiographs.

2.1 Lack of Penetration

Detecting lack of penetration in welds through radiography is a critical aspect of ensuring the structural integrity and performance of welded components. Lack of penetration occurs when the weld fails to extend fully into the joint, leading to weak points that compromise the overall strength of the weld. Radiography, with its ability to provide internal views of welds, plays a pivotal role in identifying such defects. During the radiographic inspection process, X-rays pass through the weld, creating an image that reveals the internal structure. In the case of lack of penetration, the radiographic image may show a distinct line or void where the weld fails to fully penetrate the joint. Skilled radiographers interpret these images to determine the extent and severity of the lack of penetration. Detection of this defect is crucial for preventing structural failures and ensuring welds meet specified standards. Addressing lack of penetration may involve adjustments to welding parameters, such as current and travel speed, and careful examination of welding procedure specifications. As industries increasingly rely on radiography for non-destructive testing, accurate detection of lack of penetration remains integral to maintaining the quality and safety of welded structures.

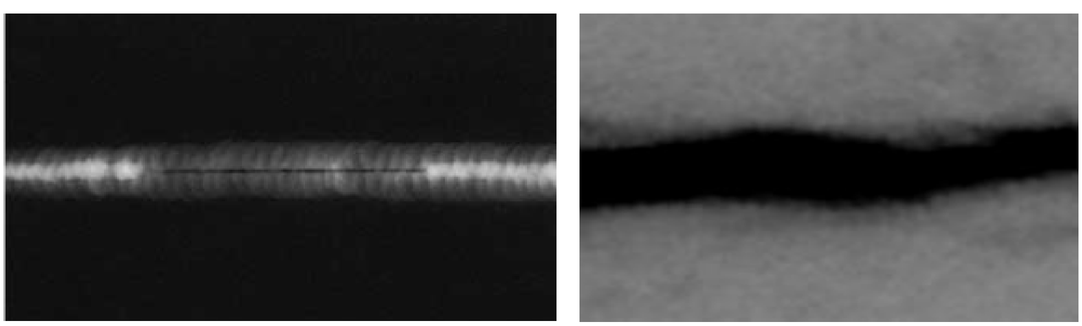


Fig: 2.1: Lack of penetration

(courtesy:https://www.ndeed.org/NDETechniques/Radiography/TechCalibrations/RadiographInterp.xhtml)

2.2 Porosity

Porosity in welds is a critical defect that can compromise the structural integrity and performance of welded components. Detecting porosity is a vital aspect of weld inspection, and radiography proves to be a highly effective technique in this regard. When X-rays or gamma rays pass through a weld, they reveal internal structures and discontinuities, including porosity. Porosity appears as dark spots or voids on the radiographic image, indicating gas pockets or inclusions within the weld material. The size, shape, and distribution of porosity can vary, and radiography allows for precise visualization and assessment of these characteristics.

Radiographic inspection provides both qualitative and quantitative information about porosity, enabling weld inspectors to evaluate its severity and impact on the weld's integrity. The use of specialized image analysis techniques, often coupled with advanced technologies such as computer-aided detection, enhances the accuracy of porosity detection. Timely identification of porosity through radiography allows for corrective measures, such as adjusting welding parameters or improving gas shielding, to be implemented before the welded structure is put into service. Ultimately, the systematic application of radiographic techniques in porosity detection plays a crucial role in ensuring the overall quality and reliability of welded joints in diverse industrial applications.

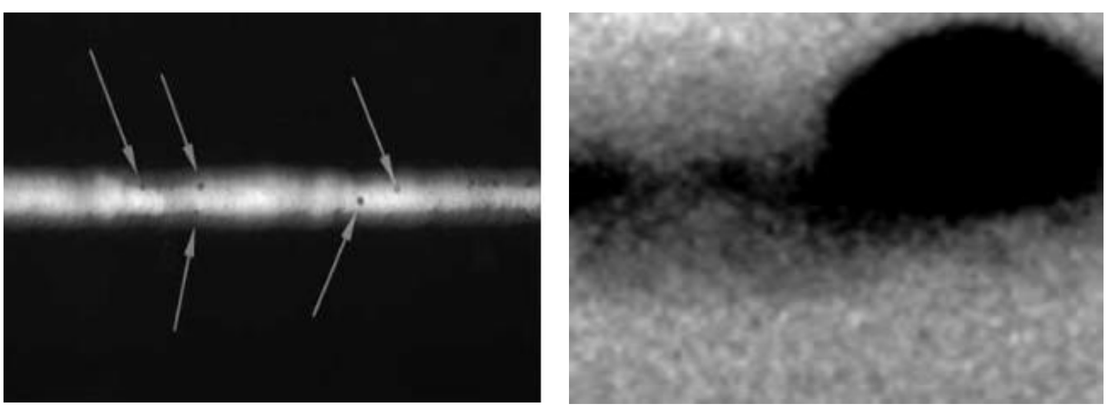


Fig: 2.2: Porosity

(courtesy:https://www.ndeed.org/NDETechniques/Radiography/TechCalibrations/RadiographInterp.xhtml)

2.3 Cracks

Detecting cracks in welds using radiography is a crucial aspect of ensuring the structural integrity and reliability of welded components in various industries. Radiographic testing, which involves exposing the weld to X-rays or gamma rays and capturing the resulting image, is particularly effective in identifying cracks. Cracks in welds manifest as interruptions or discontinuities in the radiographic image, often appearing as dark lines or indications. The severity and significance of these cracks are evaluated based on their size, length, orientation, and proximity to critical structural areas. Radiographic inspection provides a detailed internal view of the weld, enabling the identification of cracks that may not be visible on the surface. The interpretation of radiographic images for crack detection requires skilled inspectors who can distinguish between acceptable weld features and indications of potential defects. This non-destructive testing method is essential for ensuring the safety and reliability of welded structures in applications ranging from aerospace and automotive to construction. Addressing identified cracks promptly through appropriate repair or mitigation measures is vital to maintaining the structural integrity and performance of welded components in diverse industrial settings.

