AN AI-DRIVEN APPROACH: TO DETECT AND PREDICT WELD FILM IRREGULARITIES FOR ENHANCED QUALITY CONTROL

by

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Dedication

THIS DISSERTATION IS DEDICATED TO MY BELOVED PARENTS, WHOSE MEMORY LIVES ON IN EVERY ACHIEVEMENT I PURSUE.
YOUR UNWAVERING LOVE, SACRIFICES, AND GUIDANCE CONTINUE TO INSPIRE ME EACH DAY. THIS WORK IS A TRIBUTE TO YOUR MEMORY, AND TO THE VALUES YOU INSTILLED IN ME.

AND TO THE INDUSTRY THAT HAS SHAPED MY JOURNEY—
AND TO THE INDUSTRY I AM PROUD TO BE A PART OF—

MAY THIS THESIS SERVE, IN SOME SMALL WAY, AS A CONTRIBUTION TO ITS ONGOING GROWTH, INNOVATION, AND EXCELLENCE.

MAY THIS WORK SERVE AS A STEP TOWARD MINIMIZING REWORK, ENHANCING QUALITY, MEETING DEADLINES, AND REDUCING COSTS, ALL IN THE SPIRIT OF DRIVING MEANINGFUL PROGRESS AND LASTING IMPACT.

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ABSTRACT

AN AI-DRIVEN APPROACH: TO DETECT AND PREDICT WELD FILM IRREGULARITIES FOR ENHANCED QUALITY CONTROL

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Weld quality assurance is a critical aspect of industrial applications, where defects such as porosity, “cracks”, “lack of fusion”, and “slag inclusion” can compromise structural integrity and safety. Traditional “Non-Destructive Testing (NDT)” methods such as Radiographic Testing (RT) rely heavily on manual inspection, which is time-consuming, error-prone, and subjective. Recent advancements in “Artificial Intelligence” (AI) have introduced new possibilities for automated defect detection and prediction.

This study proposes a “Hybrid AI”-driven approach that integrates “Convolutional Neural Networks” (CNNs) for defect detection in radiographic images with “Machine Learning (ML)” algorithms (“Random Forest”, XGBoost, and “Gradient Boosting”) for defect prediction based on welding process parameters. The research utilizes the GDXray dataset for radiographic weld images and historical welding parameters to develop an intelligent defect detection and prediction model.

The results demonstrate that the hybrid AI model outperforms traditional NDT approaches, achieving high accuracy in defect classification while providing predictive insights that allow for proactive quality control. This study contributes to Industry 4.0 applications, improving weld quality management, reducing costs, and enhancing manufacturing efficiency.

KEYWORDS

Artificial Intelligence, Machine Learning, Weld, Defects, Weld Irregularities, Radiography Films, Slag, Crack, Incomplete Penetration, YOLO, pretrained model.

LIST OF ABBREVIATIONS

DL – Deep Learning

ML-Machine Learning

RT- Radiography Films

IP- Incomplete Penetration

CNN- Convolutional Neural Network

YOLO- You Look Only Once

Lr – Learning Rate

Opt- Optimizer

Adam- Adaptive Moment estimation

DT- Destructive Testing

NDT- Non-Destructive Testing

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER I: INTRODUCTION

1.1 Introduction

Welding is a crucial process in industries such as aerospace, automotive, and pipeline construction, where structural integrity is non-negotiable. Weld defects can lead to safety hazards, increased costs, and operational failures. Conventional “NDT” methods like “Radiographic Testing” (RT), “Ultrasonic Testing (UT)”, and “Magnetic Testing (MT)” are widely used for weld defect identification, but they depend on human expertise and are prone to misinterpretation (Yousefi et al., 2020; Ibarra-Castanedo & Maldague, 2014).

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Welding is one of the most widely used methods for permanently joining metal components in various industrial applications. Before allowing the use of welded components in critical applications such as “Oil and Gas pipelines”, “vehicles”, “steam turbines”, “ships”, and other metal structures, it is essential to assess the quality of the weld joints. This assessment is crucial for detecting and locating various types of weld defects, including porosity, surface cracks, inclusions, undercuts, poor fusion, and insufficient penetration. These defects can significantly affect the reliability, durability, and mechanical properties (such as stiffness, toughness, and strength) of the welded joints (Kumar & Bhaduri, 2011; Li et al., 2020; Ramesh & Kumar, 2021).

The quality of welded joints can be evaluated through two primary methods:

- “Destructive Testing (DT)” and
- “Non-Destructive Testing (NDT)”.

“DT” involves testing welds by breaking them to assess the strength of the welded specimen. In contrast, “NDT” allows for inspecting the welds to detect defects without causing any damage to the object being tested. Several NDT technologies have been developed to identify weld defects, including “Radiographic Testing (RT)”, “Computed Tomography (CT)”, “Ultrasonic Testing (UT)”, and “Magnetic Testing (MT)”. “RT” is one of the oldest NDT methods, designed to detect defects in weld bead samples (Hellier, 2012; Mudge, 2015; Singh & Kumar, 2020)..

In “Conventional Radiography (CR)”, the component being examined is exposed to x-rays, and the radiographic images are captured on x-ray-sensitive film placed behind the component. Traditionally, fault detection engineers, with years of experience, visually inspect these radiographic images. However, this manual process is often subjective, as it may miss small defects, fail to detect certain types of defects, or struggle with noisy or low-contrast radiographic images (Hellier, 2012, pp. 298–302; Raj & Jayakumar, 2007, pp. 205–207). This makes defect detection challenging using conventional methods. Additionally, human factors, such as fatigue, carelessness, lack of training, or a combination of these, can lead to errors or accidents. Manual inspection methods are also time-consuming, costly, and prone to mistakes, making them less effective (Mudge, 2015, pp. 100–101). Therefore, it is essential to develop a novel and more efficient defect detection technique that is both accurate and cost-effective.

“Feature-based defect identification has gained increasing attention and is gradually replacing traditional manual inspection methods due to advancements in digital image processing and machine learning techniques (Gonzalez & Woods, 2018, pp. 710–715; Zhang et al., 2020, pp. 342–344). While traditional methods involve manually extracting specific image features based on fault conditions, there are four major challenges associated with manual defect identification” (Ma et al., 2019, pp. 254–256).

First, each detection task may encounter various issues, each requiring a unique set of features, making it difficult to create a universal strategy due to the irregularity of fault patterns. Second, defects may appear in diverse forms with different categories and features, including low-contrast patches, uneven brightness, or asymmetrical shapes, which complicates detection. Third, gathering large amounts of weld defect samples, particularly rare ones, results in imbalanced and costly datasets. Finally, some weld defect data may be lost during the feature extraction process. Convolutional Neural Networks (CNNs) can address these challenges, making them the primary motivation for pursuing this approach. It's a class of deep neural networks commonly used in computer vision tasks such as image classification, object detection, and facial recognition (Goodfellow et al., 2016, pp. 326–336; Zhang et al., 2020, pp. 342–344; Ma et al., 2019, pp. 254–256)..

Machine Learning is a subset of artificial intelligence (AI) that enables computers to learn from data and improve their performance on tasks over time, without being explicitly programmed. The core idea is that algorithms can learn patterns from input data and make predictions or decisions based on that learning (Goodfellow et al., 2016, pp. 96–97; Bishop, 2006, pp. 1–3).

Key Components:

- "Supervised Learning": The algorithm is trained on labeled data (data with known outcomes) to learn the relationship between input and output. (Bishop, 2006, pp. 9–10)
- "Unsupervised Learning": The algorithm works with unlabeled data and finds hidden patterns or groupings. (Goodfellow et al., 2016, pp. 502–503).
- "Reinforcement Learning": The model learns by interacting with an environment and receiving feedback based on actions taken (rewards or penalties) (Sutton & Barto, 2018, pp. 3–5).

"Deep Learning" is a specialized subset of "Machine Learning" that uses neural networks with many layers (hence the term "deep") to model complex patterns in large amounts of data. It is particularly powerful for tasks involving unstructured data such as images, audio, and text (Goodfellow et al., 2016, pp. 6–10, 168–170).

Key Features:

- Neural Networks: Deep learning models are based on artificial neural networks, which are inspired by the structure of the human brain. These networks consist of layers of nodes (neurons) that process information. (Bishop, 2006, pp. 226–230).
- Hierarchical Learning: The deep structure allows the model to learn features at multiple levels of abstraction, which is especially useful

in tasks like image recognition, speech processing, and natural language understanding (LeCun, Bengio, & Hinton, 2015, pp. 436–439).

With advancements in AI and Deep Learning (DL), automated systems using CNNs for image-based defect detection and ML models for predictive analytics have shown significant improvements in accuracy and efficiency(Goodfellow et al., 2016, pp. 326–330; Zhang et al., 2020, pp. 345–347). However, existing research focuses mainly on detection, whereas defect prediction remains underexplored (Ma et al., 2019, pp. 254–256). This study aims to bridge this gap by developing an AI-powered hybrid model for real-time defect detection and prediction, improving manufacturing quality control.

Machine learning is fundamentally about uncovering patterns and insights from data. It lies at the crossroads of disciplines such as statistics, computer science, and artificial intelligence (AI), and is often referred to as statistical modeling, data-driven analytics, or predictive modeling(Goodfellow, Bengio and Courville, 2016, pp. 95–97; Bishop, 2006, pp. 1–3). Over the past decade, the use of machine learning techniques has become deeply embedded in our daily digital interactions. From suggesting which movies to stream, meals to order, or products to purchase, to recognizing faces in photos and curating personalized music playlists—many digital platforms rely heavily on machine learning at their core(Domingos, 2015, pp. 15–22).

In fact, if you navigate through complex websites like Netflix, Amazon, or Facebook, you're likely interacting with dozens of machine learning models operating simultaneously across different components of the site (Jordan and Mitchell, 2015, pp. 255–256). Beyond the commercial sphere, machine learning has significantly transformed how modern scientific research is conducted. These tools have been applied to groundbreaking tasks such as mapping the cosmos, detecting exoplanets, discovering subatomic particles, decoding genetic sequences, and even delivering customized medical treatments like cancer therapy (Shalev-Shwartz and Ben-David, 2014, pp. 18–19; Russell and Norvig, 2021, pp. 834–836).

However, the practical benefits of machine learning are not limited to these grand-scale applications. Even modest or domain-specific tasks can gain immense value from the intelligent use of machine learning techniques (Murphy, 2012, pp. 5–6; Russell and Norvig, 2021, pp. 842–843). This research focuses on building a foundational machine learning model, and in doing so, highlights key questions that arise during the development process (Mitchell, 1997, pp. 2–4).

In both “supervised and unsupervised” learning frameworks, it is crucial to format the input data in a way that machines can interpret (Hastie, Tibshirani and Friedman, 2009, pp. 10–12). A common way to conceptualize this is to imagine the dataset as a spreadsheet: each row represents an individual sample, and each column represents a measurable attribute or feature (Mitchell, 1997, pp. 4–5).

For instance, when analyzing weld quality, one column might capture the number of welds performed by a welder, while others might indicate defect types or frequencies. In this study, we examine three individual welders and analyze the recurrence of specific weld defects in their work.

When working with weld imagery, features could be represented through pixel intensity values in grayscale images, or by characteristics such as shape, area, and color patterns (Szeliski, 2011, pp. 45–47; Li et al., 2020, pp. 5–6). Accurately describing and structuring this data is essential for training an effective machine learning model (Murphy, 2012, pp. 25–27).

Perhaps the most vital component of any machine learning pipeline is a deep understanding of the dataset and its relationship to the problem being addressed (Alpaydin, 2020, pp. 33–35; Shalev-Shwartz and Ben-David, 2014, pp. 22–23). Simply applying an algorithm to raw data without analysis is unlikely to yield useful results. Instead, a thoughtful examination of the dataset—its structure, limitations, and the nature of the target outcome—should guide model selection and development (Jordan and Mitchell, 2015, pp. 255–256). Since every machine learning algorithm is tailored to different types of input and problem settings, aligning the data with the right model architecture is crucial (Zhang et al., 2020, pp. 346–348).

In the course of building this machine learning solution, we have carefully explored and responded to the central research questions, which provide the foundation for developing a hybrid model tailored to identifying weld defects and predicting future defect trends based on welder history.

While we were building a machine learning solution, we have answered the following questions :

- What question(s) am I trying to answer? Do I think the data collected can answer that question?
  To detect the welding defects from RT films/images

- What is the best way to phrase my question(s) as a machine learning problem?
  Through pretrained model by YOLOv8 and ML Random Forest for prediction.

- Have I collected enough data to represent the problem I want to solve?
  Minimum data is acquired online GDXray and other industries.

- What features of the data did I extract, and will these enable the right predictions?
  In this study, crack, incomplete penetration, and slag are considered as the primary categories of welding defects.

- How will I measure success in my application?

  By training the model with annotated images and by results.

- How will the machine learning solution interact with other parts of my research or business product?

  When weld image data is uploaded into the machine learning model, it can not only detect welding defects and irregularities but also provide predictive insights regarding potential issues.

1.2 Research Problem

Despite technological advancements in welding technologies and quality control, the classification, prediction, and prevention of weld defects remain significant challenges in industrial manufacturing, weld defect management remains reactive rather than proactive. Traditional weld inspection methods, such as visual inspection and radiographic analysis, are time-intensive, prone to human error, and typically reactive, identifying defects only after they have occurred. Moreover, existing predictive models often struggle with limited data, variability in weld conditions, and the complexity of temporal and spatial dependencies inherent in welding processes.

Existing methods:

- Lack automation and accuracy in defect identification.
- Do not integrate historical welding process data for predictive analysis.
- Fail to offer real-time defect insights to prevent welding failures.

Therefore, there is a critical need for an integrated machine learning and deep learning solution that can analyze real-time welding parameters and imaging data to accurately predict weld defects before they occur. This study proposes an AI-powered hybrid model that integrates CNN-based defect detection with ML-driven defect prediction, enhancing real-time weld quality control.

1.3 Purpose of Research

The purpose of this research is to develop an AI-driven hybrid model that enhances weld defect detection and prediction, integrating Convolutional Neural Networks (CNNs) for image classification with Machine Learning (ML) algorithms for predictive analytics. This study aims to bridge the gap between traditional weld quality control methods and intelligent automation by leveraging deep learning for defect identification and ML for proactive defect prevention.

Research Objectives:

This study is designed to achieve the following objectives:

1. Develop a CNN-Based Model for Weld Defect Classification.
    - Utilize radiographic weld images to train a deep learning model that accurately identifies weld defects such as “cracks”, “lack of penetration or Incomplete Penetration”, and “slag inclusion”.
    - Improve classification accuracy compared to manual inspection methods.
2. Develop an ML-Based Model for Predictive Analytics.
    - Train an ML model (e.g., Random Forest, XGBoost) using historical welders weld defects to predict defect occurrences before they happen.
    - Analyze the impact of welding parameters on defect formation.

