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# PYTHON-DRIVEN IMAGE PROCESSING FOR WELD DEFECT DETECTION AND QUALITY CONTROL

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**ABSTRACT:**
Welding defects pose a significant threat to both safety and structural integrity. Conventional manual inspection methods, while widely used, are time-consuming, prone to human error, and often influenced by subjective judgment, which can impact the consistency and reliability of defect detection. To address these limitations, this research proposes an automated defect detection system using the YOLOv3 deep learning algorithm. A diverse dataset of welding radiographic images in DICOM and JPEG formats was collected from public repositories and collaborative sources. The data underwent preprocessing steps, including conversion to PNG/JPEG formats using PyDICOM. The prepared dataset was utilized to further refine and optimize the pre-trained YOLOv3 model, enhancing its accuracy and performance in defect detection tasks.. Transfer learning was employed, freezing initial layers trained on ImageNet and training the final layers on our specific weld defect dataset. The model's architecture and loss function were optimized to accurately detect defects. Performance was evaluated using metrics such as the DRE (Defect Recognition Efficiency) ratio. The model demonstrated high accuracy in detecting defects such as porosity, cracks, and lack of fusion, surpassing traditional manual inspection methods. The DRE ratio, in particular, highlighted the model's effectiveness in identifying and correctly classifying defects, providing a comprehensive measure of its performance. An intuitive graphical user interface (GUI) was developed using Python's Tkinter library to enhance user interaction and improve the practical usability of the system, making it more accessible for defect detection and analysis tasks. This interface simplifies the process of uploading images, performing analysis, and visualizing results, ensuring accessibility for users with diverse levels of technical expertise.
The research significantly advances automated weld defect detection, leading to improved quality control, increased safety, and reduced costs in the welding industry. Future work may explore advanced data augmentation techniques, hyperparameter tuning, and ensemble learning to further enhance performance.
This study highlights the effectiveness of YOLOv3 in automated defect detection, providing a reliable tool for the welding industry. By leveraging deep learning, the approach minimizes human error and delivers consistent, objective results, promising safer and more reliable welding practices.
**Keywords:** Welding, Radiograph, Image processing technique, YOLOv3.

## INTRODUCTION:

Fabrication process play the major role in Process Equipment Manufacturing industry. Process industry required pressure vessel in different sized with different pressure rating. Selection of material is depend on the process fluid which going to use during the process and its reaction during process. Commonly the process equipment uses Stainless steel grade, carbon steel grade, Duplex grade and Super duplex grade material. Even though pressure equipment construction involve multiple material, one common requirement for each type of process is sound joining process. Joining Process consider permanent joint such as welding, brazing, soldering, cementing, and temporary joint such as bolting

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& riveting. In this joining process welding is one of the widely used process in industry. Welding is a widely used industrial technique for joining two or more metal workpieces, providing strong and durable connections essential for various manufacturing and construction applications [1]. further welding process divided in manual welding, Semi-automatic and automatic welding, machine welding, which is depend on degree of involvement required to complete welding process. Apart from this classification welding process classified further in Gas welding, Resistance welding, Arc welding, solid state welding which is depend on process of welding. Figure 1 list down various welding process commonly used in industry, we have limited commonly used welding process. Welding is widely used in many area, such as aerospace manufacturing, bridge engineering, and mechanical manufacturing. Due to the complexity of the welding process, the instability of the welding parameters, or the influence of welding stress and deformation in the structure, welding defect are inevitable, such as the lack of penetration, porosity, slag inclusion, and crack [2].

Welding defect are imperfection that occur in the welding joint, and their development can be attributed to various factor including incorrect welding technique, improper materials or unfavorable environmental condition. Table 1 lists various welding processes, defects, and their cause Lack of penetration occurs when the weld metal does not properly penetrate the base material., often due to sufficient heat or improper welding speed. Porosity refers to the presence of gas pocket or voids withing the weld, which can be caused by contaminated materials or improper shielding gas. Slag inclusion occurs when non-metallic inclusions are trapped in the weld metal , also as a result if improper cleaning between two weld passes or incorrect flux used during welding process. Crask, the most severe form of the welding defect, can develop during cooling due to excessive stress or a rapid rate, potentially compromising the structure integrity of the weld.