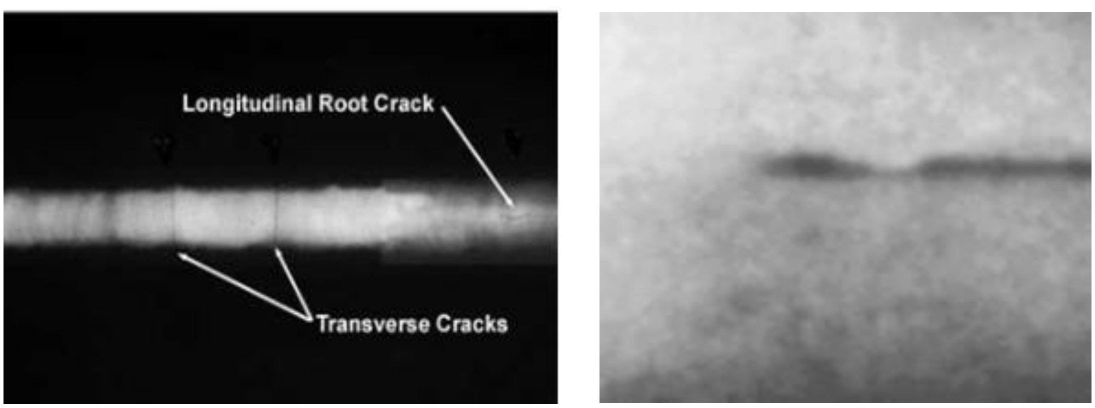


Fig: 2.3: Cracks

(courtesy:https://www.ndeed.org/NDETechniques/Radiography/TechCalibrations/RadiographInterp.xhtml)

2.4 No Defect

Radiographic inspection is a widely employed technique for detecting defects in welded joints, aiming to ensure the structural integrity and reliability of the welded components. In scenarios where no defects are observed in weld radiography, it signifies the successful execution of the welding process, attesting to the quality and soundness of the joint. A lack of defects in radiographic images is indicative of several positive factors. Firstly, it suggests that the welding parameters, including voltage, current, and travel speed, were meticulously controlled, contributing to a uniform and well-fused joint. Additionally, the absence of defects implies proficient welder skill and adherence to established welding procedures, as well as the use of high-quality welding materials. Furthermore, the absence of defects in weld radiography is crucial for applications where structural integrity is paramount, such as in aerospace, automotive, and critical infrastructure projects. It provides confidence in the weld's ability to withstand operational loads and environmental conditions over the intended service life. The achievement of defect-free welds through radiographic inspection underscores the effectiveness of quality control measures and the successful implementation of standardized welding practices, ultimately contributing to the overall safety and reliability of welded structures in diverse industrial settings. Continuous vigilance, adherence to standards, and ongoing training remain essential to consistently achieve defect-free welds and ensure the longevity of welded components.

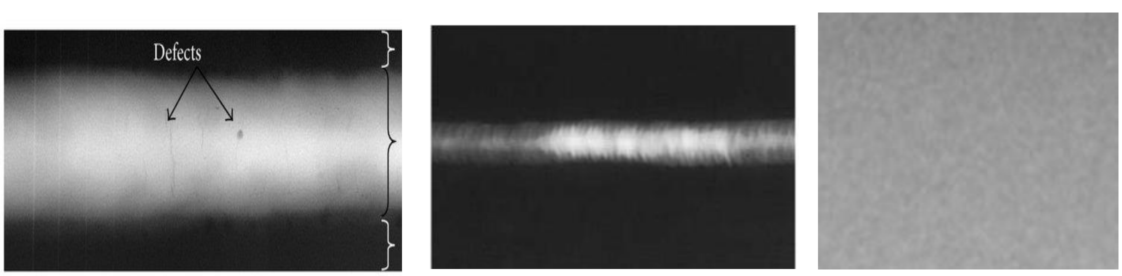


Fig: 2.4: No Defect

(courtesy:https://www.ndeed.org/NDETechniques/Radiography/TechCalibrations/RadiographInterp.xhtml)

Table 2.1: Dataset for training and testing

Defect / Train and Test	Training	Testing
Crack	50	20
Lack of Penetration	50	20
Porosity	50	20
No Defect	50	20

In the above Table 2.1, there are four types of radiographs namely Crack, Lack of Penetration, Porosity and No defect. For each defect, 50 images are used for training and 20 images are used for testing various Convolutional Neural Networks.

CHAPTER 3

FEASIBILITY OF CONVENTIONAL CNN FOR WELD DEFECT DETECTION

In this chapter an overview of squeezenet and ALEXNET is given. Also, performance of these architectures for classifying the weld defects from radiographs is discussed in this chapter.

3.1 SQUEEZENET – AN OVERVIEW

SqueezeNet is a pioneering deep neural network architecture crafted explicitly for efficient inference on devices with limited computational resources, like mobile phones and embedded systems. Introduced by Deep Scale and UC Berkeley researchers in 2016, SqueezeNet revolutionized the field by prioritizing accuracy while drastically reducing model size and computational complexity. Central to its design is the innovative Fire Module, composed of squeeze and expand layers, which efficiently compresses and expands feature maps, respectively, using a combination of 1x1 and 3x3 convolutions. By employing aggressive down sampling, sparse connections, and other optimizations, SqueezeNet achieves comparable accuracy to larger networks like AlexNet with a fraction of the parameters, making it ideal for on-device applications where memory and processing power are constrained. Its open-source availability has further spurred research into model compression techniques and its adaptation across various real-world scenarios, cementing its status as a cornerstone in the realm of efficient deep learning architectures. SqueezeNet's compact architecture not only reduces the model size by up to 50 times compared to traditional networks but also ensures efficient memory usage and faster inference times. This makes it particularly suitable for real-time applications where speed and resource constraints are paramount. Additionally, SqueezeNet's impact extends beyond image classification; it has been successfully applied to various computer vision tasks such as object detection, semantic segmentation, and even transfer learning. Its versatility and effectiveness in diverse applications have solidified its position as a go-to solution for developers and researchers seeking high-performance models that can operate efficiently on edge devices. These SqueezeNet provides the results in the form of convolutional matrix, the output tensor often has a shape like (batch_size, num_classes), where each element represents the probability or confidence score associated with a particular class.