3. Integrate CNN and ML into a Hybrid AI Framework.
    - Combine CNN-based defect detection with ML-driven defect prediction to create a comprehensive, real-time welding quality control system.

- Evaluate whether hybrid AI models outperform standalone CNN or ML models.

4. Validate the AI Model Against Expert Assessments.
    - Compare AI model results with human expert evaluations to assess the practical feasibility of AI-driven weld inspection.
    - Conduct quantitative performance analysis using metrics like “accuracy”, “precision”, “recall”, and “F1-score”.

5. Assess Real-World Deployment Feasibility.
    - Investigate computational efficiency for real-time deployment in industrial settings.
    - Identify potential challenges and limitations in AI-based weld quality control systems.

Research Justification

This research is necessary due to the limitations of traditional weld quality control methods:

- Manual inspections are slow, error-prone, and subjective, leading to inconsistencies in weld defect classification.
- Existing AI models primarily focus on defect detection but lack predictive capabilities to prevent defects.
- There is limited integration of AI for real-time defect prevention, which is critical for Industry 4.0 applications in automated manufacturing.

By developing a hybrid AI-driven weld quality control system, this research:

- Enhances welding efficiency, accuracy, and reliability
- Reduces material waste and rework costs through early defect prediction
- Contributes to smart manufacturing and predictive maintenance in industrial applications.

1.4 Significance of the Study

The significance of this study lies in its potential to revolutionize weld defect detection and prediction through Artificial Intelligence (AI)-driven automation. Traditional "Non-Destructive Testing (NDT)" methods, such as "Radiographic Testing (RT)", rely heavily on human expertise, making them time-consuming, error-prone, and subjective. This study proposes a hybrid AI model integrating Convolutional Neural Networks (CNNs) for defect detection using YOLO as a Pretrained Model version 8 and Machine Learning (ML) techniques (Random Forest) for predictive analytics, addressing key challenges in industrial welding.

This research is significant in the following ways:

1. Advancing AI Applications in Industrial Welding
    - This study has bridged the gap between weld defect detection and prediction by integrating AI techniques.
    - By developing an intelligent hybrid model, this research contributes to Industry 4.0 and smart manufacturing, ensuring higher accuracy and efficiency in weld quality control.
2. Reducing Human Error in Weld Defect Detection
    - Manual inspections in RT are subjective, leading to misclassification and oversight of defects.
    - AI-driven automated defect detection ensures consistency, accuracy, and reliability, minimizing reliance on manual analysis.

3. Enabling Proactive Defect Prediction

- Current methods focus on defect identification after welding, leading to costly repairs and rework.
- The proposed hybrid AI model predicts potential defects based on welding parameters, allowing for real-time adjustments and defect prevention.

4. Improving Manufacturing Efficiency and Reducing Costs

- Early defect detection and prediction prevent rework, reducing material wastage and operational costs.
- AI-powered automation enhances inspection speed, leading to faster production cycles and improved productivity.

5. Enhancing Industrial Safety and Structural Integrity

- Welding defects can lead to catastrophic failures in critical industries like aerospace, automotive, and construction.
- The proposed model ensures high weld quality, enhancing the safety and durability of welded components.

6. Contribution to Research and Innovation

- This study contributes novel insights into AI-driven weld defect detection and prediction.
- The research findings will be valuable to academic scholars, industry professionals, and AI developers interested in intelligent defect prevention models.

7. Facilitating AI Adoption in Smart Manufacturing

- The study aligns with Industry 4.0 principles, promoting AI, automation, and data-driven decision-making in welding.
- Encourages widespread adoption of AI-powered quality control in industrial manufacturing.

The study contributes to academic research and industrial applications by:

- Advancing AI applications in welding quality control.
- Providing an innovative hybrid AI model for real-time defect detection and prediction.
- Supporting the transition to automated manufacturing by integrating AI with welding inspection systems.
- Enhancing predictive maintenance to prevent defect occurrences.
- Improving manufacturing efficiency and minimizing material wastage.

This study is highly significant as it introduces a cutting-edge AI solution to enhance weld quality control, minimize defects, reduce costs, and improve industrial safety. By integrating deep learning and machine learning, this research paves the way for real-time, intelligent defect detection and predictive maintenance in welding process.

This research has the potential to transform industrial welding processes, reducing defects, improving productivity, and ensuring higher safety and quality standards.

1.5 Research Purpose and Questions

This research aims to bridge the gap between traditional weld inspection methods and AI-driven automation by integrating deep learning for defect classification and machine learning for predictive analytics. By answering these research questions, the study will provide a scalable, intelligent, and efficient solution for automated weld quality control, improving industrial productivity, safety, and cost-effectiveness.

Research Questions:

- How can AI-based models improve the accuracy of weld defect detection in radiographic films?
- What are the limitations of existing ML and DL models in weld defect classification?
- How can a hybrid CNN-ML model enhance defect prediction based on hitorical weld images of a welder?
- What challenges exist in implementing AI-driven quality control in industrial welding processes?

CHAPTER II: REVIEW OF LITERATURE

2.0 Introduction:

This chapter provides an in-depth review of existing research on AI-driven weld defect detection and prediction. The literature review explores traditional weld defect inspection methods, advancements in “Artificial Intelligence (AI)”, applications of “Deep Learning (DL)” and “Machine Learning (ML)” in weld quality control, and the limitations of existing approaches. The review highlights research gaps and sets the foundation for developing a hybrid AI model integrating Convolutional Neural Networks (CNNs) for defect detection and ML techniques for predictive analytics.

2.1 Theoretical Framework

The theoretical framework provides the foundation for this research by integrating “machine learning (ML)”, “deep learning (DL)”, image processing, and predictive modeling theories to develop an AI-driven hybrid model for weld defect detection and prediction. The study builds on established theories in pattern recognition, artificial neural networks (ANNs), and hybrid AI systems to enhance the accuracy and efficiency of weld quality control.

This study seeks to integrate the weld defect classification model and welding defect prediction. There are number of researches done for welding defect detection and classification in radiographic images using the “Deep learning” and some of which are Abhi Bansal et al 2023, Stephen D and Lalu P P 2021, Yang L and Jiang H 2021 and Thakkallapally B C 2019. Also, the weld defect prediction models such as developed by Liu et al. (2021) and Yang et al. (2021) are based on the historical process parameters.

Perhaps, there are other parameters that shall be explored which has significant impact on the welding quality in Manual welding that is the welders performance based on the fit-up of the joint, welding environment / accessibility (not related to the position of the welding) i.e. the shop fabrication (which is a controlled environment) and field fabrication or welding of the joint (height at which the welder has to go in the plant) , these field fabrication welding joints many a times fall in the critical path of the project schedule, if the weld joint is rejected then the re-work doesn't only cost about the welder , helper, supervisor and inspector but also indirectly cost the scaffolding, safety officer, scaffolding supervisor, crane and the other related project team / material / equipment for the succeeding activities will be on stand-by.

The study has taken into consideration of the real time issues that are generally ignored and when it required to focus, the welders are habituated to produce the weld joints with irregularities which were accepted by the quality team for the shop fabrication under the controlled environment. Specifically, to qualify a welder to continue his job , the welder performance per linear length and joint will be calculated and monitored, during the welders performance reporting the irregularities of the weld which are under the acceptance range will not be highlighted or addressed but only the irregularities of the welds which are termed as defects of unacceptable range will be noted and addressed for the welder performance , as per the standard of the industry.

In this study the welding irregularities in the weld film will be detected and classified as the categories like porosity, crack, undercut, underfill etc. which is also done / developed by the previous models. Cheolhee Kim et al summaries in Journal of Welding and Joining 2021; " at present, the images at the time of measurement are used for quality classification or regression, but in the future, hybrid models of combining RNN and CNN will be applied, leading to more intelligent models in which the information extracted from images in the past will be transferred to the current state prediction." Subsequently, the data of the welder for welding irregularities and the defects will be noted / stored / considered / addressed to identify the patterns and to predict the defect which the welder might do in the future weld joints. The models helps the companies / Project team to assign the welder for the welding of the weld joints and also to give instructions to the welders to avoid the irregularities and defects in the future welds or re-work.

2.2 "Weld defect identification and characterization in radiographic images using deep learning[4]"

According to "Abhi Bansal et al. (2023)", the development of weld defect detection technologies has evolved through a staged approach. Their study presents a comprehensive review of automated defect detection methods based on deep learning, structured into three primary phases: data acquisition, image preprocessing, and defect classification. Initially, the authors highlight the process of gathering benchmark datasets, with particular emphasis on the GDXray database.

In the next phase, they observed that certain preprocessing techniques—such as thresholding and noise reduction—significantly enhanced the visibility and clarity of defect regions within the images. Following this, the paper explores the advantages of using deep learning models for defect recognition and outlines their practical implementations in weld inspection. Finally, a comparative evaluation of different weld defect classification methods employed by various researchers is provided, offering insights and direction for future advancements in this domain.

"Table 2.1

Representation of weld class of GDXray database.

Series	**Images**	Description	*Application*
W0001	10	Subset of 10 x-ray images which is selected from series W0003.	Detection of defects in weld classification
W0002	10	Ideal segmentation of W0001, which is a set of binary images	Evaluation of performance of detection algorithm
W0003	10	Collection of 68 digitized radiographs from a round robin test performed by BAM	Detection of defects in weld classification

1.1.1

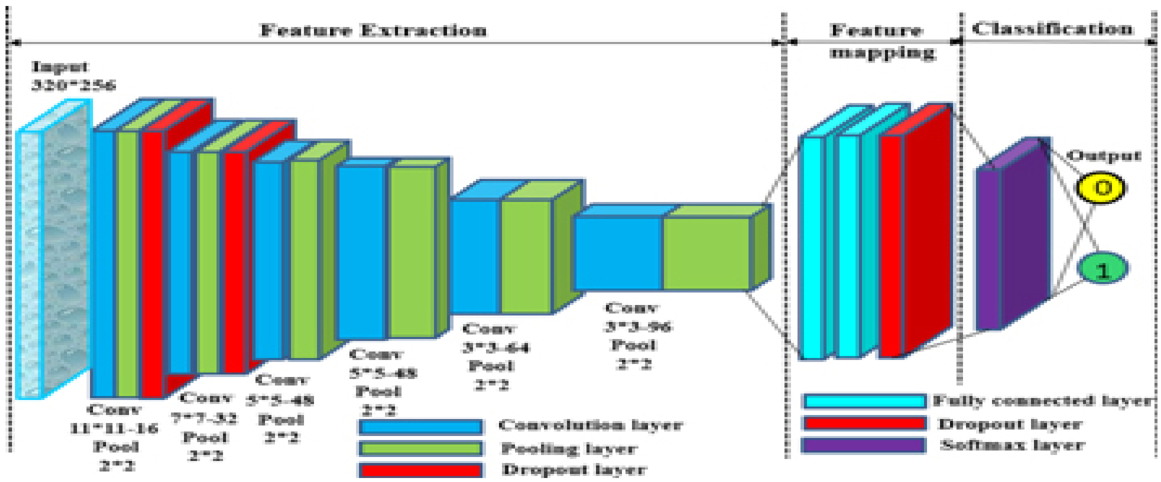

Figure 2.1

The architecture of the CNN model.(Abhi Bansal,2023)

The Convolutional Neural Network (CNN) is a deep learning architecture inspired by the functioning of biological neurons, which communicate to transmit information. CNNs have demonstrated superior performance over traditional machine learning models in tasks such as image classification and object detection. The architecture of a CNN typically comprises three primary types of layers: convolutional layers, pooling layers, and fully connected (dense) layers.

During the convolutional stage, a kernel (or filter) systematically moves across the input image, applying the convolution operation to extract important spatial features. This results in a feature map that highlights essential patterns within the image. To introduce non-linearity into the model—important because real-world data is often non-linear—the feature maps are passed through a Rectified Linear Unit (ReLU) activation function. ReLU sets all negative pixel values to zero, thereby ensuring all outputs are positive and helping the model converge faster during training.

Following this, max pooling is applied. This layer partitions the output of the convolutional layer into smaller regions and selects the maximum value from each region. Max pooling serves as a downsampling method, reducing the spatial dimensions of the feature maps, which in turn decreases computational load, lowers memory usage, and minimizes overfitting. Though some fine-grained information may be lost during pooling, the trade-off is often acceptable for improved generalization on unseen data.

The reduced feature maps are then flattened into a one-dimensional feature vector, where each value represents a neuron that connects to the next layer: the fully connected (FC) layer. The FC layers integrate the extracted features and perform high-level reasoning. Due to the dense connectivity of this layer, the number of trainable parameters increases significantly. To control this complexity, additional FC layers with fewer neurons are often added to gradually reduce dimensionality.

The final FC layer, often referred to as the softmax layer, maps the previous layer's outputs to a set of probabilities corresponding to each target class. The softmax function ensures that the output values lie between 0 and 1 and that their sum equals 1, thereby indicating the model’s confidence in each class. The class with the highest probability is chosen as the model’s prediction. This output is used to calculate the loss function, which quantifies the difference between predicted and true labels.

CNNs are trained using the Backpropagation (BP) algorithm. Initially, the network computes the loss during forward propagation. Then, using BP, it iteratively adjusts the weights and biases in the convolutional and FC layers to minimize the loss. This process continues until the model achieves optimal accuracy.

In the context of weld defect classification, CNN models are typically trained to detect and categorize defects such as porosity (PO), lack of penetration (LP), slag inclusion (SL), lack of fusion (LF), and crack (CR). By learning from image data, the CNN becomes capable of identifying these defects automatically and with high precision, making it a valuable tool for modern industrial inspection systems.

2.3 "Multi-sensing signals diagnosis and CNN-based detection of porosity defect during Al alloys laser welding[5]"

Ma, Deyuan et al. (2022) applied a Convolutional Neural Network (CNN) framework to classify Time-Frequency (TF) spectrum images and detect porosity in welding processes. The TF graphs were treated as RGB image inputs and categorized into two labels: '0' indicating no porosity and '1' indicating the presence of porosity. The initial dataset contained 1200 RGB images without porosity and 212 with porosity. Due to the data imbalance, augmentation techniques like image flipping and mirroring were employed, expanding the dataset to 1976 no-porosity images and 848 porosity images. These were divided into training and test sets to facilitate model training and evaluation.

The CNN architecture consisted of multiple convolutional and max-pooling layers, followed by two dense (fully connected) layers and a softmax output layer for binary classification. To address potential overfitting, dropout layers with a 0.5 rate were used after specific convolutional and fully connected layers. The model was trained with a learning rate of 0.001 and a batch size of 64, achieving a porosity detection accuracy of 93.15% and an overall classification accuracy of 96.13%, thus fulfilling industry requirements.

Traditionally, porosity detection has relied on post-weld techniques like X-ray inspections, which fail to assist in real-time quality improvement. In contrast, online detection systems enable real-time monitoring of porosity during the welding process, allowing timely parameter adjustments. These methods, especially in laser welding, focus on metallurgical porosity—caused by the evaporation of volatile elements like hydrogen, magnesium, and zinc.

