Hybrid YOLOv8 and auto-encoder based welding defect detection model for industrial inspection

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Abstract. Welding serves as an essential process that determines the strength and safety of industrial manufacturing welds. The detection of material defects through cracks and porosity and improper fusion leads to material failure during early stages of the process. Traditional inspection methods require substantial time and high costs while depending on human expertise which creates a high risk of mistakes. The research presents a hybrid deep learning approach which combines YOLOv8 for object detection with an auto-encoder based anomaly detection system. The YOLOv8 model detects known defects, while the auto-encoder identifies deviations from normal weld patterns. The hybrid system, which consists of both supervised and unsupervised learning methods, helps to enhance system reliability. The experimental results demonstrate that the model achieves an accuracy of 70% and a precision of 62% together with a 100% recall rate which guarantees detection of all defective welds. The proposed system is suitable for industrial applications where safety is a priority.

1 Introduction

Welding serves as the most common method for joining materials which manufacturers use to create complex products and machines. The weld quality determines how reliable and safe welded parts will perform in their applications. Structural weaknesses which result in mechanical failure may occur because of defects which include cracks and porosity and lack of penetration and uneven bead formation [1]. Industries like automotive manufacturing and aerospace engineering and shipbuilding and infrastructure development all require organizations to establish weld quality control systems. The industry has used manual visual inspection and advanced non-destructive testing techniques for weld inspection since its inception [2]. The methods prove effective when applied but they create multiple restrictions because they require expensive resources and skilled workers and their results depend on human performance. The process of manual inspection has two main problems because inspectors experience both fatigue and subjectivity which produces unreliable results. Non-destructive testing methods provide accurate results but their operation needs both costly equipment and specialized knowledge [3]. Researchers have investigated automated

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inspection systems which utilize artificial intelligence and machine learning technology to solve these problems [4].

Deep learning research has achieved major breakthroughs that benefit computer vision technology through current research achievements. The use of Convolutional Neural Networks (CNNs) produces outstanding results when applied to image classification and object detection challenges. YOLO (You Only Look Once) has become a common choice because it delivers accurate object detection results while operating in real-time [5].

Traditional object detection systems depend on supervised learning to function because they need labeled data for their operations. The training data establishes detection parameters for these models which results in their ability to identify known defects while they remain incapable of detecting new or infrequent defects. The solution to this problem requires using anomaly detection methods which include auto-encoders as a detection solution. Auto-encoders function as unsupervised neural networks that build normal data representations to identify anomalies through reconstruction error analysis. The combination of object detection with anomaly detection creates a strong system that can find both known and new defects. This research introduces a mixed method which combines the capabilities of YOLOv8 and an auto-encoder-based system for detecting anomalies. The detection system provides improved accuracy which guarantees operational dependability during industrial welding inspection procedures.

2 Literature Review

Scholars have studied deep learning methods for defect detection because they effectively identify industrial defects. Manufacturing organizations use object detection systems that include YOLO and Faster R-CNN and SSD to detect faults in their operational pictures [6]. The speed and efficiency of YOLO make it ideal for use in real-time systems. The latest version of the YOLO family, YOLOv8, brings enhancements that improve feature extraction and detection performance and reduce computational needs [7]. The system uses contemporary architectural designs together with modern optimization techniques to reach improved operational performance. Researchers have investigated anomaly detection techniques as additional methods for identifying defects which go beyond object detection [8]. Auto-encoders enable system training on standard data patterns while they function as detectors of unusual patterns. Industrial inspection operations have implemented two different types of auto-encoders which include convolutional auto-encoders and variational auto-encoders]9].

The existing systems which operate today continue to use two primary techniques which include supervised learning and anomaly detection. The system can only process a specific type of defect because of this limitation. The supervised models cannot detect defects which they have never encountered while the anomaly detection models do not show accurate results. The combination of both methods will create a solution that solves existing problems. The field of hybrid models for welding defect detection has not received sufficient research attention. The research gap gets solved through the introduction of a new system which merges YOLOv8 with an autoencoder [10].

3 Methodology

The proposed design includes three main components: preparation of dataset, defect detection based on YOLOv8, and anomaly detection based on autoencoder.