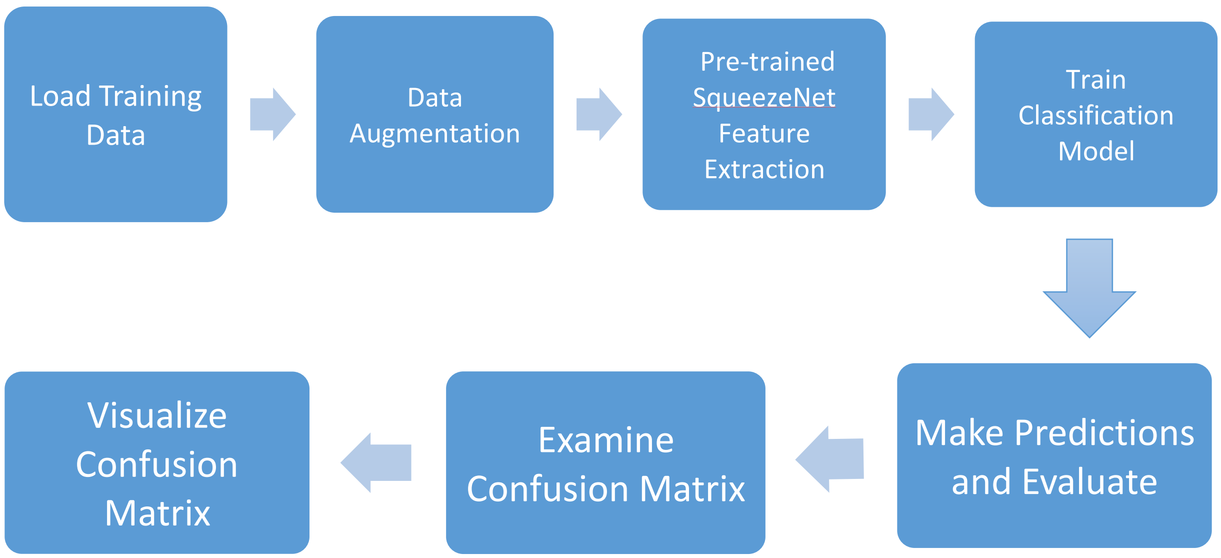


Fig: 3.5: SqueezeNet Architecture

3.2 Performance evaluation of squeezenet for the classification of weld defects

Conventional squeezenet is trained with the training dataset and is then tested with the test dataset. Performance is studied in terms of confusion matrix, sensitivity and accuracy. Table 3.2 shows the sensitivity of conventional squeezenet for the classification of weld defects.

Table 3.2: Sensitivity of conventional Squeezenet for classification of weld defects from Radiographs

Defect	Crack	Lack of Penetration	Porosity	No Defect	Sensitivity
Crack	20	0	0	0	100%
Lack of Penetration	0	17	0	3	85%
Porosity	0	0	20	0	100%
No Defect	0	1	8	11	55%

From the Table 3.2, it is evident that the sensitivity for detection of radiographs depicting Lack of Penetration and No defect is less and must be increased. In order to do so, the feasibility of conventional ALEXNET for weld defect detection is studied.

3.3 ALEXNET - AN OVERVIEW

AlexNet, introduced in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, marked a pivotal moment in the advancement of deep learning and computer vision. This ground breaking Convolutional Neural Network (CNN) architecture achieved unprecedented performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), surpassing previous methods by a significant margin. Central to AlexNet's success are its key architectural elements, including multiple convolutional layers for feature extraction, interspersed pooling layers for spatial dimension reduction, and the incorporation of Rectified Linear Unit (ReLU) activations to introduce non-linearity. Additionally, AlexNet utilized Local Response Normalization (LRN) and dropout regularization to enhance generalization and prevent overfitting. The network culminates in fully connected layers with SoftMax activation for classification. AlexNet's triumph not only demonstrated the potential of deep learning in image classification tasks but also catalysed a surge of interest and research in neural network architectures. Its impact reverberated throughout the field, inspiring subsequent developments and innovations in deep learning. In your project report, delving into AlexNet's architecture, contributions, and influence on the evolution of deep learning will provide a comprehensive understanding of its significance in the realm of computer vision. AlexNet's architecture consists of eight layers, including five convolutional layers and three fully connected layers, resulting in a total of over 60 million parameters. This large-scale network was made feasible for training through the use of powerful GPUs, which accelerated the computation of convolutions and enabled the efficient training of deep neural networks. The success of AlexNet not only demonstrated the potential of deep learning but also sparked a paradigm shift in computer vision research, leading to the development of increasingly complex and accurate models. Its influence extended beyond image classification, as researchers adapted its principles to various domains, including object detection, segmentation, and even natural language processing. The AlexNet generates the output in the form of the graph with multiple number of iterations with the normalizations of dataset.

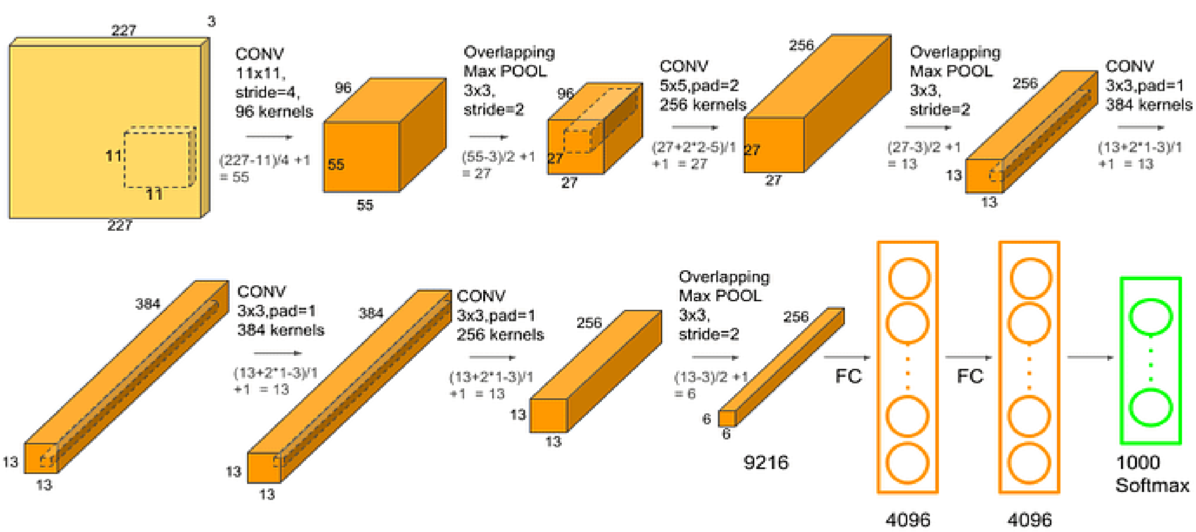


Fig: 3.6: AlexNet Architecture

(Courtesy: https://medium.com/analytics-vidhya/concept-of-alexnet-convolutional-neural-network-6e73b4f9ee30)