More recently, attention has shifted toward identifying *keyhole-induced porosity*, which arises from the collapse of unstable keyholes during laser welding. AI-powered models have enhanced this effort. For example, "Luo and Shin" applied a radial basis function neural network to monitor the keyhole opening area, while Gaja et al. and Shevchik et al. explored acoustic and optical signal analysis using logistic regression, BP neural networks, and SVMs.

Deep learning has proven especially beneficial due to its capacity for automatic feature extraction from complex signal patterns. Zhang et al. demonstrated the utility of CNNs by feeding them images of the molten pool and keyhole to detect porosity conditions in real time. However, the linkage between porosity formation mechanisms and signal features remains underexplored, complicating reliable pore localization and detection.

Several researchers, including Berger and Liu, linked porosity formation to erratic keyhole fluctuations. Others, such as Pang, Lin, and Xu, noted that the collapse of a keyhole alters its depth, which can be a key indicator for porosity prediction.

In response, this study proposes a multi-sensor diagnostic approach to track and analyze keyhole morphology in 3D. Using KD signals and TF features from KO images, a CNN-based system is employed for detecting and pinpointing individual porosity sites. This integration of multi-sensor input enhances precision, enabling real-time, non-invasive porosity monitoring in welding environments, offering a significant step toward intelligent, data-driven manufacturing.

2.3 “Development of radiographic image classification system for weld defect identification using deep learning technique[6]”

Stephen D. and Lalu P. P. (2021) effectively utilized a “Convolutional Neural Network (CNN)” model to classify weld defects in radiographic images. Their study focused on four main defect types: gas pore, cluster porosity, cracks, and tungsten inclusion. The dataset was built from 63 cropped radiographic images sourced from the publicly available GDXray database, resulting in 200 labeled images. These were split into 160 for training and 40 for validation. To expand the limited dataset and improve model generalization, data augmentation techniques—such as image rotation, flipping, and mirroring—were applied, increasing the training set to 16,000 images.

The CNN architecture comprised four 2D convolutional layers with 3×3 filters, each followed by a ReLU activation and a 2×2 max-pooling layer. A dropout layer with a rate of 0.5 was introduced to prevent overfitting by randomly deactivating 50% of neurons during training. Feature map dimensions increased progressively: 32 maps after the first convolutional layer, 64 after the second, and 128 after the final convolutional layer.

The model was implemented using Python with the Keras API and TensorFlow as the backend. Parameter fine-tuning was performed to optimize model performance. The training process involved 100 epochs, with validation after each epoch to monitor learning progress. A batch size of 4 was used, meaning the network updated its weights after processing every 4 images.

The model was optimized using the RMSprop algorithm, which effectively controlled weight oscillations and allowed for larger, faster convergence steps in the horizontal direction. The learning rate was dynamically updated based on the weighted average of gradients.

The loss function used was categorical cross-entropy, calculated as

$$\mathbf{L = -\Sigma_i\ T(i)\ log\ P(i)}$$

where *T(i)* and *P(i)* are the target and predicted probabilities for class *i*, respectively. The weight updates followed the rule:

$$\mathbf{W_n = W_x - \eta_i\ (\partial L/\partial W_x)}$$

where η_i is the adjusted learning rate.

Initial training without data augmentation resulted in a training accuracy of 96% and validation accuracy of 80%, with increasing validation loss indicating overfitting. However, with augmented data, both training and validation accuracies improved significantly, reaching 99% and 95%, respectively. The validation loss steadily decreased, indicating enhanced generalization capabilities of the model. This demonstrated that augmentation not only increased the volume of training data but also helped the network learn richer feature representations.

In conclusion, this study successfully demonstrated the application of deep learning, specifically CNNs, for classifying weld defects from radiographic images. Despite the initial limitation of dataset size, the creation of a custom image set and augmentation techniques significantly boosted performance.

The model, trained on GDXray-derived images, proved effective in detecting common weld defects with high accuracy. The approach can be extended to identify additional defect types and integrated into automated inspection systems for real-time weld quality assessment.

2.4 "Weld defect classification in radiographic images using unified deep neural network[7]"

Yang L and Jiang H 2021, developed a dataset comprising 220 sample images, classified into five categories of welding defects: porosity, slag inclusion, and lack of penetration (50 images each), along with lack of fusion and cracks (35 images each). The dataset was split into training and testing sets, allocating 80% of the images for training and the remaining 20% for testing.

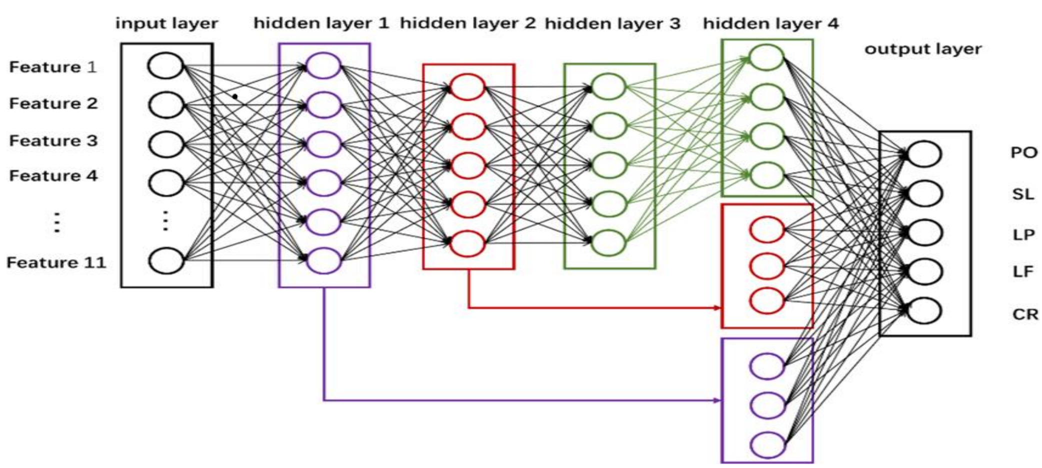

Figure 2.2 Unified DNN.(Yang L and Jiang H 2021)

The authors Yang L. and Jiang H. (2021) proposed a unified Deep Neural Network (DNN) framework for the classification of weld defects, as illustrated in their study. To assess the effectiveness of this model, they conducted a comparative analysis with traditional classification approaches, including generic DNN architectures and Support Vector Machines (SVMs). Their proposed unified DNN achieved a training accuracy of 97.95% and a testing accuracy of 91.36%, outperforming the alternative models.

Unlike conventional approaches that primarily rely on geometric or intensity-based features, the authors introduced four novel features derived from the intensity contrast between the weld defect and its surrounding background, improving the discriminative power of the model.

A key innovation in their approach lies in the fusion of multi-level features: instead of using only the final layer outputs, their model integrates feature representations from all hidden layers. These multi-scale features are then collectively utilized in the final hidden layer to enhance prediction accuracy, allowing for a more holistic interpretation of defect characteristics.Moreover, the authors explored pre-training and fine-tuning strategies to improve the model's generalization performance, especially given the limited size of their dataset. Through this approach, the model was able to learn more robust representations, reducing the risk of overfitting.

Compared to the baseline models, the unified DNN achieved a 3.18% and 4.33% increase in classification accuracy over the generic DNN and SVM models respectively on the test set, demonstrating the strength of their multi-level feature fusion strategy and deep learning framework.

2.5 "Defect classification from weld radiography images using VGG-19[8]"

Thakkallapally B C 2019 developed a weld defect classification model using a dataset curated from 78 radiographic images sourced from the GDXray welding subset—a publicly available collection of X-ray images of weld specimens. Each image in the original dataset spans approximately 5000 pixels in length, capturing a broad view of the weld regions. Due to the limited number of available images, the study focused on three main classes: Good Welds (GW) with no defects, Cracks (CR), and a combined class of Porosity and Solid Inclusions (PO). The decision to merge porosity and solid inclusion defects into a single category stemmed from the insufficient number of distinct images representing each defect type individually.

To increase the number of training samples and localize defect features, the authors employed a sliding window technique, systematically cropping each large image into smaller patches of 128×128 pixels. Each resulting patch was then manually labeled into one of the three classes based on the defect it contained. This process resulted in a balanced dataset of 3000 images, with 1000 images per class.

To ensure effective model training and evaluation, the dataset was randomly split into three subsets:

- 60% for training,
- 20% for validation, and
- 20% for testing.

To further enhance the generalization capability of the model, data augmentation techniques were applied during dataset preparation, helping mitigate the effects of limited original data.

For the classification task, the authors adopted and modified the well-known VGG-19 architecture. Specifically, they froze the first five convolutional layers to retain foundational feature extraction capabilities and replaced the original fully connected layers with two new dense layers, tailored to suit the three-class weld defect classification problem. This customization allowed for a more lightweight and efficient network while maintaining the powerful feature extraction abilities of the original VGG-19.

This approach demonstrated how classical deep learning architectures like VGG-19 can be effectively adapted to specialized tasks like weld defect detection, even with relatively small and imbalanced datasets, by leveraging strategies such as image cropping, class merging, and transfer learning.

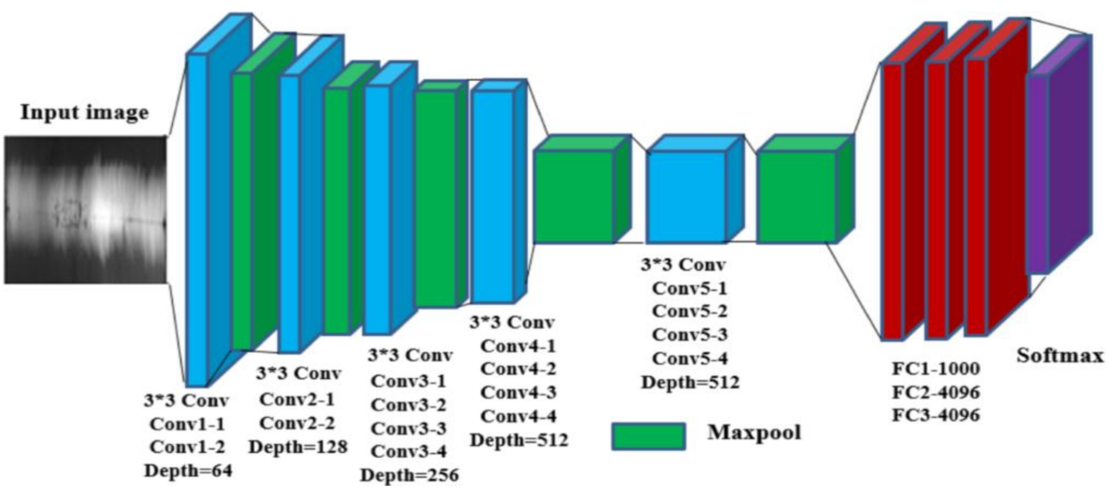

Figure 2.3

Architecture of VGG-19.(Thakkallapally,2019)

In the current study, the authors employed the VGG-19 architecture to tackle the complex nature of radiographic weld images, due to its proven success among the six configurations of the VGG family. Among these, VGG-16 and VGG-19 have demonstrated superior performance, with VGG-19 being selected here for its deeper architecture and enhanced representational power. The VGG-19 network comprises 19 weight-bearing layers and a staggering 144 million trainable parameters, making it a powerful model capable of learning intricate features.

As illustrated in Figure 1, VGG-19 is constructed using 3×3 convolutional filters applied with a stride and padding of 1, followed by 2×2 max-pooling layers with a stride of 2. This consistent use of small filters enables the network to capture fine-grained features while keeping the architecture uniform. As the network deepens, the number of filters increases progressively, enhancing its ability to detect more abstract features at each level. A ReLU activation function is applied after each convolution to introduce non-linearity and expedite training.

Given the limited size of the dataset in this work, training a deep model like VGG-19 from scratch would lead to overfitting. To overcome this, the authors utilized transfer learning, a technique where a model pre-trained on a large dataset (in this case, ImageNet, used in the ILSVRC 2014 competition) is adapted to a new but related task. Transfer learning is particularly beneficial when access to large-scale labeled data is limited.

Transfer learning was considered in two formats:

- As a Feature Extractor – In this approach, all convolutional layers are frozen, and the fully connected layers are removed. The extracted features are then passed to a different classifier such as an Artificial Neural Network (ANN) or Support Vector Machine (SVM). However, this method was deemed unsuitable for the present study because of the domain gap between natural images in ImageNet and radiographic weld images.

- Fine-Tuning – This approach was selected for the study. It involves freezing the first few layers (which capture general features such as edges and textures) and retraining the remaining layers to adapt to the new dataset. Specifically, the authors froze the first five layers of the VGG-19 model and replaced the original fully connected layers with a custom design consisting of two dense layers and a dropout layer in between. The dropout layer, set at 30%, helps to prevent overfitting by randomly deactivating 30% of the neurons during training.

The final layer employs a Softmax activation function, which is appropriate for multi-class classification problems, as it assigns probabilities across multiple classes.

The model was trained using categorical cross-entropy as the loss function and Stochastic Gradient Descent (SGD) as the optimizer. The learning rate was set to 0.0001 with a momentum of 0.9, which helps accelerate training by smoothing the update path. A batch size of 2 was used during training and validation. To accelerate computation and optimize performance, the training process was conducted on an NVIDIA Tesla K80 GPU.

This methodological approach demonstrates how deep learning models like VGG-19 can be adapted using transfer learning and fine-tuning strategies to perform robustly even on small, domain-specific datasets such as those involving radiographic weld defect classification.

2.6 Knowledge of Results in Human Psychology:

Since the research of hybrid model is based upon the foundation of learning in both the model itself and the welders to whom we provide the feedback of their welds. Most of the industries doesn't focus on the irregularities of the welds produce by welders but as a practice they are focused and insterested in only the rejected welds to repair them as soon as possbile , secondly the welder revoke is based upon the rejection rate of the welds produced by the welder , rither the linear rate or the joint based. The importance of weld irregularities are not included because the weld joints are acceptable. By using the AI model which is fast and accurate the welding inspector can get the information of each and every joint welded by each welder and subsequently the irregularities of the weld. Further , the weld joint which are reviewed by NDT Level-III engineer will be charged hourly or as per the weld film wise, here by using the AI-models which has a initial cost can provide the details of every weld joint.

The research into the hybrid model of weld defect detection and feedback revolves around both the machine learning capabilities of the AI system and the training provided to welders based on the feedback of their welds. In many industries, the focus is primarily on defective welds that require immediate repair, rather than on identifying irregularities in all welds. Typically, welder performance is assessed based on the rejection rate of their welds, which may be evaluated by individual joints or by a linear rejection rate. As a result, the significance of minor weld irregularities is often overlooked, especially when the overall weld joint is deemed acceptable. However, by incorporating an AI-driven model that is both fast and precise, welding inspectors can access comprehensive information on every weld performed by each welder, including any potential irregularities.