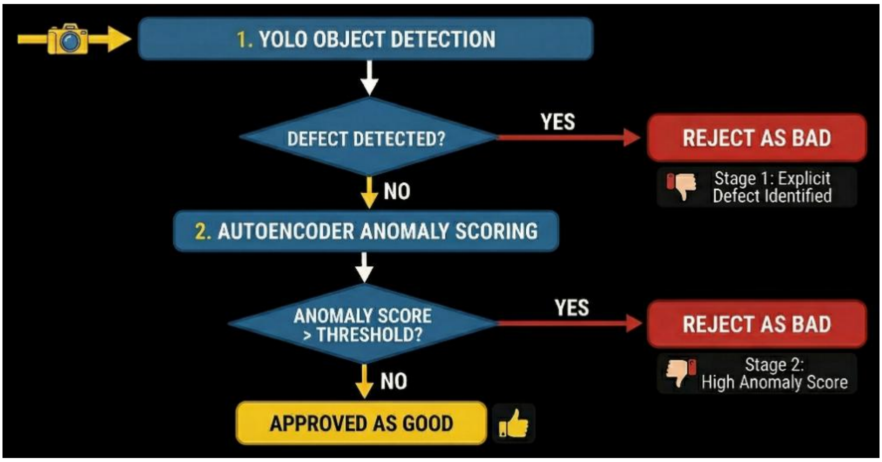

Fig. 1. Proposed Hybrid Quality Control Pipeline

3.1 Dataset Description

The dataset is obtained from Kaggle which serves as a popular resource for machine learning datasets. The dataset contains welding images which are divided into two categories that include good welds and defective welds. The images of defective welds display multiple defect types which include cracks and porosity and irregular weld bead formation. The dataset was split into three separate groups which included training and validation and testing datasets.
The YOLOv8 model trained on labeled images that contained bounding box annotations while the auto-encoder learned from normal weld images only.

3.2 YOLOv8-Based Defect Detection

The single-stage object detection model YOLOv8 achieves efficient image processing through its ability to process images in a single operation. The model consists of three main components:

1. Backbone for feature extraction
2. Neck for feature aggregation
3. Head for prediction.

The system generates defect detection results by predicting bounding box locations together with their corresponding class probabilities. The system uses a confidence threshold to eliminate unverified predictions.

3.3 Auto-encoder Based Anomaly Detection

The auto-encoder functions as a neural network which reconstructs input data. The system operates through two components which are an encoder and a decoder. The encoder compresses the input into a latent representation, while the decoder reconstructs the image. The model trains on normal weld images as its only training material. The system shows increased reconstruction error when users input defective images which serve as indicators of an anomaly.

3.4 Hybrid Model Logic

The final classification uses a hybrid approach to reach its conclusion through these steps-
Defects detected by YOLO result in a BAD classification
The system computes an anomaly score when no defects are found
Anomaly scores that exceed the threshold result in a BAD classification
All other cases receive a GOOD classification

3.5 Implementation Details

Platform: Google Colab
Framework: PyTorch
YOLOv8: Ultralytics implementation
Auto-encoder: Custom CNN

4 Results and Analysis

The model was evaluated using a test dataset consisting of good and defective weld images.

4.1 Confusion Matrix

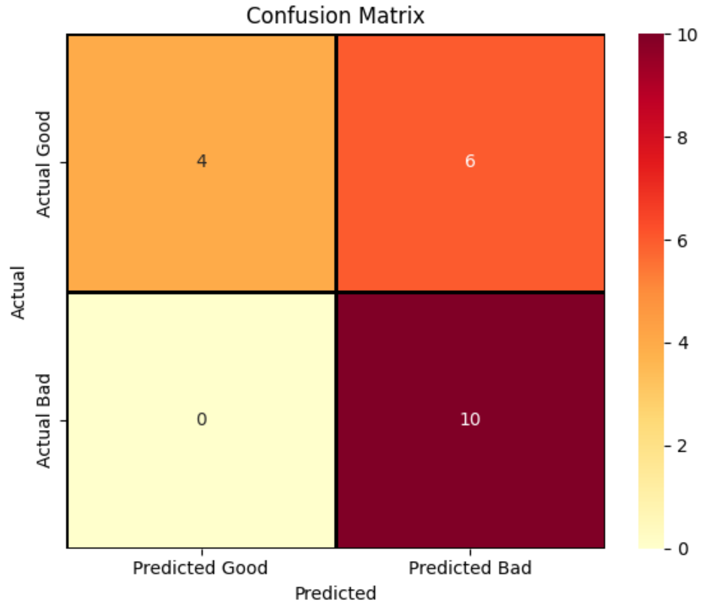

Fig.2. Confusion Matrix

Table 1. Confusion Matrix Table

	Predicted Good	Predicted Bad
Actual Good	4	6
Actual Bad	0	10

The confusion matrix shows how the classification model performs through four key elements which include True Positives and True Negatives and False Positives and False Negatives.

True Positives (TP = 10): Defective welds correctly identified as defective
True Negatives (TN = 4): Good welds correctly identified as good
False Positives (FP = 6): Good welds incorrectly classified as defective
False Negatives (FN = 0): Defective welds incorrectly classified as good

The matrix shows that the model detects all defective welds because it produces no false negative results. The industrial inspection systems require this capability because any missed defect will result in extreme safety risks. The system produces false positives which result in the incorrect identification of certain good welds as defective. The system operates with reduced precision but this design choice helps the system maintain its protective functions against defect detection mistakes.