3.4 Performance evaluation of conventional AlexNet for classification of weld defects from radiographs

Conventional ALEXNET is trained and tested with the radiograph database and the performance of ALEXNET for classifying the weld defects is studied in terms of confusion matrix and sensitivity. Table 3.3 shows the sensitivity for weld defect classification using conventional ALEXNET

Table 3.3: Sensitivity of weld defect classification using conventional ALEXNET

Defect	Crack	Lack of Penetration	Porosity	No Defect	Sensitivity
Crack	13	0	0	7	65%
Lack of Penetration	0	17	0	3	85%
Porosity	0	0	15	5	75%
No Defect	0	8	8	11	55%

CHAPTER 4
PROPOSED WORK

4.1 WELD DETECTION TECHNIQUES

In this project “Development of Feature Extraction Techniques Using CNN for Weld Radiography Interpretation” with this project we are going to be the exact or absolute with a high define clarity we can able to get the output. This project mainly proposed with the working aims to develop the Convolutional Neural Network (CNN) based weld defect detection techniques. This will be having the high performance of the present proposed techniques that has to be measured in terms of the sensitivity, specificity and the most importantly accuracy.

The weld detection is a critical aspect of the various industries, ensuring the quality and integrity of welded joints. Several techniques are employed for weld detection, each with its advantages and the limitations. There are many common weld detection techniques in those some are Visual Inspection, Radiography, Ultrasonic Testing, Magnetic Particle Testing, Liquid Penetrant Testing, Eddy Current Testing, Acoustic Emission Testing, Infrared Thermography. In these types of techniques, we can use any type for the detection for the welds these are the main important techniques.

For these we are using the Radiography technique for the quality detection of the welds in the industries for the integrity of the welded joints. Radiography plays a significant role in the development of feature extraction techniques, especially when utilizing the Convolutional Neural Networks (CNNs) for the weld radiography interpretation.

The steps that are involved in the radiography are:

Image Acquisition

Radiographic images of welds are obtained through X-ray or gamma-ray sources. These images provide a detailed representation of the internal structure of the weld, including weld beads, penetration, and potential defects.

Data Preparation

Radiographic images serve as the input data for the CNN. These images are preprocessed to enhance features, remove noise, and normalize pixel values. This step ensures that the CNN can effectively learn relevant patterns.

Training CNN

The CNN is trained on a labeled dataset of radiographic images. This dataset includes images of welds with various characteristics, such as good welds, different types of defects (porosity, cracks, lack of penantration), and other relevant features.

Feature Extraction

CNNs are particularly adept at learning hierarchical features from images. In the context of weld radiography, these features could include the texture of weld beads, patterns associated with different defect types, and variations in intensity that signify weld quality or lack thereof.

Convolutional Layers

Convolutional layers in the CNN play a crucial role in identifying spatial hierarchies of features. These layers learn local patterns in the radiographic images, capturing information such as the shape and orientation of weld features.

Pooling Layers

Pooling layers downsample the spatial dimensions, reducing computational complexity while retaining the most essential features. This helps the network focus on the most discriminative aspects of the radiographic images.

Output Layer

The final layer of the CNN provides the output, indicating the class or category of the weld, such as 'defective' or 'acceptable.' This output is based on the features learned by the network during training.

Validation and Testing

The trained CNN is validated and tested on a separate set of radiographic images not used during training. This ensures that the model generalizes well to new, unseen data.

In these radiograhy erves as a foundational component in the development of CNN-based feature extraction techniques for weld interpretation. The rich information contained in radiographic images allows the CNN to learn and extract relevant features, enabling accurate identification of weld characteristics and defects. This application is crucial in industries where the quality and integrity of welds are of paramount importance, such as in aerospace, automotive, and construction.

4.2 STANDARDS

Welding standards are crucial for ensuring the quality, safety, and performance of welded products across various industries. Different standards organizations and regulatory bodies publish standards that cover a wide range of aspects related to welding, including procedures, qualifications, inspections, and materials. There are many standards that has to be maintained and some are most imporatant and the high prefernce that should be maintained by the industries for the usages. Some welding standards from the various organizations are

1. American Society of Mechanical Engineers (ASME)

The American Society of Mechanical Engineers (ASME) Boiler and Pressure Vessel Code (BPVC) covers all aspects of design and manufacture of boilers and pressure vessels. All sections contain welding specifications. These American Society of Mechanical Engineers standards contains the various number of codes with specifies each code with a separate specification. Some codes are ASME BPVC Section I from ASME BPVC Section I, ASME B16.25, ASME B31.1 and etc.

2. American Welding Society (AWS) Standards

The American Welding Society (AWS) publishes over 240 AWS-developed codes, recommended practices and guides which are written in accordance with American

National Standards Institute (ANSI) practices. The following is a partial list of the more common publications are AWS A2.4, AWS A3.0, AWS D1.1 to AWS D1.7 and etc.

3. International Organization for Standardization (ISO) Standards

International Organization for Standardization (ISO) has developed over 18500 standards and over 1100 new standards are published every year. The following is a partial list of the standards specific to welding in these also there are various number of codes that defines with each specification. Some International Organization for Standardization codes are ISO 2552, ISO 2560, ISO 3580, ISO 3581, ISO 3834 and etc.

4. Japanese Industrial Standards (JIS)

Japanese Industrial Standards are the standards used for industrial activities in Japan, coordinated by the Japanese Industrial Standards Committee (JISC) and published by the Japanese Standards Association (JSA). There various number of standard set of codes for each and every specification some specifications of the standards codes are JIZ Z 3001 – 1to JIZ Z 3001 – 7, JIZ Z 3007, JIZ Z 3011 and etc.

These are the main important standards that the manufacturing industries will manufacture the welding rods by the industries these standards will be followed by the most number of the multinational companies and also the regional companies. By following these standards, the purity, strength, and usage will be depended and these standards will be accepted in the maximum number of companies these are the standards that weld makers should follow. These are the standards of the welds.