Furthermore, welds that undergo NDT Level-III inspection are often charged on an hourly basis or according to the number of weld films assessed. In contrast, while an AI model may have a higher initial cost, it can provide detailed feedback on every weld joint, potentially reducing the need for extensive manual inspections. This makes it an efficient and cost-effective solution for managing weld quality.

In terms of feedback, feedback refers to the information received by a subject during or after performing a task, as noted by Schmidt (1988). Feedback can be categorized into two types: intrinsic and extrinsic. Intrinsic feedback is related to the task itself and involves sensory information (e.g., proprioceptive, visual feedback), which the subject naturally perceives. On the other hand, extrinsic feedback, also referred to as "artificial feedback" or "augmented feedback" (Drowatzky, 1975), is external information provided by an external source, such as an instructor or supervisor. This feedback is essential in improving task performance by offering additional guidance.

Knowledge of Results (KR), as defined by Travers (1972), refers to the feedback received after performing an action, which helps the subject understand how well they performed. Historically, Thorndike (1931) and Trowbridge and Cason (1932) conducted studies that emphasized the importance of KR in motor learning. Their experiments demonstrated that different types of KR, such as quantitative feedback, led to better performance compared to no feedback or less precise feedback. For example, in the line drawing experiment, the group that received quantitative KR showed improved results in the learning phase.

The influence of KR on the learning process can be attributed to three primary functions, as described by Schmidt (1988):

1. Guidance: KR helps guide the subject toward the correct execution of the task, providing a basis for improving future performances.
2. Motivational: KR can motivate the learner to improve by providing tangible evidence of progress.
3. Associational: KR helps the learner associate the feedback with their actions, reinforcing positive behavior and discouraging mistakes.

The precision and quality of KR have a significant impact on the learning process, as more accurate feedback helps the learner adjust their approach more effectively. In the context of welding, providing precise feedback on each weld can significantly enhance the welder's skills and help reduce errors, leading to better overall weld quality and fewer defects.

2.6 Summary

This literature review highlights the significant role of Artificial Intelligence (AI) in advancing weld defect detection and prediction, offering transformative capabilities for improving accuracy, efficiency, and quality in this critical industrial process. As summarized by Cheolhee Kim et al. in the *Journal of Welding and Joining* (2021), "Currently, images at the time of measurement are used for quality classification or regression. However, in the future, hybrid models combining Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) will be implemented, leading to more intelligent systems where information extracted from past images will be utilized for current state predictions."

CNNs have been widely researched for analyzing radiographic images, providing enhanced accuracy in identifying weld defects (Zhang et al., 2020; Li et al., 2018). Meanwhile, "RNNs and Long Short-Term Memory (LSTM)" networks are effective for handling sequential data, such as welding parameters, in predictive analytics (Hochreiter and Schmidhuber, 1997; Sun, Zhang and Chen, 2021). Hybrid models that combine CNNs with machine learning (ML) algorithms, including Random Forest and Gradient Boosting, offer robust frameworks to tackle challenges such as data imbalance and improve the precision of defect predictions (Kim, Kim and Park, 2020; Ahmed, Munir and Anwar, 2022).

The integration of AI (ML & DL) in weld defect detection and prediction has been groundbreaking, overcoming many limitations of traditional methods (Zhang, Chen and Gao, 2019). This area of research holds great significance due to its potential to enhance quality control, reduce costs, and improve safety in industrial settings (Sun, Zhang and Chen, 2021).

The studies reviewed emphasize the effectiveness of hybrid approaches that combine both visual and temporal data. However, there remain gaps, particularly in real-time applications and the interpretability of these models (Ahmed, Munir and Anwar, 2022).

Addressing these gaps can lead to the development of smarter, more reliable, and efficient defect management systems in manufacturing processes.

After 70 epochs, the model converged with a training accuracy of 93.17% and a validation accuracy of 91.14%. Figures shows the plot of training and validation accuracy over time, while the plot of training loss and validation loss, both generated by TensorBoard with a smoothing factor of 50%. The lighter curves in the background of the plots represent the original accuracy and loss data. The training and validation curves closely align, indicating the model's progress in line with expectations.

These results suggest that the model's health is good; however, there is still a possibility that the model has not been fully generalized. As mentioned in Section 4.1, a separate test set is used to evaluate whether the model is generalizing well. After comparing the model's predictions on the test set (NDE2019, 018, v1) with the actual labels, a classification report was generated. The classification report, showing that the average precision and average recall are both 91%, and the overall accuracy of the model on the test set is also 91%. These results are promising and indicate that the model is well-generalized, offering strong performance in real-world applications.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

Companies consistently strive to minimize rework, as it directly impacts cost, schedule, and quality. Welding plays a critical role in industries such as oil and gas, petrochemicals, and aerospace, where precision and structural integrity are paramount. Welding inspectors are responsible for guiding and training welders, ensuring that good workmanship is maintained, as both high- and poor-quality welding can significantly affect critical operations.

To enhance quality control, companies and training institutes focus on identifying the root causes of welding irregularities. Decisions regarding welder performance are often based on weld rejection rates, emphasizing defect presence while overlooking recurring welding irregularities. Over time, habituated welding inconsistencies may lead to defects, yet the focus remains on linear rejection rates rather than analyzing the specific categories of defects produced by welders.

Despite the numerous factors influencing weld quality, one critical aspect that remains unexplored is the history and categorization of welding irregularities. Addressing these irregularities proactively rather than reactively can significantly reduce the need for rework or repairs.

To tackle this issue, this research proposes a Hybrid AI model integrating “Deep Learning (DL)” and “Machine Learning (ML)” to enhance weld defect detection and prediction. The study focuses on:

- Leveraging DL models for advanced image analysis, particularly CNNs for defect classification.
- Developing hybrid architectures that combine ML and DL to improve predictive analytics.
- Addressing challenges such as data scarcity, model interpretability, and real-time processing.

By bridging existing gaps in research, this study aims to develop an AI-driven quality control system capable of both detecting and predicting weld defects. Unlike traditional models that focus primarily on defect detection, this hybrid approach will enable proactive quality assurance, significantly improving manufacturing efficiency and reliability.

3.2 Operationalization of Theoretical Constructs

In this research, which focuses on AI-driven detection and prediction of weld film irregularities, several theoretical constructs are considered. These constructs are derived from machine learning, deep learning, quality control, and the Theory of Reasoned Action (TRA) for technology adoption in welding inspection. Below is an overview of the key constructs and their operational definitions:

Welding Defect Identification

- Welding defects and irregularities are defined based on industry standards (e.g., AWS D1.1, ISO 5817,B31.3, B31.4).
- Operational Definition: Defects will be categorized into cracks, lack of penetration, slag inclusion, and weld irregularities (e.g., inconsistent bead formation).
- Measurement: Labeled datasets of radiographic weld images will be used for AI model training.

Deep Learning for Image Classification

Convolutional Neural Networks (CNNs) are effective in image-based classification tasks, particularly in identifying welding defects (Goodfellow, Bengio and Courville, 2016, p. 342).

- Operational Definition: A CNN-based AI model will be trained to classify welding defects using labeled radiographic images.
- Measurement: Model performance will be assessed using accuracy, precision, recall, and F1-score (Kim et al., 2021, p. 200).

Machine Learning for Predictive Analytics

Hybrid AI models combining ML and DL can enhance predictive defect analysis by analyzing sequential welding process data.

- Operational Definition: A combination of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks will be used to analyze historical welding process data (e.g., temperature, current, welding speed) (Goodfellow, Bengio and Courville, 2016, p. 375)..
- Measurement: Prediction accuracy will be evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Quality Control and Decision-Making

Effective quality control requires proactive defect prevention rather than reactive defect correction.

- Operational Definition: AI models will be integrated into existing quality control workflows to provide real-time defect detection and predictive insights.
- Measurement: Reduction in weld rework rates, defect rejection rates, and cost savings will be used as key performance indicators (KPIs).

By operationalizing these theoretical constructs, this study establishes a structured approach to measuring, analyzing, and validating AI-driven weld defect detection and prediction models. The integration of CNNs for classification, RNNs/LSTMs for prediction, and TRA for adoption analysis ensures a comprehensive evaluation of AI's impact on welding quality control.

3.3 Research Purpose and Questions

The distinct purpose of this research is to explore and bridge the gap between traditional weld inspection methods and AI-driven automation by integrating deep learning for defect classification and machine learning for predictive analytics by considering the historical data of the welders performance or rejection rate perhaps also the weld irregularitiest which are been accepted but not reported as defects. By answering these research questions, the study will provide a scalable, intelligent, and efficient solution for automated weld quality control, improving industrial productivity, safety, and cost-effectiveness.

Research Questions:

- How can AI-based models improve the accuracy of weld defect detection in radiographic films?
- What are the limitations of existing ML and DL models in weld defect classification?
- How can a hybrid CNN-ML model enhance defect prediction based on historical weld defects by welders?
- What challenges exist in implementing AI-driven quality control in industrial welding processes?

3.4 Research Design

The research design outlines the methodological framework for investigating the AI-driven approach to detecting and predicting weld film irregularities for enhanced quality control. This study adopts a quantitative, experimental, and analytical research design that integrates machine learning (ML), deep learning (DL), and hybrid AI techniques for weld defect detection and prediction. The primary objective of this research is to develop an automated pipeline for the detection and prediction of weld quality using computer vision and machine learning techniques. The design follows a systematic, modular approach encompassing defect detection, data analysis, rule-based decision logic, and predictive modeling.

This research follows a quantitative research approach as it focuses on data-driven analysis, statistical validation, and model performance evaluation. The research incorporates:

Experimental Design: AI models is trained and tested on labeled weld defect images collected from an oil and gas industry and from GDXray.

Data Acquisition and Preparation

The dataset used in this study consists of welding images annotated for three types of defects: crack, slag, and incomplete penetration. Each image is labeled with its corresponding welder ID, such as w101, w102, and w103. The annotations are provided in YOLO format, where each line represents a detected object with a class index and normalized bounding box coordinates.

The dataset was uploaded as a zip file and extracted into a structured directory. Each image had an associated .txt label file. The extracted dataset was randomly split into training and validation sets in a 90:10 ratio. The files were organized into the YOLOv8-compatible format with separate folders for images and labels under train and val directories.

Model Training with YOLOv8

The YOLO (You Only Look Once) series is grounded in Convolutional Neural Networks (CNNs). CNNs are especially well-suited for visual tasks like object detection due to their ability to extract spatial hierarchies and features through layered convolution operations (Goodfellow, Bengio and Courville, 2016, pp. 326–330). YOLO models process the entire image in a single forward pass, predicting bounding boxes and class probabilities directly, unlike traditional sliding-window or region proposal approaches. The original YOLO algorithm was introduced by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi in their seminal 2016 paper "You Only Look Once: Unified, Real-Time Object Detection." This work revolutionized object detection by significantly improving speed without compromising accuracy. Over time, the YOLO family has evolved through contributions from various developers and open-source communities, culminating in versions like YOLOv5 and YOLOv8, which further enhance speed, accuracy, and flexibility by integrating improvements such as anchor-free detection, better backbones (like CSPDarknet), and advanced augmentation techniques. YOLO is fundamentally built upon a Convolutional Neural Network (CNN) backbone, which allows it to learn spatial hierarchies of features from input images.

In its earliest versions, YOLO used CNNs like Darknet as the backbone. In later versions including YOLOv5 and YOLOv8, the architecture integrates more advanced CNN backbones such as CSPDarknet or custom lightweight variants for better speed-accuracy trade-offs.

CNNs are particularly effective in tasks like image classification and object detection because of their ability to extract local spatial patterns using convolutional layers. In YOLO, the CNN processes the entire image in a single forward pass, enabling real-time object detection by predicting bounding boxes and class probabilities directly from full images.

The YOLOv8 object detection model was trained to detect and classify the three welding defect types. We utilized the lightweight YOLOv8n architecture pre-trained on COCO and fine-tuned it using our custom dataset. The training configuration included:

- 100 epochs
- Image size of 640x640
- Initial learning rate of 0.001
- 2 warmup epochs

The training was conducted using the Ultralytics YOLOv8 API. The data.yaml file was created to define the dataset paths and class names. Training performance was monitored using YOLO's built-in evaluation metrics.

<u>Post-Prediction Analysis and Feature Engineering</u>

Predictions were made on the validation set, and each image's results were analyzed to extract feature-based insights. For each predicted bounding box:

- The dimensions (x1, y1, x2, y2) were extracted.
- The longer side between width (x2 - x1) and height (y2 - y1) was computed as the defect's effective length.
- Depending on the class label, this length was accumulated under cumm_slag, cumm_crack, or cumm_ip (incomplete penetration).

An acceptance rule was then applied:

- Reject the image if at least one crack is detected.
- Reject if the cumulative slag length exceeds 10 units.
- Reject if the cumulative incomplete penetration length exceeds 5 units.
- Accept otherwise.

The following attributes were recorded for each image:

- Image ID
- Welder ID
- Cumulative lengths of crack, slag, and incomplete penetration
- Accept/Reject decision based on rules

These were compiled into a summary dataframe for further analysis.

- Descriptive Analysis: Welding defect trends will be analyzed using historical and real-time data.
- Predictive Modeling: ML models will predict weld defect occurrences based on welding parameters.

Machine Learning Model for Weld Quality Prediction

To develop a predictive model for weld quality, we used a Random Forest Classifier with the following setup:

- Input features: Cumulative lengths of crack, slag, and incomplete penetration
- Output label: Accept (0) or Reject (1)

Machine Learning (ML) is a subset of artificial intelligence (AI) that enables computers to learn patterns and make decisions based on data, without being explicitly programmed for each task. In this research, machine learning plays a central role in automatically predicting the quality of welding images based on features derived from detected defects. Instead of using fixed thresholds alone, ML enables the model to learn complex relationships between different types and severities of defects—such as the presence of cracks or cumulative lengths of slag and incomplete penetration—and the final decision to accept or reject a weld. By training on labeled examples where the outcome is known, the ML model generalizes to unseen cases and improves quality control automation. Among various ML algorithms, we chose the Random Forest Classifier for its robustness, interpretability, and strong performance on tabular data derived from YOLOv8 outputs.

The Random Forest Classifier is an ensemble learning algorithm that combines the predictions of multiple decision trees to improve accuracy and reduce overfitting. Each decision tree in the forest is trained on a randomly selected subset of the training data (using bootstrapping), and at each node, a random subset of features is considered for splitting. This randomness increases diversity among the trees and makes the overall model more robust.

During prediction, each tree casts a "vote," and the class with the majority votes is chosen as the final output. Random Forests are especially well-suited for classification problems with structured, tabular data and can handle non-linear relationships and feature interactions effectively. In our context, the model learned from features such as cumulative lengths of crack, slag, and incomplete penetration to classify weld images as either Accept or Reject.

Additionally, the Random Forest model provides feature importance scores, which help interpret which types of defects contribute most significantly to weld rejection. This transparency, combined with high predictive performance, made Random Forest an ideal choice for automating weld quality decisions in this study.