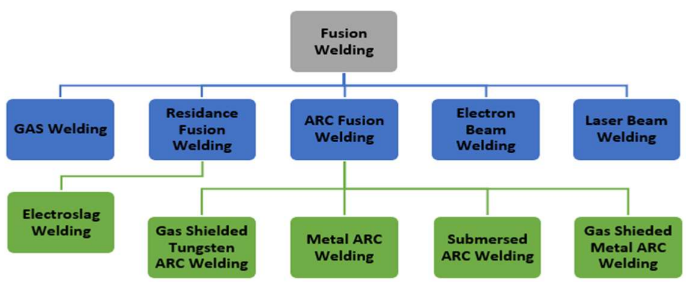


**Figure 1:** Welding Process

**Table 1: Welding Defects: An In-depth Look at Processes and Causes**

| Welding Process | Lack of Penetration | Porosity | Slag Inclusion | Cracks | Lack of Fusion | Undercut |
|---|---|---|---|---|---|---|
| Gas Metal Arc Welding (GMAW) | Insufficient heat input, improper welding speed, incorrect electrode angles | Contaminated materials, improper shielding gas, moisture in the workpiece | Improper cleaning between weld passes, incorrect flux usage | Excessive heat input, rapid cooling, high residual stress | Insufficient heat, improper arc length, incorrect torch angle | High welding speed, excessive current, improper torch angle |
| Gas Tungsten Arc Welding (GTAW) | Insufficient heat, improper arc length, | Contaminated materials, improper shielding gas, moisture in | Improper cleaning between weld passes, | Improper preheating or post-weld treatment, | Insufficient heat, improper arc length, | High welding speed, excessive current, |

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| | | | | | | |
|---|---|---|---|---|---|---|
| | incorrect torch angle | the workpiece | incorrect flux usage | high residual stress | incorrect torch angle | improper torch angle |
| Shielded Metal Arc Welding (SMAW) | Incorrect current setting, improper welding technique, insufficient heat input | Improper electrode storage, contaminated base materials, insufficient shielding gas | Improper electrode manipulation, incorrect current settings, improper cleaning between weld passes | Poor welding technique, rapid cooling, high residual stress | Insufficient heat, improper arc length, incorrect torch angle | High welding speed, excessive current, improper torch angle |
| Resistance Spot Welding (RSW) | Insufficient current, improper electrode alignment, inadequate pressure | Contaminated materials, improper shielding gas, moisture in the workpiece | Improper cleaning between weld passes, incorrect flux usage | High residual stress, improper cooling rate | Insufficient current, improper electrode alignment, inadequate pressure | High welding speed, excessive current, improper torch angle |

Traditional methods of weld defect detection include visual inspection, X-ray inspection, ultrasonic inspection, eddy current inspection, and magnetic particle inspection [1]. In recent years, radiography testing (RT) is one of the most popular technique for welding defects in non-destructive testing (NDT) [10]. Radiography technique utilize gamma rays or X-rays to examine the internal structure of material and components without causing damage to material. By placing the test specimen between the radiation source and film, variation in material density and thickness are captured as radiograph. These radiograph reveal internal defect such as crack, porosity, inclusion, lack of fusion. During the RT process, the quality of the weld image is consistently affected by several factors, including environmental conditions, the level of photographic exposure, and other influencing variables. As film producing contrast effect due to absorbed density in radiograph which is basically depend on thickness at that location and how much energy absorbed by radiograph at that location. As acceptable film required some desired density to consider as useful further for interpretation. X-ray image must have 1.8 to 4 and Gamma rays 2 to 4. To interpret this film required separate qualifications and expertise. A precise understanding of the geometry of weld defects is a fundamental step in assessing the overall quality of a weld. Accurate defect characterization is essential for ensuring structural integrity and reliability in welded components [3]. Film interpreter need to make arrangement in dark room to effectively review radiographic film and keeping one by one film on film illuminator. This process is time consuming and due to fatigue film interpreter may miss some defect.