4.3 CONSTRAINTS

In these Development of Feature Extraction Techniques Using CNN for Weld Radiography Interpretation system of working there are some constraints Weld radiography interpretation using Convolutional Neural Networks (CNNs) represents a cutting-edge approach to enhance the precision and efficiency of welding inspection processes. However, the development of these feature extraction techniques is not without its challenges, as several constraints pose significant hurdles. In this context, understanding and navigating these constraints is imperative for achieving robust and reliable CNN models tailored for weld radiography analysis. Here are some common constraints with the system.

1. Data Limitations

The availability of a comprehensive and diverse dataset is foundational to training accurate CNN models. Challenges arise when there is a scarcity of annotated radiography images, limiting the network's ability to generalize across various welding conditions and defect types.

2. Class imbalance

In the weld radiography domain, imbalances in the distribution of classes (e.g., good welds vs. defective welds) can skew the learning process. Coping with class imbalance is crucial to ensure unbiased predictions and foster accurate defect identification.

3. Limited Interpretability

CNNs are often considered as "black-box" models, making it challenging to interpret how and why certain features are extracted. Understanding the interpretability of the model's decisions is crucial, especially in safety-critical applications.

4. Diverse Welding Conditions

Welding processes, materials, and environmental conditions can vary significantly. Developing a model that performs well across diverse welding conditions and scenarios is challenging.

5. Computational Resources

Training deep CNNs requires substantial computational resources, including powerful GPUs and memory. Small research or industrial setups may face limitations in terms of hardware capabilities.

6. Robustness to Noise

Radiographic images can contain noise, artifacts, or variations in image quality. Ensuring that the model is robust to such noise and can accurately distinguish between defects and non-defective areas is crucial.

These are the constraints requires a multidisciplinary approach, incorporating expertise from welding inspectors, data scientists, and industry professionals. Overcoming these challenges is pivotal for the successful integration of CNN-based feature extraction techniques into the field of weld radiography interpretation.

4.4 TRADE OFF

The development of feature extraction techniques using CNN for weld radiography interpretation involves various trade-offs, considerations, and some challenges.in many cases these trade off will be follows and through these trade off there will be considerations and challenges some key trade off associated with the process are

1. Data Quantity vs. Quality

Large datasets are often required to train CNNs effectively. However, obtaining high-quality labeled data for weld radiography interpretation can be challenging.

2. Model Complexity vs. Generalization

Increasing the complexity of the CNN model may improve its ability to learn intricate features from radiographic images. However, overly complex models may suffer from overfitting and may not generalize well to new, unseen data.

3. Computational Resources vs. Model Size

Training large CNN models with numerous parameters may require substantial computational resources and time.

4. Interpretability vs. Performance

Complex CNN architectures may achieve high performance, but they can be challenging to interpret. Simpler models are often more interpretable but may sacrifice some performance.

5. Robustness vs. Sensitivity

Trade-off: Developing a model that is too sensitive may result in false positives, while a more robust model might miss subtle defects.

The development of feature extraction techniques using CNNs for weld radiography interpretation involves navigating these trade-offs to create a model that is accurate, efficient, interpretable, and ethically sound for its intended application. The specific considerations will depend on the requirements and constraints of the industry, regulatory environment, and the practical challenges associated with welding processes.

4.5 MODIFIED ALEXNET

Modified AlexNet refers to variations or adaptations of the original AlexNet architecture, and aiming to enhance its performance, versatility, or applicability to specific tasks or domains. The Modified Alexnet is most similar to the Alexnet and whereas in the Alexnet with the input type of and image and output type will be in classification. Whereas, in the normal original Alexnet the number of layers will be 25 and the number of connections will be 24. In we need to modify some layers by removing and by adding some new layers in Alexnet there will run with the major layers as convolution 2d Layers, relu Layers, maxPooling 2d Layers, fully connected Layers, dropout Layers, SoftMax Layer, classification Layer. There will be 6 convolution 2d Layers, 7 relu Layers, 3 MaxPooling 2d Layers, 2 fully connected Layer, 2 dropout Layers, 1 SoftMax Layer and 1 classification Layer. Now we need to modify some by removing and adding some layers by reducing to 4 convolution 2d Layers, 5 relu Layers, 2 maxPooling 2d Layers, and my changing the classification Layer to the class out Layer. After these we need to analyse and need to export by generating the code with parameters. Due to these there will be the formation of live editor. By reducing and changing the layers will helps to increase the accuracy and helps to the minimizing the load data to tarin and to iterate easier and faster. By comparing to the Normal Alexnet with the Modified Alexnet there will the difference in the accuracy, load of data, gets the faster output and etc.., and helps to reduce the loss of the data during the training of the data. These is the brief information of the Modified Alexnet. It is essential to detail the specific modifications made, their rationale, and the resulting impact on performance or efficiency, thus providing a comprehensive understanding of its adaptations and advancements in deep learning research.