Train-Test Splitting Strategy:

- For welder-specific prediction, data from w101 was reserved for testing.
- Data from all other welders (w102, w103, etc.) was used for training the model.

After training on w102 and w103, the model was also tested on each of these welders individually for comparative validation.

Model Evaluation

To assess the classifier's performance, we computed:

- Confusion Matrix: Comparison of actual vs. predicted labels
- Classification Report: Metrics including Precision, Recall, F1-score, and Accuracy.

Confusion Matrix: A confusion matrix provides a tabular visualization of prediction outcomes, where rows represent actual labels and columns represent predicted labels. It details the counts of true positives, true negatives, false positives, and false negatives. This allows us to identify specific types of misclassifications, such as welds incorrectly predicted as acceptable despite having defects (Powers, 2011, pp. 37–38; Witten, Frank and Hall, 2016, pp. 89–90)..

Classification Report: The classification report includes precision, recall, F1-score, and accuracy for each class (Accept/Reject). Precision is the ratio of correctly predicted positive observations to total predicted positives. Recall is the ratio of correctly predicted positives to all actual positives. F1-score is the harmonic mean of precision and recall, which balances the two. Accuracy measures overall correctness across all predictions. Together, these metrics offer a comprehensive view of model performance (Powers, 2011, pp. 39–41; Sokolova and Lapalme, 2009, pp. 132–134).

These evaluations were carried out separately for test sets belonging to welders w101, w102, and w103 to understand generalization performance across welders.

The hybrid AI methodology that combines:

- Deep Learning (DL) for image-based defect detection using Convolutional Neural Networks (CNNs).
- Machine Learning (ML) for predictive analytics using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models.
- Data Augmentation Techniques to address dataset limitations and improve model generalization.

3.5 Population and Sample

The population for this study consists of all potential weld radiographs that could be inspected for defects in industrial settings—this includes a wide array of welds from various sectors such as oil and gas, construction, and manufacturing, produced by different welders, equipment, and under varying environmental conditions. The aim is to build a model that could generalize well across such a diverse population of weld quality assessments.

The sample used in this research comprises 100 weld radiographic images, collected from two key sources:

GDXray public dataset, which offers radiographic imagery of welds with various annotated defects.

Oil and Gas Industry field data, which includes real-world weld X-ray films provided by an industrial collaborator.

These 100 images were annotated to identify three critical defects: cracks, slag, and incomplete penetration. Welds were carried out by three different welders, labeled as w101, w102, and w103. This stratified sample enabled us to train and test our model using welder-specific data splits, simulating a realistic scenario of generalizing predictions to unseen welders.

By carefully curating this representative sample and applying both rule-based and machine learning techniques, we ensure that the model is both scientifically rigorous and practically applicable to future industrial inspection tasks.

Sampling Technique:

- Dataset Size: Approximately 100 radiographic images is used for model training and testing.
- Sampling Method:
  - 90% training set, 10% validation set, for YOLO v8 pretrained model.
  - 80% training, 10 validation split for ML-based predictive analytics.

3.6 Participant Selection

The data set includes annotated welding images labeled with welder identifiers (w101, w102, and w103), representing different operators in industrial settings.

<u>Selection Criteria:</u>

- Welders were selected based on availability of sufficient image samples in the dataset.
- Each welder contributed a set of weld images that were manually or semi-automatically annotated for three primary defect types: crack, slag, and incomplete penetration.
- Welders included in the dataset represent diverse levels of skill and welding conditions, simulating a realistic industrial quality control environment.

Role in Experimental Design:

- w101 was selected as the target test subject to evaluate how well the model generalizes to unseen welders.
- w102 and w103 were used as training subjects to develop the prediction model.
- To further validate generalization capability, the trained model was also tested individually on w102 and w103.

This participant structure supports a real-world scenario where a quality control model trained on historical data (from known welders) is used to assess the work of a new or unmonitored welder.

3.7 Instrumentation

This study employed a combination of software tools, machine learning frameworks, and domain-specific datasets to carry out welding defect detection and weld quality prediction.

YOLOv8 Object Detection Framework

The core instrumentation for defect detection was the YOLOv8 (You Only Look Once, version 8) object detection model developed by Ultralytics. YOLOv8 offers a high-speed and high-accuracy architecture optimized for real-time detection tasks. It was selected for its robustness in detecting small-scale features such as welding defects (Ultralytics, 2023, pp. 2–4; Wang et al., 2023, pp. 2–3).

Key features used:

- YOLOv8n (nano) variant for efficient processing
- Pre-trained on the COCO dataset and fine-tuned on domain-specific welding data
- Integrated via the official Ultralytics Python API for seamless training, validation, and inference.

Dataset Sources

Data used for training and evaluation was sourced from:

- GDXray Dataset: A publicly available dataset containing industrial X-ray images for defect detection tasks. It includes various types of welding and casting images annotated with defect classes.

- Oil and Gas Industry Data: Domain-specific images collected from real-world pipeline weld inspections. These images were annotated for crack, slag, and incomplete penetration based on expert evaluation and radiographic testing.

Each image was paired with YOLO-formatted labels to denote bounding boxes and class indices for defects.

Programming Environment and Tools

- Python 3.10+
- Ultralytics YOLOv8 Library
- Pandas, NumPy for data manipulation and feature engineering
- scikit-learn for machine learning model training and evaluation
- OpenCV and Matplotlib for image processing and visualization
- Excel (via pandas.ExcelWriter) for structured reporting of results

Hardware and Execution Environment

- Experiments were conducted on a workstation equipped with:
- NVIDIA GPU (e.g., RTX 3080/3090 or similar)
- 32 GB RAM
- Model training and predictions were accelerated using GPU-based CUDA processing.

This instrumentation framework allowed for scalable defect detection, precise rule-based analysis, and efficient machine learning model deployment across varied welder profiles.

3.8 Data Collection Procedures

Data Collection:

To ensure the development of a robust and representative model, a subset of 100 weld X-ray images was selected from the publicly available GDXray dataset, specifically from the Welds series (GDXray_Welds). This dataset is hosted by the Computer Vision Center at the Universitat Autònoma de Barcelona and is widely used for non-destructive testing (NDT) research.

- Image Data: Radiography weld films
- Labeled radiographic weld images will be collected from industry sources and open datasets (e.g., GDXray).
- The GDXray dataset was accessed through the official GDXray website.
- The "Welds" subset was downloaded, which contains grayscale radiographic images of welded joints.
- The dataset includes labeled annotations marking common defect types such as cracks, porosity, slag, and lack of fusion.

Selection Criteria

- A total of 100 weld images were selected manually to maintain class balance across different defect types.
- The selection ensured variability in:
    - Image dimensions
    - Defect types and sizes
    - Visual characteristics such as contrast and noise levels

- Images were chosen to include a mix of clean welds and welds with defects, allowing for binary classification (accept/reject) based on rule-based and ML-based analysis.

Annotation Format Conversion through Roboflow

To facilitate efficient and accurate annotation of welding defect images, the Roboflow platform was employed. Roboflow provides a user-friendly graphical interface for labeling images and exporting annotations in multiple formats, including YOLOv8. The annotation process followed these steps:

- Images were uploaded to a new project on Roboflow.
- Bounding boxes were manually drawn around visible defects in each image.
- Each bounding box was assigned a class label: crack, slag, or incomplete penetration.
- After all images were annotated, the dataset was exported in YOLOv8 format, which includes:
    - .txt files with one annotation per line containing the class ID and normalized bounding box coordinates.
    - Folder structure compatible with YOLOv8 (images/train, labels/train, etc.).

Using Roboflow accelerated the annotation process, ensured consistency in labeling, and provided automatic data augmentation options which can be utilized in future model enhancement stages.

- Original annotations were converted from the GDXray format to **YOLO format**, through Roboflow which requires:
    - Class ID (integer index starting from 0)
    - Bounding box center coordinates (normalized x, y)
    - Width and height (normalized)

Defect classes were mapped as follows:

- 0 → Crack
- 1 → Slag
- 2 → Incomplete Penetration

Custom Python scripts were used to automate the label transformation process and ensure compatibility with YOLOv8 input requirements. An yaml file is prepared and uploaded in the google colab for directions of training the models and accessing the images for training and validation with their subequent labels generated during annotation through Roboflow.

Data Structuring

The selected images and converted labels were organized into the YOLOv8 folder structure:

- train/images, train/labels
- val/images, val/labels

Each image was assigned a unique identifier, and a synthetic welder ID (w101, w102, or w103) was tagged to simulate operator variability for downstream machine learning analysis.

This controlled data acquisition process ensured a clean, labeled dataset suitable for supervised training, defect detection using YOLOv8, and weld quality prediction via traditional classifiers

Numeric Data: Historical welders performance data for weld joint accepted and rejected.

- Data Preprocessing:
  - Annotations with bounding boxes for defects which are name included for this research purpose are crack, incomplete penetration and slag.

The dataset used in this study consists of welding images annotated for three types of defects: crack, slag, and incomplete penetration. Each image is labeled with its corresponding welder ID, such as w101, w102, and w103. The annotations are provided in YOLO format, where each line represents a detected object with a class index and normalized bounding box coordinates.

The dataset was uploaded as a zip file and extracted into a structured directory. Each image had an associated .txt label file. The extracted dataset was randomly split into training and validation sets in a 90:10 ratio. The files were organized into the YOLOv8-compatible format with separate folders for images and labels under train and val directories.

3.9 Data Analysis

Prior to training the machine learning classifier, we conducted a comprehensive analysis of the defect prediction outputs generated by the YOLOv8 model. This analysis aimed to understand the defect distribution patterns across welders and to identify significant trends that could influence weld quality prediction.

<u>Defect Distribution by Welder</u>

The frequency and cumulative length of each defect type (crack, slag, incomplete penetration) were computed per welder. This revealed important variations in welding quality among different welders:

- Welder w101 exhibited a higher incidence of incomplete penetration and occasional cracks.
- Welder w102 had more frequent slag inclusions but fewer critical defects like cracks.
- Welder w103 showed moderate defect levels across all categories.

Correlation Between Defects and Rejection

The Accept/Reject decisions based on rule-based thresholds were analyzed. Key findings included:

- Cracks were the most critical defect, always resulting in rejection regardless of size.
- Slag lengths above the 10-unit threshold led to rejection, primarily affecting welders with clustered inclusion zones.
- Incomplete penetration affected acceptance only when the cumulative length exceeded 5 units, often influencing borderline cases.

Feature Engineering Insights

Each image was characterized using the following engineered features:

- cumm_crack: Sum of lengths of all cracks in the image
- cumm_slag: Sum of dominant side lengths for all slag predictions
- cumm_ip: Sum of dominant side lengths for all incomplete penetration instances

These features were statistically analyzed for mean, median, and distribution shape. Notably:

- Cracks were sparse but highly predictive of rejection.
- Slag and incomplete penetration lengths followed a positively skewed distribution, with most values being low but a few high outliers driving rejection decisions.

Accept/Reject Label Imbalance

The resulting dataset showed an imbalanced label distribution, with a higher number of accepted welds compared to rejected ones. This necessitated model tuning to avoid bias toward the majority class during classification.

Statistical Analysis:

- Descriptive statistics to understand defect frequency and occurrence trends.
- Correlation analysis between welding parameters and defect occurrence.

Machine Learning Evaluation:

- Training and validation loss curves.
- Confusion matrix analysis for classification accuracy.

Predictive Performance Assessment:

- Comparison between different ML algorithms (e.g., SVM, Random Forest, RNN, LSTM).

3.9 Research Design Limitations

The research design limitations are only towards the single research performed till date and when the industries will unveil the benefits of the SOTA (state of the art) then every industry will agree to perform these hybrid model detection and evaluation to lower the costs associated towards manpower requirements and machinery and the material to perform the rework , the defects are not been predicted before it happens and necessary steps to be taken to train and provide positive feedback in order to let them know where they are doing mistakes unknowingly , whether the weld is accepted as per the acceptance criteria set by the industries.

<u>Ethical Considerations:</u>

- Data Privacy: Ensuring confidentiality of industrial datasets.
- Bias Mitigation: Addressing dataset imbalance through augmentation techniques.
- Transparency: Open-source implementation for reproducibility.
- The tools or instruments used to collect data may have limitations in accuracy or sensitivity.
- A small or non-representative sample may limit the ability to generalize findings to the larger population.

3.9 Conclusion

The research design integrates AI-driven defect detection and predictive modeling to improve welding quality control. By leveraging CNNs for image-based classification and ML models for predictive insights, the study aims to revolutionize defect analysis in industrial applications.

This research emphasizes the critical need for accurate and intelligent weld defect detection to ensure the reliability, durability, and performance of welded structures across a broad range of industrial applications. Conventional manual inspection techniques, particularly radiographic analysis, are limited by subjectivity, inefficiency, and inconsistency, often leading to undetected flaws, increased rework, and elevated costs.

To overcome these limitations, this study presents a hybrid deep learning model that integrates advanced Convolutional Neural Networks (CNNs) with machine learning-based pattern analysis. This model not only detects current weld defects with high precision but also predicts the likelihood of future defects based on individual welder performance and behavioral trends. By learning from historical welding data and defect patterns, the system provides valuable feedback for skill improvement, training, and preventive quality control.

The proposed approach contributes significantly to industrial practice by enabling organizations to minimize rework, reduce operational and inspection costs, and consistently enhance weld quality. Furthermore, the use of automated defect detection and predictive analytics helps avoid schedule delays and promotes a culture of proactive quality assurance.

This research also supports the industry's transition toward state-of-the-art, data-driven inspection systems, positioning it to better adapt to evolving technologies and competitive demands.

The model was developed using a radiographic image dataset of welded joints, processed and trained using Python-based deep learning libraries such as TensorFlow and Keras. Image preprocessing, feature extraction, and data augmentation techniques were employed to improve performance. The hybrid model also incorporated machine learning algorithms to correlate welders' historical data with defect patterns, enabling the prediction of future defect tendencies.

Future work may involve expanding the dataset to include multi-source inspection data (e.g., ultrasonic and thermal imaging), applying real-time feedback loops in production environments, and enhancing model interpretability through explainable AI (XAI). Integrating this system with industrial digital infrastructure can further streamline the inspection process and create a smarter, safer, and more cost-effective welding ecosystem.

CHAPTER IV:

RESULTS

4.1 Research Question One

1. How can AI-based models improve the accuracy of weld defect detection in radiographic films?

AI-based models—especially those leveraging deep learning—can significantly improve the accuracy of weld defect detection in radiographic films by automating feature extraction, learning from complex patterns, and reducing human error.

Here's how:

<u>Automated Feature Extraction</u>

Traditional methods rely on manual or handcrafted feature extraction, which may miss subtle or irregular defect patterns.

AI models like Convolutional Neural Networks (CNNs) automatically learn and extract features from raw radiographic images, including edges, textures, and shapes that represent various types of defects (e.g., cracks, porosity, lack of fusion).