4.2 Performance Metrics

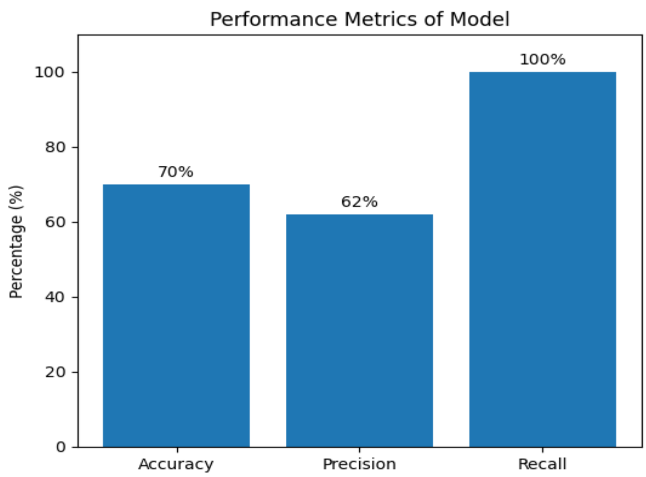

Fig. 3. Performance Matrix

Table 2. Performance Metrics Table

Sr.no.	**Metric**	**Value**
1	Accuracy	70%
2	Precision	62%
3	Recall	100%

4.2.1 Accuracy

Model accuracy shows the complete correctness of the system. The model achieved a 70% accuracy rate which shows that it successfully identified most of the weld images. The accuracy metric fails to meet the needs of defect detection problems because it does not measure the critical importance of defect identification.
Accuracy = (TP + TN) / (TP + TN + FP + FN)
= (10 + 4) / (10 + 4 + 6 + 0)
= 14 / 20 = 0.70 = 70%

4.2.2 Precision

The system measures its accuracy by determining the precise number of actual defective welds which the system has incorrectly identified as defects. The precision value of 62% indicates that some normal welds are incorrectly classified as defective. The system produces false alarms which require personnel to conduct extra inspections yet this problem does not impact operational safety.
Precision = TP / (TP + FP)
= 10 / (10 + 6)
= 10 / 16 = 0.62 = 62%

4.2.3 Recall

The model uses recall to assess its capacity to identify weld defects with good accuracy. As the model achieves 100% recall because it detects all defective welds which it needs to identify. The industrial sector considers this metric as the most important measurement because a single undetected defect can result in total structural collapse.
Recall = TP / (TP + FN)
= 10 / (10 + 0)
= 10 / 10 = 1.0 = 100%

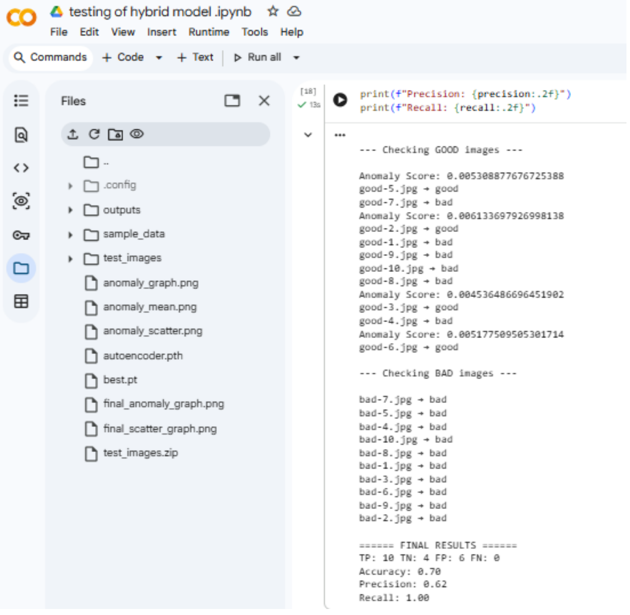

Fig. 4. Actual results

The model execution output log which contains all execution results is shown in Figure 4. The system generates predictions for good and defective weld images which it uses to compute both anomaly scores and final evaluation metrics. The output demonstrates that the proposed system functions as intended and its implementation works correctly.