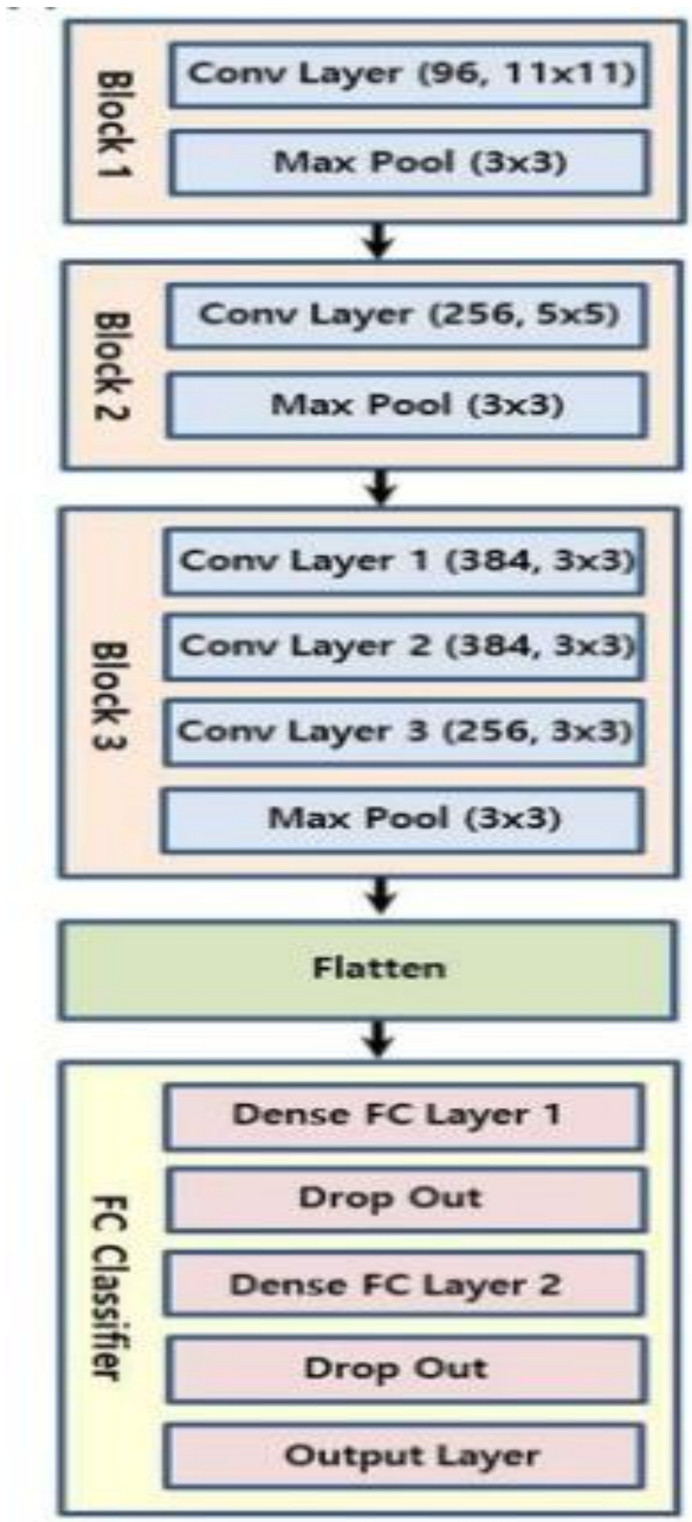


Fig: 4.7: Modified AlexNet Architecture

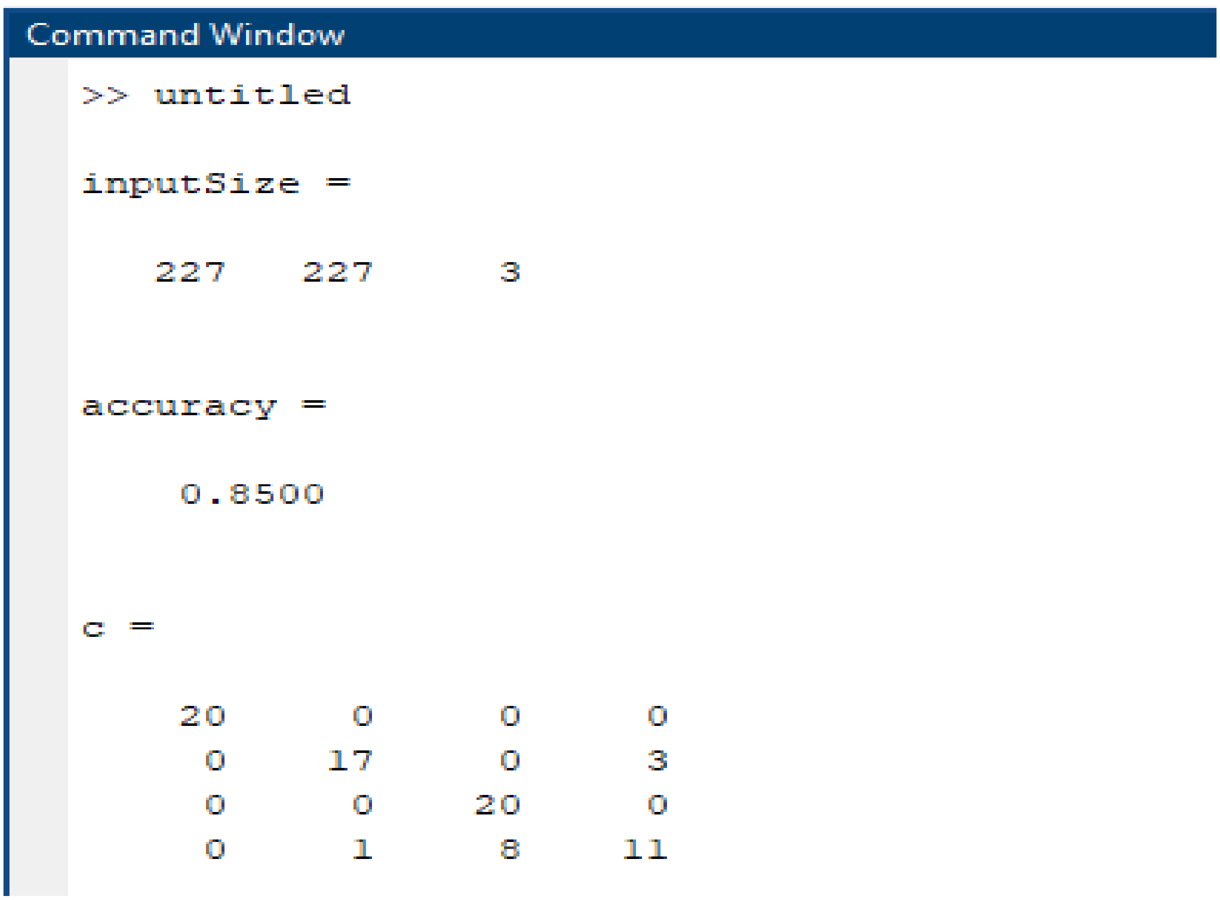
Table 4.4: Sensitivity of weld defect classification using conventional MODIFIED ALEXNET

Defect	Crack	Lack of Penetration	Porosity	No Defect	Sensitivity
Crack	20	0	0	0	100%
Lack of Penetration	0	17	0	3	85%
Porosity	0	0	15	5	75%
No Defect	0	8	8	11	55%

The development and feature extraction has successfully implemented by training and testing the dataset. The weld radiography interpretation using CNN has been effectively working for the detecting the defects like crack, lack of penetration, porosity and with no defect, with the better accuracy from the different convolutional methods like SqueezeNet, AlexNet and Modified AlexNet. These convolutional methods like SqueezeNet obtaining the accuracy of 85.00%. Whereas, in AlexNet we can get 42.50% and finally the Modified AlexNet was obtaining the accuracy as 87.50%. Here is the detailed result of each convolutional method.