In recent years, several advanced image processing techniques have been introduced to enhance the quality and clarity of radiographic images, improving their accuracy and interpretability [10], to avoid manual error and make radiography technique more effective. In past many tools such as METLAB, Python, Artificial Neural Network and different types of segmentation methods are used, tested and proposed by different authors. Radiography image processing improves image quality, making the analysis process more efficient by enabling the accurate identification and classification of defects in radiographic films. This enhancement plays a crucial role in ensuring precise defect detection and assessment in non-destructive testing [3]. The application of digital image processing techniques not only seeks to automate the detection and identification of weld defects but also enhances information visualization. Additionally, it plays a crucial role in standardizing radiographic analysis methods, making them more systematic, reliable, and efficient for defect evaluation [3].

**LITERATURE REVIEW :**
Many researchers have explored different techniques for detecting weld defects, aiming to improve accuracy and reliability in weld inspection [10]. Few of the methods are mentioned below with their research and limitation of each research.
***Rongdi Wang el al. [1],*** The researcher developed WeldNet, a lightweight network designed to surpass the industry-standard model in weld defect recognition while offering a significantly faster inference speed. To further enhance model performance, he introduced the ensemble distillation strategy—an innovative model training technique that improves weld defect recognition without increasing computational complexity during deployment [1]. ***Wenhui Hou el al. [2],*** The study employed information fusion technology to combine multiple features for the purpose of classifying weld defects. By integrating different types of data, this approach enhances the accuracy and robustness of the classification process. The authors utilized a Stacked Autoencoder (SAE) network, a type of deep learning model, to learn and extract meaningful features from patches of radiographic images of welds. This method allows the system to recognize intricate patterns and characteristics in the images, which are critical for accurately identifying different types of weld defects. The use of SAE networks helps improve the model's ability to generalize from the data, making it more effective in real-world applications for weld inspection [2].
***N. Nacereddine et al. [3],*** This research aims to achieve automatic defect detection in radiographic images by developing and implementing digital image processing algorithms that incorporate both global and local approaches. Digital radiography image processing techniques were utilized in this study to enhance defect identification and analysis [3**]. *Ben Gharsallah, M et al. [4],*** The researchers focused on developing an image segmentation technique for extracting weld defects in radiographic images. To achieve optimal results, they aimed to enhance the robustness of weld defect segmentation. Their approach utilized an off-center saliency map as a guiding mechanism along with a level set active contour method. Segmentation was achieved by minimizing an energy function. The effectiveness and reliability of the proposed technique were validated through extensive testing on weld radiography images containing various types of defects [4]. ***Mostafa, M. et al. [5],*** This study investigates Yb:YAG laser welding of dissimilar metals (steel 316L and copper), with an emphasis on the dynamics of the keyhole and weld pool. By utilizing a high-speed camera and MATLAB code, the research examines how laser power, welding speed, and beam shift influence the dimensions of the keyhole. The keyhole enlarges when laser power is increased from 1 to 4 kW, according to the results, and stabilizes at 5 kW because of radiation loss. Welding speeds between 0.5 to 2.5 m/min reduce keyhole position variability. Beam misalignment increases keyhole size. The study recommends using laser power ≥5 kW and speeds ≤2.5 m/min for optimal, stable welding performance [5].
***Madani, S. et al. [6],*** Image processing has broad applications across fields like medical, robotics, agriculture, and meteorology. However, its use in weld inspection remains underexplored. This study focuses on utilizing image processing to detect internal weld defects in radiography films, particularly for high-strength welding in pressure vessels and heat boilers. Traditional radiographic methods often lead to errors due to varying defect types and acceptance criteria. By optimizing images through techniques like edge detection and color enhancement, this approach aims to improve diagnostic accuracy and reduce human intervention. The study will explore MATLAB-based algorithms for fully automating defect detection in welds [6]. ***Sozonova, S.A. et al.*** *[7],* did work on automation of weld detection using Ultrasonic technique. In this technique using USD-8K-A scanner to track the position of the weld. And using ultrasonic testing machine to flow detection. In this method defect in weld joint were displayed directly on screen. However, this method's drawback is that it can be challenging

to pinpoint the precise type of current deviation in the metal structure [7]. ***Pan, H. et al. [8],*** A novel MobileNet-based transfer learning model was utilized as a feature extractor for weld defect classification. Initially, the MobileNet model was pretrained on the ImageNet database, which contained non-welding defect data, and later adapted for weld defect classification. However, two key limitations affect the effectiveness of this approach: first, the development of a welding defect database requires prior knowledge to manually select defect images, and second, the study did not incorporate weld defect detection in real-time online inspection processes [8]. ***Hassan, J. et al. [9],*** did study defect detection system using radiographic images. They introduced a method for detecting and classifying weld defects using geometric features, which includes noise reduction, defect localization, and feature extraction [9].