4.3 Analysis

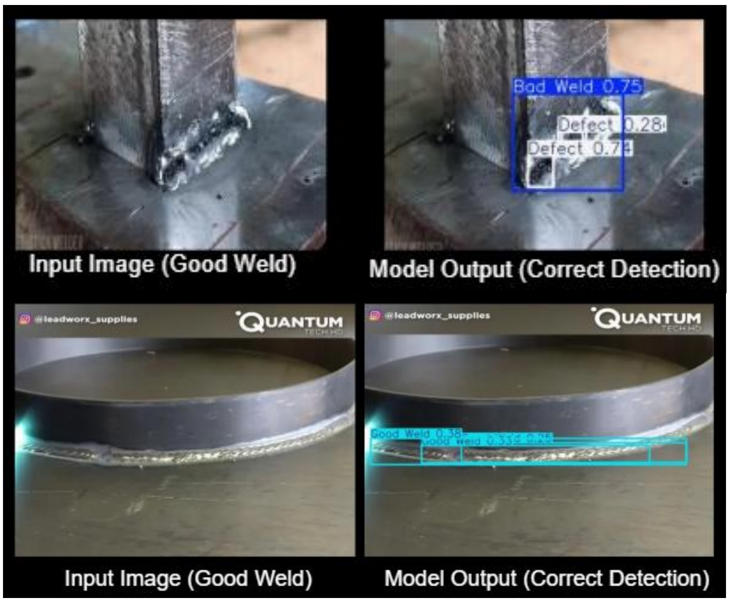

Fig. 5. Sample Images

The sample output images of the proposed model are shown in Fig. 5. The model successfully detects good welds and defective welds while using bounding boxes to show which areas contain defects. The first row demonstrates correct classification of a good weld, while the second row shows accurate detection of defects in a bad weld. The model makes false positive errors because it confuses good welds with defective ones, which occurs when two weld patterns and surface textures show strong similarities. The model demonstrates excellent detection abilities because it reliably detects welding defects.

4.3.1 Anomaly Score Analysis

The anomaly score fig-6 shows that 20 images were used for tesing of the model. The test set contained 10 good weld images and 10 bad weld images. The figure shows the reconstruction error which measures the difference between the input image and the autoencoder model's reconstructed image. The system uses the image to determine how much the image structure differs from standard welding patterns. The system uses lower anomaly scores to identify good welds which show normal weld characteristics. The system uses higher anomaly scores to show that the weld pattern shows major differences from standard patterns which indicates defective welds. The analysis shows that most good weld images produce lower anomaly scores which defective weld images show as higher scores. The model uses reconstruction error to differentiate between normal and abnormal welding conditions.

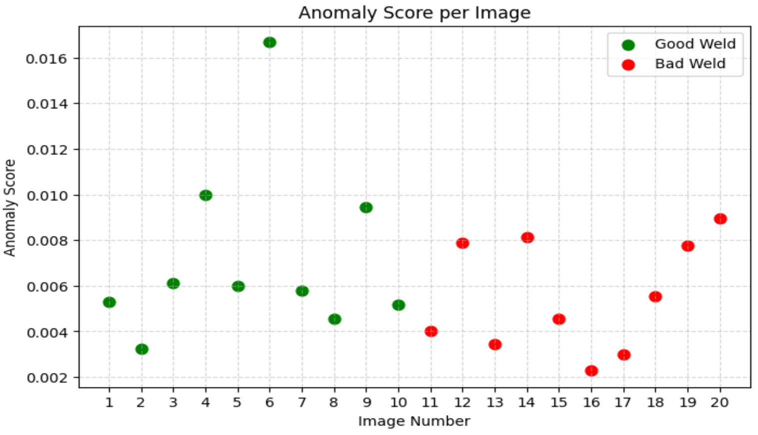

Fig. 6. Anomaly Scores

5 Discussion

The proposed system demonstrates that anomaly score–based analysis successfully separates normal weld images from defective weld images according to the test results. Anomaly scores decrease for weld images which show high similarity to learned normal patterns yet the scores increase when patterns are broken thus showing that defects exist. The analysis shows that most good weld images are concentrated in the lower anomaly score range, whereas defective weld images tend to have higher scores. A small section of the two distributions overlaps because weld texture and lighting conditions and image quality changes create similar patterns. The first data point shows that two groups have overlapping membership. The weld quality assessment maintains its accuracy through anomaly score measurements which detect nonstandard welding conditions. The approach proves especially useful for industrial inspection needs because it enables detection of any deviations from established operational standards. The results show that the proposed method assesses weld quality because it provides consistent and beneficial assessment results.

6 Future Scope

The present study investigates welding defect identification through methods that use anomaly score measurements for defect detection. The system will be expanded into a dedicated hybrid model which will handle specific welding techniques that include butt joints and T-joint welding and TIG and MIG welding methods. Researchers will establish a dedicated dataset by gathering authentic welding images which they will capture during controlled environment testing to enhance model accuracy and testing capabilities. The system will acquire additional weld information through its ability to learn detailed weld characteristics which are specific to different welding processes. The project will achieve better results through three specific enhancements which include increasing the dataset size and enhancing the model design and creating systems for real-time inspection. The advancements will create a more accurate and dependable automated welding inspection system which will function effectively in industrial settings.

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