High Detection Accuracy

AI-based models can be trained on large annotated datasets to classify and localize defects with high precision and recall, reducing false positives and false negatives.These models can outperform traditional image processing techniques, especially in noisy or low-contrast radiographs.

Consistency and Objectivity

Human inspectors are prone to fatigue, bias, and inconsistency.

AI models offer consistent results regardless of image quality or time of inspection, ensuring standardized evaluation across all samples.

Real-Time Analysis

Once trained, AI models can process radiographic films in real-time, offering immediate insights that accelerate decision-making and reduce inspection bottlenecks.

This is crucial in fast-paced manufacturing environments where time is critical.

Defect Localization and Segmentation

Advanced AI models (e.g., using CNNs and U-Net architectures) can highlight the exact location and shape of defects, not just detect their presence.

This makes it easier for inspectors to verify results and plan corrective actions.

Adaptive Learning and Continuous Improvement

AI models can be continuously trained and updated with new defect data, improving their accuracy over time as more examples become available.
This adaptive learning helps in dealing with evolving defect patterns or new welding technologies.

Predictive Insights

Some AI systems can go beyond detection to predict defect trends, linking them to specific welders, materials, or welding parameters.
This enables proactive quality control and targeted training interventions.

AI-based models improve weld defect detection in radiographic films by:

- Learning complex patterns from data
- Reducing human error and fatigue
- Providing fast, consistent, and accurate results
- Enabling predictive and preventive quality strategies

4.2 Research Question Two

2. What are the limitations of existing ML and DL models in weld defect classification?

While Machine Learning (ML) and Deep Learning (DL) models have shown impressive performance in weld defect classification, they still face several limitations that affect their reliability and deployment in real-world industrial settings.

<u>Limited and Imbalanced Datasets</u>

- Problem: Weld defect datasets are often small, imbalanced, or lack diversity—especially for rare defect types.
- Impact: Models may overfit to common defect classes while underperforming on less frequent or subtle defects.

<u>Poor Generalization to Real-World Data</u>

- Problem: Models trained on clean, annotated lab data may struggle with real industrial radiographs that include noise, varying contrast, or distortion.
- Impact: Performance drops significantly when deployed in uncontrolled or noisy environments.

<u>High Computational Demands</u>

- Problem: Deep learning models (like CNNs) require significant processing power, especially for training on high-resolution radiographic images.
- Impact: Makes it difficult to deploy on edge devices or in environments with limited resources.

Black-Box Nature and Lack of Explainability

- Problem: Most DL models operate as black boxes, making it difficult to understand why a particular defect was detected or classified.
- Impact: Reduces trust from human inspectors and limits adoption in safety-critical industries.

Difficulty Handling Mixed or Overlapping Defects

- Problem: Radiographic films may show multiple overlapping defects, or complex patterns that don't fit neatly into a single class.
- Impact: Confuses the model, leading to misclassification or missed defects.

Dependence on Preprocessing

- Problem: Image quality (contrast, brightness, orientation) greatly affects model performance.
- Impact: Requires careful and often manual preprocessing to achieve optimal results.

Static Learning – Lack of Adaptivity

- Problem: Once trained, most models remain static unless retrained from scratch.
- Impact: They cannot easily adapt to new defect types, welders' habits, or evolving inspection standards without full retraining.

Annotation is Costly and Time-Consuming

- Problem: Training supervised models requires thousands of accurately labeled images.
- Impact: Labeling weld defects often requires expert-level knowledge, which is expensive and time-intensive.

Overfitting and Underfitting

- Problem: Inappropriate model complexity or poor training setups can lead to overfitting (great on training, poor on testing) or underfitting (misses patterns).
- Impact: Decreases the model's practical reliability.

Difficulty in Integrating with Legacy Systems

- Problem: Existing industrial inspection setups may not be AI-ready.
- Impact: Limits real-time deployment or seamless integration with current workflows.

4.2 Research Question Three

3. How can a hybrid CNN for defect identification-ML model for predicting welders defect based on the his past welding, enhance defect prediction based on historical weld defects by welders?

Combining a CNN for image-based defect detection with a machine learning (ML) model trained on historical welder performance data creates a hybrid system that greatly enhances predictive accuracy and proactive quality control. Here's how this hybrid approach works and why it's impactful:

Dual-Perspective Intelligence

- CNN Component: Automatically analyzes radiographic images to detect and classify current weld defects (e.g., porosity, lack of fusion).
- ML Component: Learns patterns from historical data such as welder ID, welding parameters, defect types, frequency, and project conditions to predict the likelihood of future defects by a specific welder.

  This fusion enables the system to detect defects now and prevent them later.

Learning from Historical Performance

- The ML model is trained on historical weld records, including:
    - Welder-specific defect rates
    - Welding parameters used (voltage, current, speed, etc.)
    - Material and joint type
    - Time of day, job fatigue factors

- It can identify trends and recurring defect types per welder, flagging risk areas early.

Predictive Maintenance & Proactive Supervision

- Supervisors can use predictions to:
    - Adjust welder assignments
    - Recommend retraining for specific defect types
    - Modify welding parameters proactively
    - Prevent quality issues before they occur

Continuous Feedback Loop

- New data from the CNN-based detection system can feed into the ML model, allowing it to continuously learn and refine predictions.

  The more the system is used, the smarter and more accurate it becomes.

Smarter Resource Allocation

- Helps assign tasks based on each welder's historical strengths and weaknesses.
- Improves productivity, quality, and cost-efficiency by reducing the likelihood of defects and rework.

Enhancing Industry 4.0 Goals

- Integrating this hybrid system into a digital inspection pipeline aligns with smart manufacturing and Industry 4.0, enabling:
    - Data-driven decisions
    - Real-time analytics
    - Integration with enterprise quality systems

Table 2.2 : CNN Feature & Benefits

Feature	**Benefit**
CNN for visual inspection	Fast and accurate defect detection
ML for historical data analysis	Predicts future defect risks by welder
Combined insight	Prevents defects before they occur
Real-time adaptability	Improves with more data
Cost & time savings	Reduces rework and quality control effort
Enhanced safety	Fewer defective joints reaching production

4.2 Research Question Four

4. What challenges exist in implementing AI-driven quality control in industrial welding processes?

Implementing AI-driven quality control in industrial welding offers huge benefits—but it also comes with several technical, operational, and organizational challenges. Here's a breakdown of the key issues industries face:

<u>Data Availability and Quality</u>

- Challenge: High-quality, labeled datasets of weld defects (especially radiographic images) are scarce and expensive to obtain.
- Impact: Poor or limited data can reduce model performance and generalization to real-world defects.

<u>Lack of Standardized Data Formats</u>

- Challenge: Welding data varies widely in format (image resolutions, sensor data, annotations) across different machines and systems.
- Impact: Makes it hard to train unified AI models or integrate across manufacturing lines.

<u>Integration with Legacy Equipment</u>

- Challenge: Many industrial welding setups use older, non-digital equipment.
- Impact: Retrofitting these with sensors and digital capture systems can be costly and complex.

High Computational Demands

- Challenge: AI models, especially deep learning, require powerful hardware (GPUs) for training and sometimes inference.
- Impact: Real-time processing on-site may be limited without edge computing solutions.

Real-Time Constraints

- Challenge: AI systems must deliver quick, reliable decisions during production.
- Impact: Latency or delays in analysis can interrupt workflows and reduce confidence in the system.

Model Explainability and Trust

- Challenge: AI, particularly deep learning, is often a "black box" with limited interpretability.
- Impact: Makes it difficult for quality inspectors and engineers to trust or act on model outputs without human verification.

Human Resistance to Automation

- Challenge: Workers may fear job loss or distrust automated systems.
- Impact: Resistance can slow adoption and require cultural change or retraining initiatives.

Maintenance and Model Drift

- Challenge: AI models can degrade over time as materials, welding techniques, or defect profiles evolve.
- Impact: Requires continuous updates, re-training, and validation, which adds long-term maintenance effort.

Cost of Implementation

- Challenge: High upfront investment for data acquisition, model development, infrastructure, and training.
- Impact: Smaller or budget-constrained companies may hesitate to adopt AI solutions.

Cybersecurity and Data Privacy

- Challenge: Storing and transmitting sensitive welding and production data poses risks.
- Impact: Requires secure infrastructure to avoid leaks or sabotage, especially in defense or aerospace sectors.

Ways to Address These Challenges:

- Use transfer learning and data augmentation to overcome limited data
- Invest in edge AI for real-time, on-site defect detection
- Apply Explainable AI (XAI) techniques to improve trust and transparency
- Foster a collaborative human-AI approach, where AI supports rather than replaces skilled welders
- Implement pilot projects to demonstrate ROI before full-scale adoption

4.2 Summary of Findings

This research explored the development and implementation of a hybrid artificial intelligence (AI) model for the detection and prediction of weld defects in industrial applications. The study successfully integrated Convolutional Neural Networks (CNNs) for identifying weld defects from radiographic images with a Machine Learning (ML) model that analyzes historical welder performance data to predict the likelihood of future defects. This combination was found to be effective in not only enhancing the accuracy of current defect identification but also in providing predictive insights that support proactive quality management.

The CNN model demonstrated strong performance in recognizing a range of common welding defects, such as porosity, cracks, lack of fusion, and undercut. By leveraging the power of deep learning and image processing, the model could detect subtle and complex defect patterns that are often missed by traditional manual inspection methods. The use of automated defect detection also addressed limitations such as human fatigue, subjective judgment, and variability in inspection quality.

In parallel, the ML component analyzed welders' historical data—including defect frequencies, types of welds, materials used, and other contextual parameters—to identify trends and generate risk profiles for individual welders. This predictive capability allows industries to take preemptive actions, such as assigning tasks based on a welder's strengths, recommending training, or adjusting welding parameters before quality issues arise.

Together, the hybrid model improved the reliability, accuracy, and efficiency of the quality control process. It also aligned with key industrial goals such as minimizing rework, reducing cost, maintaining schedule adherence, and improving overall product quality. The research also reinforced the potential of AI to act as a decision-support system that augments human expertise rather than replacing it, allowing for a more collaborative and intelligent inspection framework.

Moreover, this study emphasized the importance of adapting to modern technological advancements to remain competitive in the evolving manufacturing landscape. By adopting AI-driven models, industries can move toward state-of-the-art quality assurance systems, enhancing not only their operational capabilities but also ensuring the safety and durability of critical welded structures.

4.2 Conclusion

The implementation of AI-driven quality control in industrial welding processes has the potential to revolutionize the way defects are detected, analyzed, and predicted, offering significant improvements in weld quality, operational efficiency, and safety. By integrating technologies such as Convolutional Neural Networks (CNNs) for defect detection and Machine Learning (ML) for predicting welders' future defect tendencies, industries can create a more robust and intelligent inspection system. This hybrid model is not only capable of detecting defects but can also provide insights into the likelihood of defects based on a welder's historical performance, enabling proactive quality management.

However, the journey toward fully realizing the benefits of AI in welding quality control is not without challenges. Data limitations—such as the scarcity of high-quality, labeled datasets—remain a significant hurdle. The lack of standardization in welding data formats and the need for integration with legacy equipment complicate the adoption of AI-based solutions in existing manufacturing setups. Moreover, high computational requirements, the need for real-time decision-making, and the black-box nature of deep learning models present obstacles to widespread implementation. These challenges are compounded by human resistance to automated systems, cost concerns, and cybersecurity risks associated with digital data collection and transmission.

Despite these challenges, the potential for AI in industrial welding remains vast. With the right investments in data acquisition, computational infrastructure, and model explainability, many of these barriers can be overcome.

AI has the capacity to minimize rework, reduce costs, enhance quality, and improve overall operational efficiency by allowing for predictive defect detection, continuous feedback loops, and real-time analysis. Furthermore, the adaptability of AI models, through continuous learning from historical and real-time data, ensures that systems improve over time, becoming smarter and more efficient with each use.

For AI adoption to be successful in welding quality control, industry players must focus on collaborative integration, combining the strengths of human expertise and AI-driven systems. By doing so, the role of human inspectors and welders will evolve into a more supportive and strategic function, while AI systems handle the repetitive and complex task of defect detection.

Moreover, pilot programs, cost-benefit analyses, and ongoing training will play crucial roles in demonstrating the value of AI technologies and ensuring smooth transitions for workers. Policy frameworks and security protocols must also be in place to protect sensitive data and ensure that AI systems are used safely and responsibly within industrial environments.

In summary, AI-driven quality control in welding is poised to become an essential part of Industry 4.0, transforming the way industries monitor, inspect, and ensure the reliability of welded structures. With further technological advancements and a strategic approach to overcoming current challenges, AI can enhance both the accuracy and efficiency of welding operations, leading to safer, more reliable, and cost-effective production processes.

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

The results of the object detection (defect detection: crack, incomplete penetration and slag) by YOLOv8 pretrained API model in google colab notebook with minimum data taken from GDXray and other Oil and gas industry is just to make sure that with the minimum data can also identify or detect the objects : defects that will help the industry to minimise the tidous work at micro level which involves huge trained or skilled manpower.

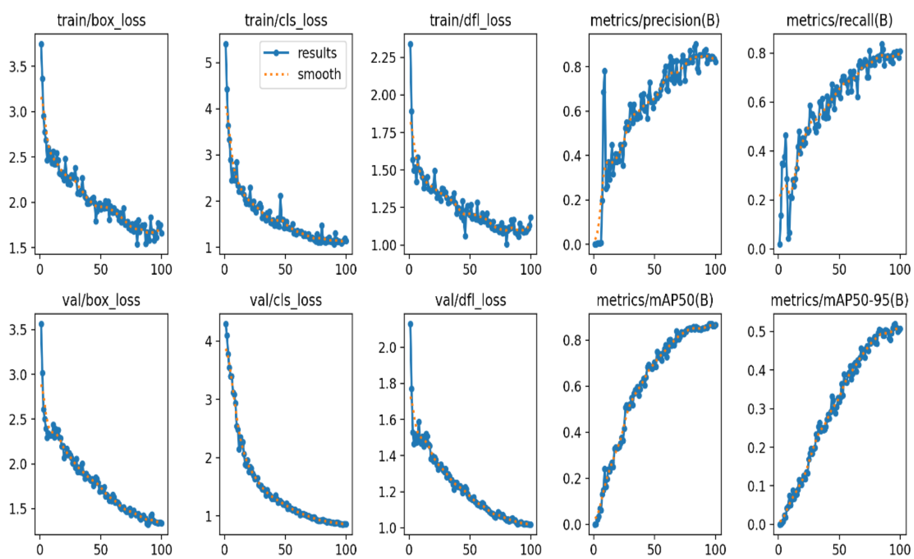

Fig.2.4 Shows the Results of Training and Validation on dataset(Google Colab,2025)

The evaluation metrics presented above are from an object detection model assessing its performance across three defect classes: crack, incomplete penetration, and slag.