***Lin, Z. et al. [10],*** This study showcased the application of local image enhancement techniques to improve the detection of weld defects. By utilizing this approach, the accuracy of weld defect segmentation was significantly enhanced. The algorithm considered the necessity of contrast enhancement when extracting the weld seam and segmenting weld defects, ensuring more precise identification [10]. ***Ajmi, C. et al. [11],*** This paper employs a classification method that is based on a deep learning network. The pretrained AlexNet architecture has been utilized to classify weld defects and enhance recognition accuracy in weld inspection databases. This study aims to evaluate the effectiveness of AlexNet and other pretrained architectures, incorporating transfer learning techniques, in accurately classifying weld defects in X-ray radiographic images [11]. ***Sundaram, M. et al. [12],*** This paper explores various types of welding defects and details the process of extracting defect regions from the weld area. It further discusses the application of the C-means segmentation method for isolating these defects from the original image. However, this study focuses solely on computational image analysis and does not examine photographic images [12]. ***Nagarajan, A.P. et al. [13],*** to enhance the accuracy of weld metal image analysis, he utilized METLAB techniques, integrating fuzzy logic and edge detection methods. Additionally, he applied a filtering process known as the Gabor Filter methodology, which helped refine defect detection and improve overall image processing results [13].

*Karthikeyan, B. et al. [14],* explained five different segmentation techniques such as region growing, watershed, thresholding, split and merge, k-means clustering. This method to do segmentation of industrial image to find out various defect such as porosity, lack of fusion, slag line, incomplete penetrations and wormholes occur during welding [14].

***Velan, S.S et al. [15],*** used edge detection method on greyscale welded image and compared with quality image for ARC and MIG welding. In his study they achieved only 25% accuracy [15]. ***Haffner, O. et al. [16],*** author uses this system leverages a neural network integrated with cloud computing to enable real-time evaluation of welds. The core of the system is based on a neural network combined with a visual system specifically designed for the recognition of welds. By utilizing this approach, the system can effectively analyze and assess welds in real-time. The various algorithms used in this study are implemented within the OpenCV computer vision library, which provides powerful tools for image processing and analysis. This allows the system to efficiently detect and evaluate weld quality using advanced computational techniques [16]. ***Moinuddin, S.Q. et al. [17],*** A monitoring system was developed to detect and classify defects in the GMAW (Gas Metal Arc Welding) process. Experiments were carried out on flat-position tube-to-tube butt joints, adjusting variables like current, voltage, travel speed, and the distance between the contact tube and the workpiece. The raw data collected, including welding voltage and current readings, was used to extract statistical features [17]. ***Wang, G., et al. [18],*** In this paper, the authors introduced an advanced automated computer-aided identification system specifically designed to detect and recognize different types of welding defects present in radiographic images. To achieve this, they utilized various image processing techniques, including background subtraction and histogram thresholding. These techniques were implemented to effectively