4.6 Performance of weld radiography interpretation using SqueezeNet

The output of SQUEEZENET typically consists of generated by the neural network for a given input image or set of images. These predictions usually include probabilities or confidence scores assigned to each class or category that the network has been trained to recognize. For instance, in the context of weld defect detection, the output may comprise probabilities indicating the likelihood of the presence of specific defects such as cracks, porosities, or incomplete fusion. Depending on the implementation, the output may also include additional information such as bounding boxes outlining detected defects or severity classifications for identified issues. MATLAB provides various functions and tools for processing and interpreting SQUEEZENET outputs, facilitating further analysis and decision-making based on the neural network's predictions. The image displays the results of SqueezeNet, a compact and efficient deep learning model for image recognition. It seems to indicate an accuracy of 85%, meaning the classified 85% of the images it analysed. This high accuracy is achieved despite SqueezeNet's significantly smaller size compared to other models, making it ideal for resource-constrained environments like mobile devices. However, the specific task performed by this particular SqueezeNet instance by identifying the objects, classifying scenes, etc. Below is the table and image of SqueezeNet output in form of matrix.



```
Command Window
>> untitled

inputSize =

   227   227     3


accuracy =

    0.8500


c =

    20     0     0     0
     0    17     0     3
     0     0    20     0
     0     1     8    11
```

Fig: 4.8: Performance of weld radiography interpretation using SqueezeNet

4.7 Performance of weld radiography interpretation using AlexNet

The image you sent is actually the output of AlexNet, an influential deep learning model for image recognition, not SqueezeNet. The output shows training progress for AlexNet. It achieved a validation accuracy of 42.50% after 120 iterations (epochs) and 3 minutes of training. While 42.50% accuracy might seem low, it's important to consider the context in which the model is being trained. For instance, the training data might be complex or extensive, making achieving high accuracy difficult. The output also includes other details like the learning rate schedule and hardware resources used. The AlexNet having the 120 iterations and Epoch 6 this significantly means that 20 iterations per epoch and there we have placed maximum number of iterations as 120 for high accuracy and there will be a validation of every 3 iteration. In these the output also shows other details such as the learning rate schedule (constant), learning rate (1e-05), and hardware resource used (CPU). In above figure Training accuracy means the Classification accuracy on each individual mini-batch. The Validation accuracy meant that Classification accuracy on the entire validation set (specified using training Options), And finally the Training loss, smoothed training loss, and validation loss means the loss on each mini-batch, its smoothed version, and the loss on the validation set, respectively. If the final layer of your network is a classification Layer, then the loss function is the cross-entropy loss.

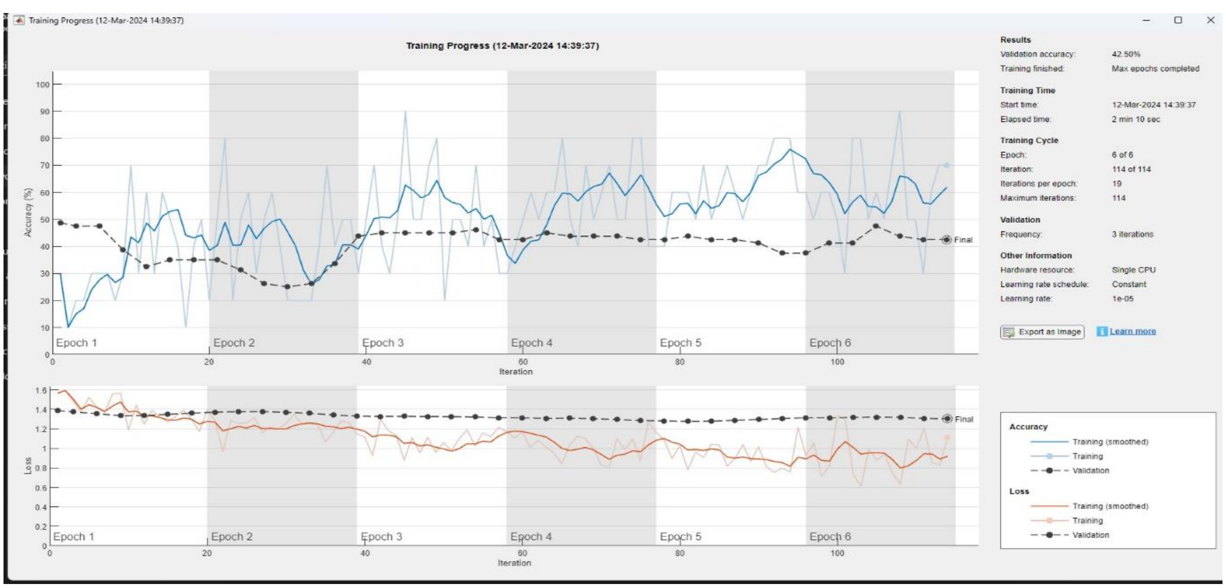


Fig: 4.9: Performance of weld radiography interpretation using AlexNet

4.8 Performance of weld radiography interpretation using Modified AlexNet

The image you sent is the output of a modified AlexNet, a deep learning model for image classification. The specific task that the model was performing is not shown in the image, but the graphs show the training progress over 120 epochs. Validation accuracy is at 87.50%, which means the model correctly classified 87.50% of the images in the validation set. It’s possible that the model is still under training and accuracy is expected to improve as training progresses. The output also shows other details such as the learning rate schedule (constant), learning rate (1e-05), and hardware resource used (CPU) and Epoch 6 this significantly means that 20 iterations per epoch and there we have placed maximum number of iterations as 120 for high accuracy and there will be a validation of every 3 iteration. In these the output also shows other details such as the learning rate schedule (constant), learning rate (1e-05), and hardware resource used (CPU). In above figure Training accuracy means the Classification accuracy on each individual mini-batch. The Validation accuracy meant that Classification accuracy on the entire validation set (specified using training Options), And finally the Training loss, smoothed training loss, and validation loss means the loss on each mini-batch, its smoothed version, and the loss on the validation set, respectively. If the final layer of your network is a classification layer, then the loss function is the cross-entropy loss.