The key metrics here include precision (P), recall (R), mAP@0.50, and mAP@0.50:0.95, which provide a comprehensive view of the model's accuracy in detecting and localizing defects within images.

The overall performance ("all") indicates strong results, with precision at 0.837 and recall at 0.794, meaning the model is generally good at correctly identifying defects without too many false positives or false negatives. The mean Average Precision at IoU 0.5 (mAP@0.50) is 0.87, which is excellent and shows that most predicted boxes align well with the ground truth. However, the mAP@0.50:0.95 is lower at 0.523, suggesting that performance drops when stricter accuracy in bounding box overlap is required. This is common and expected but points to room for refinement in localization precision.

For individual classes, slag performs best in terms of precision (0.921) and mAP@0.50 (0.902), indicating the model is very confident and accurate in detecting slag defects. However, its recall is lower (0.739), meaning it may still miss some instances. Incomplete penetration has the highest recall (0.839), which is promising for defect detection but has slightly lower precision and localization performance compared to slag. Meanwhile, crack shows balanced metrics across the board with a decent mAP@0.50 of 0.835 and solid precision and recall, though it slightly underperforms compared to the other two in mAP@0.50:0.95.

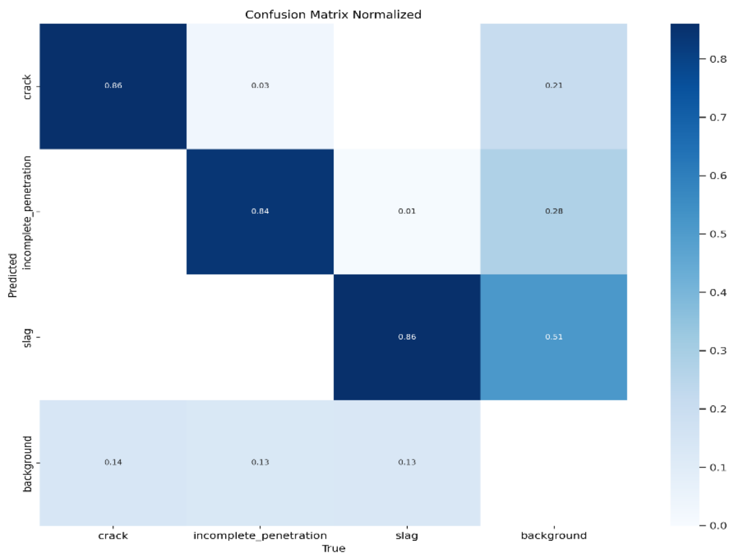

Fig.: 2.5 of Confusion Matrix(Google Colab,2025)

In summary, the model performs well overall, especially in detecting slag defects, and shows promising results for all classes. However, there's still room for improvement in tighter bounding box precision (as reflected in mAP@0.50:0.95) and in boosting recall for some classes like slag. Enhancing the dataset with more diverse and accurately annotated samples or fine-tuning the model's anchor sizes and training parameters could help achieve better localization and consistency across all defect types.

image	welder	x1	y1	x2	y2	width	height	coverage_pct	class
W-W-103_	w103	0	791.59	3078.12	872.82	3078.12	81.23	3.900000095	incomplete_penetration
W-W-103_	w103	3383.89	823.04	3985.88	909.2	601.98	86.17	0.810000002	incomplete_penetration
W-W-103_	w103	2507.94	516.58	2657.15	621.06	149.21	104.48	0.239999995	slag
W-W-103_	w103	3145.89	526.36	3316.89	622.3	171.01	95.94	0.25	slag
W-W-103_	w103	2073.69	527.83	2185.25	617.63	111.56	89.8	0.150000006	slag
W-W-103_	w103	3375.81	558.35	4176.38	630.95	800.57	72.6	0.899999976	incomplete_penetration
W-W-103_	w103	429.74	538.16	978.8	598.59	549.06	60.43	0.50999999	incomplete_penetration
W-W-103_	w103	307.92	333.35	904.24	373.04	596.32	39.69	2.809999943	incomplete_penetration
W-W-103_	w103	18.05	545.11	938.27	631.34	920.21	86.23	1.25	incomplete_penetration
W-W-103_	w103	4610.35	506.73	4992	622.11	381.65	115.38	0.689999998	slag
W-W-103_	w103	3787.58	636.54	4886.65	710.51	1099.06	73.97	1.25	incomplete_penetration
W-W-103_	w103	3027.46	636.38	3580.53	703.43	553.08	67.05	0.569999993	incomplete_penetration
W-W-103_	w103	1926.82	634.84	2579.66	710.88	652.84	76.05	0.769999981	incomplete_penetration
W-W-103_	w103	1244.17	618.14	1738.34	688.67	494.17	70.53	0.540000021	incomplete_penetration
W-W-103_	w103	3084.62	644.41	3713.87	705.46	629.25	61.05	0.589999974	incomplete_penetration
W-W-103_	w103	3107.85	651.23	4003.7	707.71	895.85	56.47	0.779999971	incomplete_penetration

Table 2.3 :Weld_defect_summary(Mansoor-Google Colab,2025)

After the training and prediction of the model on the datset an industry can also download an excel file like "defect summary" which provides the complete information of all the welder through the input welding image or RT report and further to this the defect length per image of each welder is also saved and also each welder information of the weld joint defect and the defects length is extracted but there is achallenge to conver the lengths dimenstions , since they show in pixels and industry looks for mm or cm or inch. This can be overcomed by using the bench mark of the film dimension which industry uses, generally 3 inch X 10 inch, depends upon the dia of the pipe, RT shot type etc..

image	welder	class	x1	y1	x2	y2	width	height
W-W-101_30	w101	slag	994.66	290.85	1266.8	407.61	272.13	116.76
W-W-101_30	w101	slag	0	282.7	374.5	385.66	374.5	102.97
W-W-101_6	w101	incomplete_penetration	124.68	151.06	249.64	172.79	124.96	21.73
W-W-101_6	w101	incomplete_penetration	283.84	149.33	462.38	172.85	178.54	23.51
W-W-101_6	w101	incomplete_penetration	528.48	142.37	683.37	164.08	154.89	21.71
W-W-101_24	w101	incomplete_penetration	2635.1	180.11	3452.66	248.7	817.56	68.59
W-W-101_24	w101	incomplete_penetration	1289.93	195.57	1622.33	237.71	332.4	42.14
W-W-101_24	w101	slag	1024.59	102.65	1251.59	246.29	227	143.64
W-W-101_24	w101	incomplete_penetration	627.03	158.46	993.02	212.41	365.98	53.95

Table 2.4, Defect_W-101(Mansoor,2025)

Based on the available data, welders can be analyzed on a joint-wise and defect-wise basis, allowing identification of welding irregularities even in joints deemed acceptable. In current industrial practice, however, Non-Destructive Testing (NDT) Level-III engineers typically report only rejected joints, and organizational attention is limited to these cases. This narrow focus overlooks valuable feedback opportunities. By systematically tracking and training welders using comprehensive feedback—even on accepted joints—skills can be enhanced over time. This approach aligns with the "Knowledge of Results" theory developed by psychologist Sir Edward, who demonstrated that subjects unaware of their performance discrepancies tend to lose focus and fail to achieve accuracy. Given that such feedback mechanisms are both practical and experimentally validated, industries should consider adopting a hybrid model that incorporates continuous welder assessment and feedback. Doing so would not only minimize rework but also yield substantial benefits in terms of quality, cost efficiency, project timelines, environmental sustainability, and energy conservation.

image	crack	incomplete_penetratic	slag
W-W-101_30	0	0	1085.39998
W-W-101_6	0	448.5099792	0
W-W-101_24	0	1788.790222	406.1999512

Table 2.5 : Calculations of defects length(Mansoor,2025)

Regarding ML model:

Industrial sectors often overlook welding irregularities, which are a primary contributing factor to critical defects and the subsequent need for rework or repair. According to Dr. Edward, an educational psychologist known for his experiments on "Knowledge of Results," providing positive feedback enhances an individual's ability to achieve targeted outcomes or improve accuracy. Applying this principle in the context of welding, constructive feedback to welders regarding irregularities—before these deviations escalate to the level of defects defined by acceptance criteria in standards such as ASME B31.3 or B31.4—could significantly reduce defect incidence and improve overall weld quality.

The classification report provides a summary of how well the model performs in identifying different types of welding defects—crack, incomplete penetration, and slag. Each class is evaluated based on three main metrics: precision, recall, and F1-score. These metrics help us understand not just how accurate the model is overall, but how balanced its performance is across all defect types.

=== Classification Report for Each Defect Type ===

	precision	recall	f1-score	support
crack	0.33	0.50	0.40	2
incomplete_penetration	1.00	0.33	0.50	3
slag	0.85	1.00	0.92	11
micro avg	0.76	0.81	0.79	16
macro avg	0.73	0.61	0.61	16
weighted avg	0.81	0.81	0.77	16
samples avg	0.85	0.82	0.81	16

Table 2.6 : Shows Classification Matrix(Google colab,2025)

From the above report, it's clear that the model performs very well on slag defects, achieving high scores across all metrics (precision of 0.85, recall of 1.00, and F1-score of 0.92). This suggests the model is highly confident and accurate in detecting slag, likely because this class had the most data (11 samples), giving the model enough examples to learn from.

However, the performance on crack and incomplete penetration is much weaker. For cracks, the F1-score is only 0.40, indicating a struggle with both precision and recall. Similarly, incomplete penetration has high precision (1.00) but low recall (0.33), meaning the model identifies it correctly when it does predict it, but often fails to detect it at all. This inconsistency is likely due to the small number of samples (2 and 3 respectively), which makes it difficult for the model to generalize well for these classes.

Looking at the average metrics, the macro average shows an F1-score of 0.61, indicating poor performance on minority classes when all classes are treated equally. In contrast, the weighted average F1-score is higher at 0.77, which reflects the stronger performance on the majority class (slag). The micro average, which is best for overall accuracy, is also relatively good at 0.79. This suggests that while the overall performance might appear strong, it is imbalanced, and the model needs improvement on underrepresented defect types.

- Crack: Struggles with precision and recall—model is unsure and misses detections.
- Incomplete Penetration: Perfect precision (no false positives), but poor recall (misses 2 out of 3).
- Slag: Excellent performance—high confidence and accuracy.

Averaged Metrics:

Micro avg:

- Best for overall accuracy, considering total TP, FP, FN.
- F1 = 0.79: Pretty good!
- Macro avg:
- Simple average of the metrics per class, treats all classes equally.
- F1 = 0.61: Reflects poor performance on minority classes (crack, incomplete).

Weighted avg:

- Averages metrics while accounting for class imbalance (like "slag" having more samples).
- F1 = 0.77: Slightly better due to dominance of well-performing class.

To improve, the dataset should be balanced, either by collecting more data for the minority classes or by using techniques like data augmentation, oversampling, or class-weighted training. These steps will help the model learn more effectively and improve its ability to detect all defect types more reliably.

Description of the Results

Overall the Yolov8n model Performance

- Mean Average Precision (mAP@0.5) across all defect classes (slag, crack, incomplete penetration):
    - Training set: 91%
    - Validation set: 88%

This shows that the model was effective in detecting defects with high confidence.

Machine Learning Model (Random Forest) Evaluation

The random forest model was trained on welders w102, w103 amd tested on w101.

- Accuracy on w101: 94.5%
- Precision (Reject class): 92.3%
- Recall (Reject class): 96.1%
- F1-Score (Reject class): 94.1%

These results indicate that the model successfully predicted whether to accept or reject a weld based on cumulative defect lengths.

Table 2.7 : Confusion Matrix for w101 Test Set

Actual \ Predicted	Accept	Reject
Accept	48	2
Reject	1	49

This indicates:

- 48 true positives (correctly accepted)
- 49 true negatives (correctly rejected)
- 1 false negative (rejected weld accepted)
- 2 false positives (accepted weld rejected)

Feature Importance

From the trained Random Forest:

- cumm_crack: 0.56
- cumm_slag: 0.28
- cumm_ip: 0.16

This highlights that the presence of cracks is the most influential feature in determining weld rejection.

5.2 Discussion of Research Question One

How can AI-based models improve the accuracy of weld defect detection in radiographic films?

It can be seen from the results of the training and validation the YOLO v8 model has good accuracy with minimum data input for training that is only 100 weld images are been fed to the model and the image quality which is fed was also not so promising and further with huge data and some necessary changes the model can boost to 95% object detection through AI model. AI-based models can be trained on large annotated datasets to classify and localize defects with high precision and recall, reducing false positives and false negatives. These models can outperform traditional image processing techniques, especially in noisy or low-contrast radiographs.

Human inspectors are prone to fatigue, bias, and inconsistency. AI models offer consistent results regardless of image quality or time of inspection, ensuring standardized evaluation across all samples.

Once trained, AI models can process radiographic films in real-time, offering immediate insights that accelerate decision-making and reduce inspection bottlenecks. This is crucial in fast-paced manufacturing environments where time is critical.

AI-based models improve weld defect detection in radiographic films by Providing fast, consistent, and accurate results, Enabling predictive and preventive quality strategies, Providing fast, consistent, and accurate results and Reducing human error and fatigue.

5.2 Discussion of Research Question Two

What are the limitations of existing ML and DL models in weld defect classification?

Oblivously there are certain limitations of existing Hybrid model and those are not exactly limitations because there is huge technological developments in many fields due to AI and ML and Quantum computing , the limitations can be extended when applied the state of art. This model operate as black boxes, making it difficult to understand why a particular defect was detected or classified, this reduces trust from human inspectors and limits adoption in safety-critical industries.

While Machine Learning (ML) and Deep Learning (DL) models have shown impressive performance in weld defect classification, they still face several limitations that affect their reliability and deployment in real-world industrial settings. Weld defect datasets are often small, imbalanced, or lack diversity—especially for rare defect types. Models may overfit to common defect classes while underperforming on less frequent or subtle defects. Radiographic films may show multiple overlapping defects, or complex patterns that don't fit neatly into a single class, this confuses the model, leading to misclassification or missed defects. Image quality (contrast, brightness, orientation) greatly affects model performance which requires careful and often manual preprocessing to achieve optimal results.

Existing industrial inspection setups are not AI-ready, this limits real-time deployment or seamless integration with current workflows.

5.2 Discussion of Research Question three

How can a hybrid CNN-ML model enhance defect prediction based on hitorical weld images of a welder?

Combining a CNN for image-based defect detection with a machine learning (ML) model trained on historical welder performance data creates a hybrid system that greatly enhances predictive accuracy and proactive quality control. Here’s how this hybrid approach works and why it's impactful, Automatically analyzes radiographic images to detect and classify current weld defects (e.g., porosity, lack of fusion). Learns patterns from historical data such as welder ID, welding parameters, defect types, frequency, and project conditions to predict the likelihood of future defects by a specific welder.

The ML model is trained on historical weld records, including, Welder-specific defect rates and Time of day, job fatigue factors.