separate the defects from the surrounding background, allowing for more accurate identification and analysis of the welding defects [18].
***Sumit, S.S., et al. [19],*** authors compared two image processing techniques such as Mask R-CNN and YoLo. In this paper with experiment they compared performance if YoLo and Mask R-CNN, and conclude that YoLo was successful in detecting most of human faces with higher accuracy [19]. ***Ahmad, t., et al. [20],*** This paper introduces a modified version of the YoloV1 neural network for object detection. The authors enhanced the original model by incorporating a spatial pyramid pooling layer and an inception module with 1x1 convolution kernels. Additionally, they made adjustments to the loss function to improve the network's performance. These changes aim to refine the network's ability to detect objects more effectively by improving its feature extraction and reducing errors during training [20]. *Kumar, J., et al. [21],* This paper presents a novel approach for classifying weld defects using Artificial Neural Network (ANN) classifiers, which assess geometric features along with texture feature extraction techniques. The radiographic images used in this study were initially captured digitally with a camera, and the images were subsequently converted to grayscale. To identify the most effective segmentation method for detecting flaws, various techniques, including edge-based, region growing, and watershed segmentation, were applied and evaluated on the images [21]. ***Ajmi, C.,et al. [22],*** Traditional weld defect detection relies on human experts, which is time-consuming and prone to errors. Machine learning has shown potential but faces challenges with low-contrast and poor-quality images. This paper proposes a deep learning approach using the AlexNet architecture and transfer learning to classify weld defects [22].
Data augmentation is employed to address limited datasets. Experimental results demonstrate superior performance compared to other deep learning models, highlighting the effectiveness of the proposed method for accurate and efficient weld defect detection. All these research methods offer both benefits and limitations. Most of these complex techniques require large datasets and extensive model training, which can be resource-intensive. Additionally, some methods may struggle to detect defects in both linear and perpendicular directions, or may necessitate specialized knowledge to interpret the outputs generated by image processing. Therefore, rather than developing increasingly complex software solutions, it is more practical to utilize easily accessible open-source tools and simple programming languages to develop models based on straightforward algorithms. This approach can provide clear visualizations and easily interpretable results, making the technology more user-friendly and accessible. To address the limitations of other image processing methods, this paper proposes a simpler approach. We utilized an available weld radiograph film dataset in DICOM format and developed a Python-based user interface (UI) that enables easy image upload, contrast adjustment, and defect identification. The system not only marks defects on the image but also provides their dimensions. In applications like gas pipelines and pressure vessel welds, the suggested system can efficiently identify flaws in digital radiography pictures of welding seams. Image processing algorithms were implemented using the OpenCV function library. The results demonstrate promising accuracy in detecting and classifying welding defects, offering valuable insights for welding process improvement. This paper aims to highlight the recent advancements in Python-based image processing for defect identification in welding radiographs and presents a simple, practical solution that can be applied in industrial settings to enhance productivity.

## IMAGE SET AND IMAGE PROCESSING FUNCTIONAL BLOCK DIAGRAM:

### Image Set:

The image datasets used for this project are in DICOM (.dcm) and JPG formats. The .dcm format is directly suitable for image processing, eliminating the need for conversion to other formats. We utilized both .dcm and JPG welding image datasets available on GitHub for this study.

**IMAGE PROCESSING FUNCTIONAL BLOCK DIAGRAM:**

Figure 2 presents the block diagram of the image processing procedure, outlining the step-by-step process for using a simple Python-based program to process images and detect defects in radiographic images.