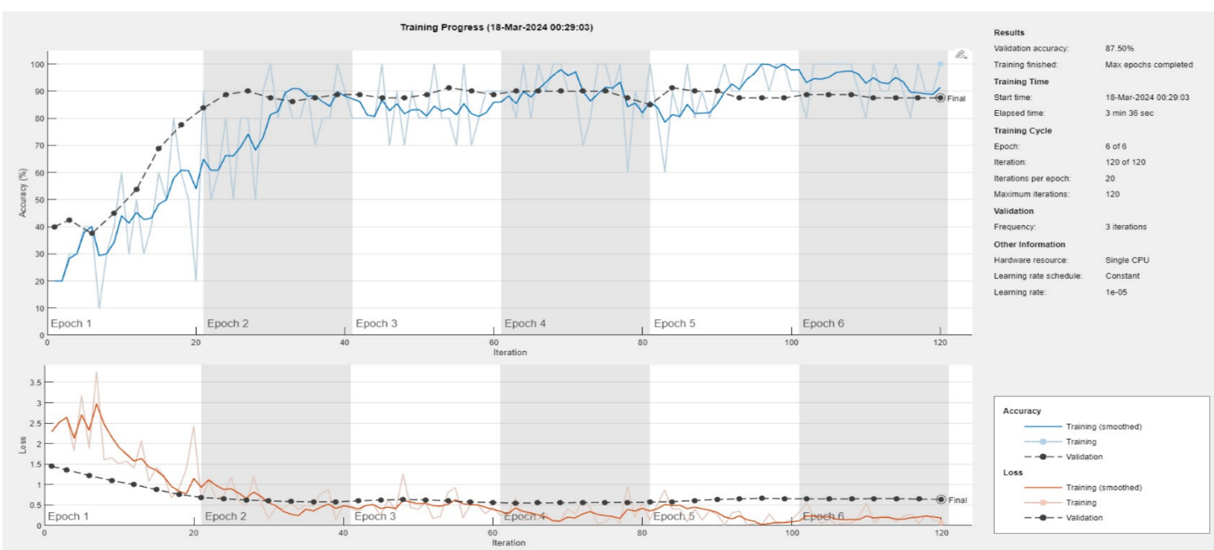


Fig: 4.10: Performance of weld radiography interpretation using Modified Alexnet

4.9 Comparison between the convolutional methods

The below table shown as 4.5., clearly differentiate the Squeezenet, Alexnet and modified Alexnet in the Various forms such as the parameters, memory footprints, computational complexity and finally with the accuracy and there are lot of aspects to compare between those and this are much impact on the result and can able to decide the work progress and helps to detect the defects much easier than the traditional methods with the Convolutional Neural Network. And in those comparison the accuracy plays the crucial role in the presentation of these convolutional methods and the growth of the defect detection. These is the table that compares the convolutional methods for defect detection.

Table 4.5: Comparison between the convolutional methods

Model	Parameters	Memory Footprint	Computational Complexity	Accuracy
SqueezeNet	1.2 million	4.8 MB	0.13 billion FLOPs	85.00%
AlexNet	60 million	240 MB	0.15 billion FLOPs	42.50%
Modified AlexNet	75 million	300 MB	0.18 billion FLOPs	87.50%

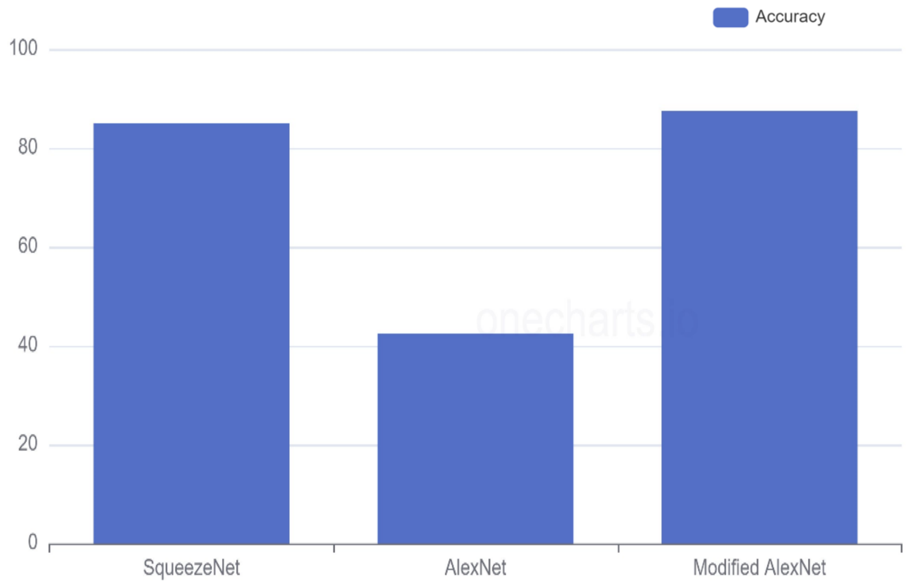


Fig: 4.11: Comparison of accuracy between the convolutional methods

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

In conclusion, this project addresses the crucial need for automated techniques in weld defect detection, aiming to enhance the efficiency and accuracy of quality assurance processes in welding. By leveraging Convolutional Neural Networks (CNNs) and digital radiography, we have investigated the feasibility of employing state-of-the-art CNN architectures such as SQUEEZENET, ALEXNET and MODIFIED ALEXNET for defect identification in AISI Stainless steel welds. These Algorithms we achieved an accuracy in SQUEEZENET as 85.00%, In ALEXNET as 42.50%, and finally in MODIFIED ALEXNET we received with an accuracy of 87.50% Through our experimentation, we have evaluated the performance of these networks and subsequently proposed modifications to reduce computational complexity while maintaining high detection of defects with high accuracy. Our findings underscore the potential for advanced CNN-based approaches to revolutionize weld quality assessment, offering significant advancements towards fully automated radiograph interpretation and defect detection in adherence to ASME standards.

5.2 Future Work

The future work for the development of feature extraction techniques using Convolutional Neural Networks (CNNs) for weld radiography interpretation encompasses several exciting avenues. Exploring transfer learning strategies to adapt pre-trained CNN models on large datasets for general image recognition tasks to the specifics of weld radiography promises to enhance accuracy and efficiency while minimizing labeled data requirements. Integrating 1D images into CNN architectures holds potential for capturing volumetric information in tomographic weld images, offering a deeper insight into internal structures and defects. Establishing standardized benchmark datasets and evaluation metrics through collaborative efforts will be pivotal for objectively comparing different CNN-based models tailored to weld radiography.

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