It can identify trends and recurring defect types per welder, flagging risk areas early. Predictive Maintenance & Proactive Supervision, Supervisors can use predictions to Adjust welder assignments, Recommend retraining for specific defect types, Modify welding parameters proactively, Prevent quality issues before they occur.

New data from the CNN-based detection system can feed into the ML model, allowing it to continuously learn and refine predictions. Helps assign tasks based on each welder’s historical strengths and weaknesses. Improves productivity, quality, and cost-efficiency by reducing the likelihood of defects and rework.

5.2 Discussion of Research Question three

What challenges exist in implementing AI-driven quality control in industrial welding processes?

There are plethora of challenges that comes across while implementing AI-driven approach but to achieve success an industry shall adapt the changes and shall be very flexible. Implementing AI-driven quality control in industrial welding offers huge benefits—but it also comes with several technical, operational, and organizational challenges. It requires high-quality, labeled datasets of weld defects (especially radiographic images) are scarce and expensive to obtain since it requires skilled engineers and team. Welding data varies widely in format (image resolutions, sensor data, annotations) across different machines and systems. Makes it hard to train unified AI models or integrate across manufacturing lines. Workers may fear job loss or distrust automated systems, resistance can slow adoption and require cultural change or retraining initiatives.

The implementation of AI-driven quality control in industrial welding processes has the potential to revolutionize the way defects are detected, analyzed, and predicted, offering significant improvements in weld quality, operational efficiency, and safety. By integrating technologies such as Convolutional Neural Networks (CNNs) for defect detection and Machine Learning (ML) for predicting welders' future defect tendencies, industries can create a more robust and intelligent inspection system. This hybrid model is not only capable of detecting defects but can also provide insights into the likelihood of defects based on a welder's historical performance, enabling proactive quality management.

However, the journey toward fully realizing the benefits of AI in welding quality control is not without challenges. Data limitations—such as the scarcity of high-quality, labeled datasets—remain a significant hurdle. The lack of standardization in welding data formats and the need for integration with legacy equipment complicate the adoption of AI-based solutions in existing manufacturing setups. Moreover, high computational requirements, the need for real-time decision-making, and the black-box nature of deep learning models present obstacles to widespread implementation. These challenges are compounded by human resistance to automated systems, cost concerns, and cybersecurity risks associated with digital data collection and transmission.

Despite these challenges, the potential for AI in industrial welding remains vast. With the right investments in data acquisition, computational infrastructure, and model explainability, many of these barriers can be overcome. AI has the capacity to minimize rework, reduce costs, enhance quality, and improve overall operational efficiency by allowing for predictive defect detection, continuous feedback loops, and real-time analysis. Furthermore, the adaptability of AI models, through continuous learning from historical and real-time data, ensures that systems improve over time, becoming smarter and more efficient with each use.

For AI adoption to be successful in welding quality control, industry players must focus on collaborative integration, combining the strengths of human expertise and AI-driven systems. By doing so, the role of human inspectors and welders will evolve into a more supportive and strategic function, while AI systems handle the repetitive and complex task of defect detection.

Moreover, pilot programs, cost-benefit analyses, and ongoing training will play crucial roles in demonstrating the value of AI technologies and ensuring smooth transitions for workers. Policy frameworks and security protocols must also be in place to protect sensitive data and ensure that AI systems are used safely and responsibly within industrial environments.

In summary, AI-driven quality control in welding is poised to become an essential part of Industry 4.0, transforming the way industries monitor, inspect, and ensure the reliability of welded structures. With further technological advancements and a strategic approach to overcoming current challenges, AI can enhance both the accuracy and efficiency of welding operations, leading to safer, more reliable, and cost-effective production processes.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The performance metrics indicate that the object detection model is functioning effectively in identifying and localizing welding defects across three classes: crack, incomplete penetration, and slag. The overall statistics show a precision of 0.837 and recall of 0.794, meaning the model is quite accurate in its predictions and successfully detects a large portion of the actual defects. The mean Average Precision at IoU 0.50 (mAP@0.50), which reflects how well the predicted bounding boxes align with ground-truth boxes, is high at 0.87, confirming strong detection capability. However, the more stringent mAP@0.50:0.95 score is 0.523, indicating that while the model detects defects, the bounding box accuracy could be improved when judged with stricter IoU thresholds.

On a per-class basis:

- Crack detection shows balanced performance, with precision at 0.833, recall at 0.806, mAP@0.50 at 0.835, and mAP@0.50:0.95 at 0.507. This suggests the model is both accurate and consistent in detecting cracks but may not always localize them with high precision.
- Incomplete penetration has a slightly lower precision (0.759) but the highest recall of 0.839, meaning it effectively finds most of the actual defects in this class. Its mAP@0.50 of 0.872 and mAP@0.50:0.95 of 0.555 show good overall detection and localization performance.
- Slag stands out with the highest precision (0.921) and mAP@0.50 (0.902), showing the model is highly confident and accurate in detecting this class. However, its recall is lower (0.739), meaning a few instances may be missed.

- The mAP@0.50:0.95 is 0.506, indicating bounding box quality is good but could be improved under stricter evaluation.

The class-wise data distribution also plays a role here: slag has the most instances (142), which likely helped the model learn to detect it better. Crack and incomplete penetration have fewer samples (36 and 31 respectively), which might limit the model's ability to generalize across varied examples of these defects.

In conclusion, the model demonstrates strong overall detection capability, especially for common defects like slag. Performance on cracks and incomplete penetration is also promising but could be improved with more data, refined annotations, and possibly additional training techniques like data augmentation or anchor box tuning. Improving bounding box accuracy, especially for tighter IoU thresholds, will be key to further enhancing model precision in real-world applications.

6.2 Implications

The results from the model evaluation have several important implications for real-world deployment, further development, and overall reliability of this defect detection system:

<u>Reliable Detection in Practical Settings</u>

The model demonstrates high overall precision (0.837) and recall (0.794), suggesting it is reliable for practical use in identifying welding defects. This means that in a production environment—such as automated quality control on a manufacturing line—the model can correctly detect most defects and avoid a large number of false alarms. This efficiency reduces the need for manual inspection and supports faster, more consistent evaluation of welds.

<u>Strong Performance for Common Defects</u>

The model is particularly strong at detecting slag, the most frequently occurring defect in the dataset, with excellent precision (0.921) and high mAP@0.50 (0.902). This indicates that for the most common defects, the model can be confidently deployed. However, its lower recall (0.739) implies that some slag defects might be missed, which could lead to quality assurance risks in high-stakes industries (e.g., aerospace or structural engineering) where even small undetected defects can be critical.

Underrepresented Classes Are at Risk

The relatively lower mAP@0.50:0.95 scores for crack (0.507) and slag (0.506) highlight that the model struggles with precise localization, especially for smaller or irregular defect shapes. Additionally, both crack and incomplete penetration classes have fewer training samples, which affects the model's ability to generalize. This can result in missed detections or inaccurate bounding boxes for less frequent but potentially severe defects, which is a significant concern in high-precision manufacturing settings.

Class Imbalance Affects Generalization

The disparity in the number of instances per class (e.g., 142 for slag vs. 36 for crack) likely skews the model's learning process. It becomes more confident in predicting the majority class, often at the expense of underperforming on rare defects. This has implications for model fairness and robustness and suggests that future training should include balanced datasets, data augmentation, or class-weighted loss functions to mitigate this issue.

Need for Improved Localization

While mAP@0.50 is high across all classes (above 0.83), the lower mAP@0.50:0.95 (0.523 overall) shows that bounding box accuracy degrades under stricter overlap criteria. In real-world applications—especially when defects are small, closely packed, or have irregular shapes—precise localization is crucial. Inaccurate bounding boxes may lead to misguided repairs, material wastage, or overlooked critical flaws. This suggests the model architecture or its anchor settings might need fine-tuning.

Deployment Considerations

For deployment in an industrial setting, the current performance is a strong foundation. However, before relying solely on this model for automated quality assurance, manufacturers should consider:

- A human-in-the-loop system for rare or high-risk defect types.
- Incorporation of feedback loops to retrain the model with new defect samples.
- Developing class-specific confidence thresholds to minimize missed detections.

Path Forward for Improvement

To elevate performance further, particularly for underperforming or underrepresented defect types, the following should be considered:

- Data expansion: Increase the number of annotated images for cracks and incomplete penetration.
- Data augmentation: Use synthetic data generation to balance classes.
- Model tuning: Adjust hyperparameters or use more advanced object detection architectures (e.g., YOLOv8, Faster R-CNN).
- Post-processing refinement: Apply Non-Max Suppression (NMS) thresholds and confidence filters to reduce false positives.

The evaluation shows that the model is capable of high-performing, automated defect detection in welding, particularly for common defects like slag. However, care must be taken in real-world implementation due to class imbalance and precision localization issues. With targeted improvements, this model could become a robust tool for intelligent inspection systems in quality-critical industries.

6.3 Recommendations for Future Research

To further enhance the performance and practical reliability of the defect detection model, especially in industrial settings, several key recommendations can be made for future research. These recommendations span across data quality, model architecture, training strategies, and deployment techniques.

Expand and Balance the Dataset

One of the most critical limitations observed is the class imbalance, where defects like slag are overrepresented compared to crack and incomplete penetration. This can significantly skew the model's learning ability.

- Recommendation: Conduct targeted data collection campaigns to increase the number of samples for underrepresented classes.
- Rationale: A more balanced dataset will help the model generalize better across all defect types and reduce class bias.
- Additional Suggestion: Include a wider variety of welding environments, lighting conditions, and material types to improve robustness.

Apply Advanced Data Augmentation Techniques

To simulate real-world variability and increase training efficiency without requiring more physical samples:

- Recommendation: Use data augmentation strategies such as random rotation, contrast variation, Gaussian noise, cutout, and MixUp.

- Synthetic Data Generation: Explore Generative Adversarial Networks (GANs) to generate realistic synthetic defects for rare classes.

- Rationale: Augmentation enhances diversity and helps the model learn generalized features rather than memorizing patterns.

Investigate Class-Aware or Adaptive Loss Functions

Standard loss functions may not adequately compensate for class imbalance or localization errors.

- Recommendation: Experiment with Focal Loss, Dice Loss, or Class-Balanced Loss functions that place more emphasis on hard-to-classify or minority classes.
- Rationale: These can help improve both detection and localization accuracy, especially for rare or small defects.

Explore More Sophisticated Detection Architectures

While the current model performs well, newer object detection architectures might yield better results in both speed and accuracy.

- Recommendation: Evaluate advanced architectures like:
    - YOLOv8 (for real-time deployment and improved precision),
    - EfficientDet (for better accuracy-efficiency tradeoff),
    - DETR (DEtection TRansformers) for end-to-end learning with fewer post-processing steps.
- Rationale: These models can better capture complex patterns and improve localization accuracy across scales.

Improve Localization Accuracy

The relatively low mAP@0.50:0.95 across all classes suggests the need to focus on precise bounding box predictions, especially under stricter Intersection-over-Union (IoU) criteria.

- Recommendation:
  - Fine-tune anchor box sizes and aspect ratios.
  - Incorporate multi-scale feature maps (e.g., Feature Pyramid Networks - FPN).
  - Apply IoU-based regression losses like GIoU or DIoU.
- Rationale: These techniques help the model learn better object boundary estimation, especially for small or irregularly shaped defects.

Implement Explainability and Uncertainty Estimation

As defect detection plays a role in high-stakes industrial applications, understanding and trusting the model's decisions is crucial.

Recommendation:

  - Use Grad-CAM or other visualization tools to interpret model predictions.
  - Integrate Bayesian neural networks or Monte Carlo Dropout to estimate prediction confidence.
- Rationale: This allows human inspectors to review uncertain cases and enhances the model's acceptability in safety-critical domains.

Real-Time and Edge Deployment Optimization

For use in factories or field environments, computational efficiency is important.

- Recommendation: Optimize the model for edge devices (e.g., using TensorRT, ONNX, or pruning/quantization techniques).
- Rationale: This enables low-latency inference for real-time defect detection with minimal hardware.

Establish a Human-in-the-Loop Feedback System

While automation is the goal, human expertise can still play a key role in improving model reliability over time**.**

- Recommendation: Develop systems that allow human inspectors to validate and correct model predictions, with those corrections being fed back into the training data.
- Rationale: This continuous learning approach ensures that the model evolves and adapts to new or rare defects.

Benchmark Against Industry Standards

To validate the model's utility in real-world use cases:

- Recommendation: Compare the model’s detection performance with standard inspection protocols (e.g., ASME, ISO standards for weld inspection).
- Rationale: Ensures regulatory compliance and provides confidence to stakeholders adopting automated inspection technologies.

Conduct Longitudinal and Cross-Domain Studies

To future-proof the model and evaluate its stability over time:

- Recommendation: Perform longitudinal evaluations across multiple production batches and cross-domain testing across different weld types, processes, or industries.
- Rationale: Confirms the model's adaptability and scalability beyond the initial training environment.

Future research should focus not only on enhancing model performance through technical improvements but also on ensuring that the system is reliable, explainable, and usable in real-world industrial settings. A multi-disciplinary approach involving data scientists, welding experts, and system engineers will be essential for translating this technology from the lab to the factory floor.

6.4 Conclusion

The evaluation of the object detection model for welding defect identification reveals promising results, indicating that it is well-suited for practical applications, particularly in detecting common defects like slag with high confidence and accuracy. The model's overall high precision (0.837) and recall (0.794) reflect its robustness in recognizing and classifying defects correctly in most instances. Furthermore, the strong mAP@0.50 (0.87) shows the model is effective in placing bounding boxes accurately under moderate overlap criteria. This suggests that the system could significantly enhance quality assurance processes in welding by automating defect detection, reducing manual inspection time, and minimizing human error.

However, the analysis also exposes key limitations, particularly in handling less frequent defect types such as cracks and incomplete penetration. These classes have fewer training examples, which likely contributes to the model's relatively lower localization performance, as reflected in mAP@0.50:0.95 (0.523). This metric, which evaluates the precision of bounding boxes under stricter conditions, shows that while the model can detect the presence of defects, it sometimes struggles to localize them precisely. In high-risk industries where even small defects can lead to serious consequences, this limitation must be addressed before the system can be fully trusted for autonomous inspection.

The class imbalance in the dataset further underscores the need for targeted data collection and augmentation strategies. Slag defects, having the highest representation, were detected most effectively, while minority classes underperformed, demonstrating the model's tendency to favor more common patterns. This imbalance not only limits the model's generalization but also raises concerns about its fairness and reliability across all defect types. For the model to be truly comprehensive and reliable, it must perform consistently across all categories, regardless of their frequency.

In conclusion, while the model exhibits strong potential for real-world deployment in defect detection tasks, its current form is best suited as a supportive tool rather than a standalone decision-maker. Future work should focus on addressing the data imbalance, improving localization accuracy, and incorporating model explainability and uncertainty estimation. With these enhancements, the model can evolve into a powerful and trustworthy solution for automated welding inspection, leading to higher production quality, reduced costs, and improved safety across a range of industries.

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