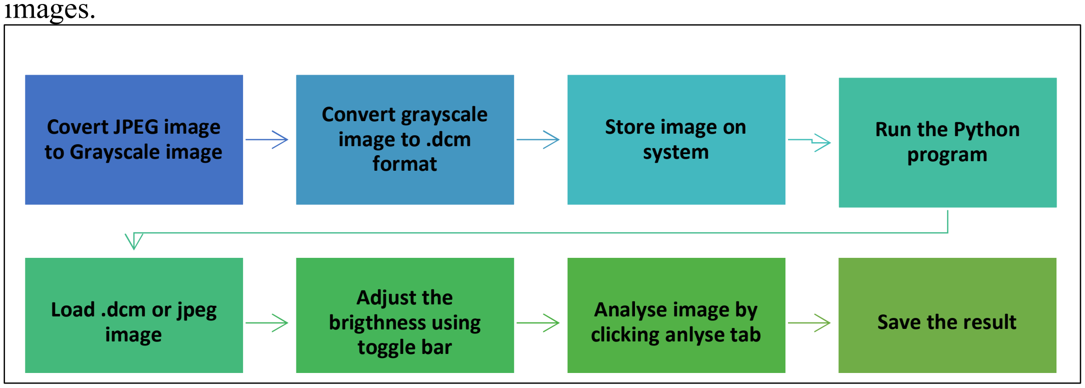


**Figure 2:** Image processing functional block diagram

**PROCEDURE:**

- **Step 1:** Complete the visual examination of welding: Before proceeding with automated testing, the initial step involves a visual inspection of the weld to identify any obvious defects or irregularities. This step typically requires a human inspector to assess the weld, ensuring that any apparent issues are detected before moving on to more advanced testing methods.
- **Step 2:** Perform the radiographic examination and generate the radiographic film using X-ray or Gamma-ray techniques, depending on the material thickness. Radiographic examination is a non-destructive testing method used to inspect the internal structure of welds with high precision. It involves utilizing X-ray or Gamma-ray methods to produce radiographic films that can reveal hidden defects within the weld, ensuring the integrity of the material without causing damage.
- **Step 3:** After generating the radiographic film, capture an image of the film using a camera and store the resulting photograph on a computer for subsequent processing.
- **Step 4:** Next, convert the JPEG image to grayscale to obtain more accurate results during image processing. Converting the image to grayscale simplifies it by reducing it to shades of gray, making it easier to detect defects and anomalies in the subsequent processing steps.
- **Step 5:** Convert the image to .dcm format, which will be readable in Python during image processing. DICOM is a standard format for medical imaging, and converting the image to .dcm ensures compatibility with Python libraries and tools commonly used for medical image analysis. If digital radiography techniques are employed, the output is already in .dcm format, which means steps 1 to 5 can be skipped.
- **Step 6:** Adjust the brightness of the .dcm image and click the "Analyze" tab :Adjusting the brightness can enhance the visibility of details within the image. Pressing the "Analyze" tab initiates the image processing software, which begins analyzing the radiographic image for potential defects.
- **Step 7:** After analysis, the image will display with defect markings. Once the analysis is complete, the software will highlight any defects or anomalies detected in the image, marking them for easy identification.

  These steps outline a process for automating the inspection of welds using radiographic examination and image processing techniques. This approach improves the accuracy and efficiency of defect detection, playing a crucial role in quality control for industries where weld integrity is critical, such as construction, aerospace, and manufacturing.

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**USED LIBRARY :**

**Yolov3_testing.cfg:** OLOv3 is a popular object detection algorithm capable of identifying and locating objects in images or videos. The **yolov3_testing.cfg** file is the configuration file used for testing the model during inference. In YOLOv3, this configuration file defines the architecture and hyperparameters of the model.The configuration file contains essential parameters that influence the model's performance during testing, including the number of defect classes to be detected, the depth of network layers, input image dimensions, anchor box settings, and other critical hyperparameters that shape the model's detection capabilities. It provides the necessary instructions on how the model should process input data and generate predictions.The **yolov3_testing.cfg** file, when used alongside the corresponding weight file, configures and runs the YOLOv3 model for object detection tasks during testing or inference.

- **Yolov3_training_last. Weights:** The weight file contains the learned parameters of the model after it has been trained on a specific dataset. These parameters, which include the values of the model's filters and biases, are essential for making accurate predictions. The weight file enables the model to apply the knowledge gained during training to detect and identify objects during testing or inference, based on the patterns it has learned from the data.
- **Tkinter:** Tkinter is a popular Python library used for creating graphical user interfaces (GUIs). It provides a set of tools and widgets that enable developers to build interactive and visually appealing desktop applications. The majority of Python installations come with Tkinter, so developers can easily access it.
- **PIL:** PIL (Python Imaging Library), now known as Pillow, is a powerful Python library for image processing and manipulation. It offers a comprehensive set of features for opening, modifying, and saving images in various formats. Pillow is widely used across multiple domains, including computer vision, web development, and scientific research, due to its versatility and ease of use.
- **Cv2:** Cv2 is a popular Python library for computer vision tasks, serving as the interface for OpenCV (Open Source Computer Vision Library) version 2. OpenCV is a versatile library extensively used for image and video processing, object detection, feature extraction, and other computer vision applications. The cv2 module provides a Python interface to access the full range of OpenCV's functions and capabilities.
- **PyDICOM:** The PyDICOM Python library simplifies the processing and analysis of DICOM (Digital Imaging and Communications in Medicine) files, a widely used format in the healthcare industry for storing and transmitting medical images along with their associated metadata. This library enables efficient handling of radiographic images, making it a valuable tool for medical imaging and non-destructive testing applications. PyDICOM provides functionalities for reading, modifying, and writing DICOM files, as well as accessing and manipulating both the metadata and pixel data of the images.
- **Glob:** The glob module in Python provides a convenient way to retrieve filenames or paths that match specific patterns, including those with wildcards, within a directory. It allows you to search for files using Unix-style pathname patterns or glob patterns.
- **Sys:** The Python **sys** module enables interaction with the Python interpreter and the underlying system environment by providing access to essential variables, functions, and system-specific parameters. This module is particularly useful for managing input/output operations, command-line arguments, and runtime configurations in various applications, including image processing and defect detection. As part of the Python standard library, it is included in every Python installation.
- **Math:** The math module in Python provides a set of mathematical functions and constants. As part of the Python standard library, it is available in every Python installation. The math module enables the execution of various mathematical operations and provides access to important mathematical constants.

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- **NumPy:** NumPy is a powerful Python library designed for efficient array manipulation and numerical computing. In addition to handling multidimensional arrays, it offers a wide range of mathematical functions, including those for linear algebra, Fourier transforms, and matrix operations, making it an essential tool for scientific computing and image processing applications.

**PLAN OF EXPERIMENT :**

The goal of this experiment is to leverage the YOLO V3 deep learning algorithm to identify weld defects in radiographic images. Known for its speed and accuracy in object detection, YOLO V3 is well-suited for this task. We aim to fine-tune its pre-trained weights to recognize a specific category labeled "Defect," which includes various welding flaws such as porosity, lack of fusion, undercuts, and inclusions. By refining the algorithm, we hope to create a reliable tool capable of accurately detecting and highlighting these defects in radiographic images, ultimately enhancing quality control in the welding industry.

**DATA ACQUISITION AND PREPARATION:**

To begin, we will compile a comprehensive dataset of welding radiographs in both DICOM and JPEG formats. The DICOM images will be sourced from platforms like GitHub or through collaborations with recognized organizations, such as welding and non-destructive testing institutes. These high-quality images are essential for developing an effective detection model.

Once acquired, the dataset will undergo preprocessing, including:

- **Conversion**: DICOM images will be converted to formats like PNG or JPEG using libraries such as PyDICOM to ensure compatibility with machine learning tools.
- **Data Augmentation**: To improve the robustness of the model and avoid overfitting, techniques like rotation, flipping, and adjustments to brightness and contrast will be applied to generate diverse training samples.
- **Annotation**: Each image will be annotated with bounding boxes around defect regions, using the Glob module to manage the image file paths and automate the annotation process. These annotations will serve as ground truth data for training the model.

Additionally, publicly available JPEG datasets of steel welding pipe radiographs, such as those found on GitHub, will supplement the DICOM images. These JPEG files will be resized for consistency and normalized to ensure smooth processing and training.

**MODEL ARCHITECTURE AND TRAINING:**

For defect detection, we will use the YOLO V3 model, which strikes a balance between speed and accuracy. By employing transfer learning, we will adapt a pre-trained YOLO V3 model to our specific task. The early layers, responsible for capturing general features, will remain unchanged, while the final layers will be fine-tuned using our defect dataset.

Training will utilize the YOLO V3 loss function, which combines:

- **Accurately locating defects:** The bounding box regression loss ensures the model predicts the correct location of defects**.**
- **Confidently identifying defects:** The objectless confidence loss helps the model distinguish between defect and non-defect regions**.**
- **Correctly classifying defects:** The classification loss ensures the model assigns the correct category to each detected defect.

**EVALUATION:**

Performance was evaluated using metrics such as the Defect Recognition Efficiency (DRE) ratio, which assesses the system's ability to accurately detect and classify defects in images. We selected 10 samples for each type of defect, including crack, porosity, lack of fusion, undercut, and slag inclusion.

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Each sample contained at least one defect of the same category. These images were uploaded to our model one by one, and the results were recorded for each radiograph. If the model correctly identified a defect, it was labeled as a True Positive (TP). However, there were instances where the model incorrectly identified a defect, which was marked as a False Positive (FP).
Additionally, some cases showed the model highlighting areas without defects, which were categorized as False Negatives (FN).
For example, Sample Figure 3 shows a digital radiograph with defects, and when uploaded into the model, the output, shown in Figure 4, was annotated with "Defect." If a defect identified in the radiograph was correctly labeled, it was considered a True Positive (TP). However, if the model highlighted an area outside the area of interest, this was marked as a False Positive (FP). This study contributes to evaluating the model's effectiveness in defect detection and provides valuable insights for future research to further enhance its accuracy, robustness, and overall performance.

## SOFTWARE AND HARDWARE REQUIREMENTS:

The experiment will be conducted using Python 3.7.7, supported by libraries such as OpenCV, NumPy, Pillow, and PyDICOM. A user-friendly GUI, built with Tkinter, will facilitate easy visualization of the defect detection results.
Hardware requirements include:

- An Intel Core i7 CPU or equivalent,
- At least 12 GB of RAM for handling large datasets.

By following this detailed plan, we aim to develop an accurate YOLO V3-based solution for detecting welding defects in radiographic images. The system will streamline quality control processes, enhancing the safety and reliability of welding practices across various industries.

## RESULT AND DISCUSSION:

A selected sample of radiographs containing defects such as lack of fusion, porosity, undercut, slag inclusion, and cracks was used, with 10 images captured for each type of defect. The model's performance was assessed by comparing its defect detection results with those identified by human observers using the same radiographic images. This evaluation aimed to determine the model's accuracy, reliability, and consistency in detecting weld defects compared to manual inspection methods. The results were quantified in terms of Defect Recognition Efficiency (DRE), which is calculated as:

$$DRE = \frac{TP}{TP + FP + FN}$$

- TP (True Positive): the quantity of flaws that the model accurately detected.
- FP (False Positive) : the quantity of non-defective regions that the model mistakenly classified as defects.
- FN (False Negative): how many flaws the model failed to detect.

**Figure 3.** Original defect sample image

**Figure 4.** Post-analysis visualization

This metric provides a comprehensive evaluation of the model's effectiveness in defect detection by balancing accurate defect identification against false positives and false negatives. When compared to manual human inspection, the Defect Recognition Efficiency (DRE) ratio highlights the model's ability to accurately classify defects while minimizing classification errors, thereby improving reliability in weld defect assessment.

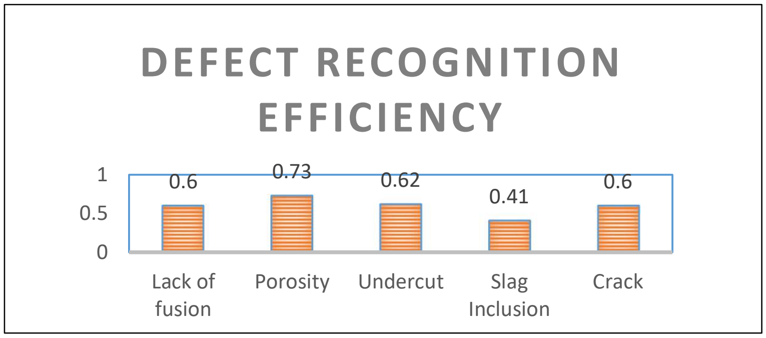


**Figure 5.** Efficiency metrics visualization

Figure 5 express the average result of 10 radiograph in the of DRE. The experimental results reveal significant variability in the Defect Recognition Efficiencies (DRE),across different defect types. Porosity demonstrated the highest DRE at 73%, indicating superior efficacy in its identification and Recognition. In contrast, lack of fusion and cracks exhibited a moderate DRE of 60%, reflecting a comparable, though less optimal, efficiency in addressing these defects. The undercut defect showed a slightly higher DRE of 62%, suggesting a marginally better removal rate. However, slag inclusion displayed the lowest DRE at 41%, highlighting the challenges associated with detecting and mitigating this particular defect. These findings suggest that while certain defects, particularly porosity, can be effectively managed, others, such as slag inclusion, present notable difficulties, necessitating further investigation to improve recognition efficiency.

## CONCLUSION :

In summary, this study shows how well the YOLOv3 deep learning algorithm works for automated weld defect detection. By leveraging a comprehensive dataset, advanced preprocessing techniques, and machine learning methods, the study presents a reliable and efficient system capable of significantly enhancing quality control processes in the welding industry. The development of a user-friendly GUI further emphasizes the practical applicability of the system, ensuring ease of adoption by practitioners and stakeholders in the field. This work marks a step forward in the adoption of AI technologies for industrial applications, promoting safer and more reliable welding practices. The accuracy of the results largely depends on the type of defect and the processing of the radiographic film. In conclusion, Python-based image processing techniques, particularly using YOLOv3, have shown promising results in the automated identification of welding defects in radiographic images. These advancements provide a more efficient and accurate alternative to manual inspection methods. Further research and development in this area can lead to improved welding quality control and enhanced industrial safety.

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