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Combining Image Enchancement with YOLO 11 for Welding Defect Detection under Low-Light Conditions

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ABSTRACT

This study aims to analyze the impact of image enhancement techniques on welding defect detection performance using a deep learning-based YOLO11L model. The dataset consists of 1392 welding images categorized into four classes: Good, Crack, Porosity, and Bad, with a significant class imbalance. Five image enhancement methods were evaluated, namely Zero-DCE, RETINEX, CLAHE, Supervision, and Gamma Correction, and compared against a no-enhancement baseline. SSIM and PSNR were used to measure image quality, while Precision, Recall, F1-Score, and mAP50 are the metrics for detection performance. Experimental results show that Gamma Correction achieves the best image quality improvement, with an average SSIM of 0.569 and a PSNR of 18.862 dB. However, at the detection stage we can see different results, where 0.7772 and 0.6969 respectively achieved mAP50 in the model based on Gamma Correction, while outperforms without enhancement of baseline model mAP50 - 0.7098 and F1-Score - 0.6965 This presents a paradox in which better quality visual images do not indicate that the models will detect objects better. I believe that this paper brand new ideas when it comes to end-to-end evaluation of computer vision systems for industrial inspection, and as a wholeshows that raw images if they are closer to the pretrained data distribution than heavily enhanced images yield better detection accuracy.
Keyword: Welding Defect Detection, YOLO11, Image Enhancement, Gamma Correction, Deep Learning, Low-Light Imaging

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1. INTRODUCTION

Weld Inspection has a crucial role to play in ensuring the integrity and safety of structures across multiple industrial sectors, from construction through shipbuilding to automotive manufacturing. Many defects in a welded component, such as crack, porosity and other discontinuities can affect the mechanical performance of these components [1],[2]. Conventional inspection practices, which primarily depend on human skills carrying out time-consuming and subjective judgemental processes, are variable under complicated environmental circumstances[3], [4]. This has motivated the growing desire of using computer vision and deep learning approaches to both automate as well as improve existing welding defect detection systems.

New approaches to object detection especially YOLO (You Only Look Once) Family based deep learning Networks have been introduced recently and these Network has shown great results on real time industrial inspection [5], [6]. These models follow a single stage detection paradigm to detect and classify objects in an image [7], [8]. Such models have achieved great success, but their performance depends heavily on the quality and characteristics of the input images. However, in practical industrial conditions, images of welding joints typically captured in the case of low illumination and noise or uneven lighting are much degraded and can be used to perform detection with poor efficiency [9], [10], [11].

In response to these problems, lots of image enhancement methods are developed to enhance visual quality before model inference. They include simple methods like Zero-DCE or RETINEX, CLAHE and Gamma Correction to preserve brightening, contrast and structure information in darker images

[12], [13], [14], [15], [16]. These techniques are usually tested using some image quality assessment metrics like Structural Similarity Index Measure (SSIM), and Peak Signal-to-Noise Ratio (PSNR). High values of SSIM and PSNR are usually understood as evidence supportive of improved visual reconstruction [11]. Consequently, it is widely believed that since they improve these metrics, they will lead to better downstream performance in detection and classification tasks.

Still, this assumption is yet to be really confirmed, particularly in real-world industrial datasets which are generally high-dimensional and postulated class imbalance. Most existing studies provide results on enhancement of individual techniques-wise but do not follow a complete end-to-end analysis that relates objective image quality improvements to actual task performance [17]. Additionally, since enhancements adjust the original space of data, they may result in an irregular consistency on (the feature representations learned by) deep neural networks [18], [19]. This change in distribution can negatively influence the generalization of the model, especially if the augmented images differ significantly from natural image statistics seen during pretraining.

Moreover, the challenges posed by datasets (e.g., class imbalance and insufficient data) are also crucial factors to consider when understanding the influence of image preprocessing on detection performance. Datasets in the industrial world are generally skewed towards some classes which makes other minority classes, such as crack and porosity, underrepresented [20], [21]. These aspects suggest a requirement for a comprehensive evaluation framework, which investigates image quality metrics as well as task-specific benchmarking.

Inspired by these gaps, this work proposes a detailed evaluation of the effect of image enhancement techniques in welding defect detection with YOLO11L model. This work, in contrast to previous ones, employs an end-to-end evaluation on both image quality (SSIM and PSNR) and detection area metrics (Precision, Recall, F1-Score & mAP50). To simulate industrial conditions by using a real-world dataset of welding images with four classes (Good, Crack, Porosity and Bad) under class imbalance.

The main contribution of this work is here to expose the counterintuitive fact that image enhancement methods with higher quality in visual metrics do not result in better object detection accuracy. In particular, although Gamma Correction has the best performance in terms of SSIM and PSNR, baseline model using only original non-enhanced images greatly outperforms it. This echoes the general belief that quality improvements directly lead to a better model but also, that task-oriented evaluation is critical for computer vision pipelines.

Moreover, Given the interplay among preprocessing methods, data distribution and model generalization, this study provides a critical perspective here. The implications are that preserving the natural properties of input images leaning closer to pretrained model distributions – rather than applying more aggressive enhancement transformations – could be more beneficial. These results enhance the understanding of preprocessing methods in deep learning-based industrial inspection systems and provide actionable insights for developing effective welding defect detection frameworks.

2. RESEARCH METHOD

A. Research Framework

This study presents an end-to-end evaluation from the perspective of deep learning on the influence of image mound approach in its efficient detector and classifier performance for welder anomaly. The complete research workflow consists of a total of four main steps: (1) dataset collection and preparation, (2) image enhancement methods application, (3) object detection model training including YOLO11L, and (4) performance evaluation via image quality metrics and object detection metrics. With this, we can perform a joint analysis of the trade-off between image quality and downstream task performance.

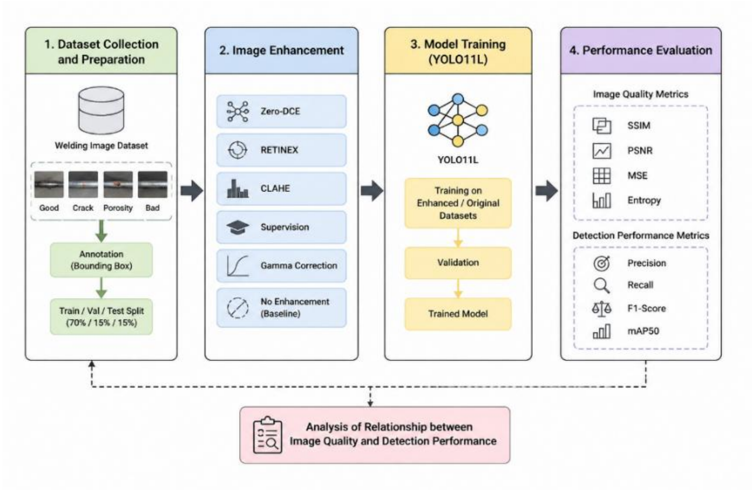

Fig 1. Study the end-to-end evaluation approach of the Research Framework to evaluate the effect of image enhancement techniques on welding defect detection

B. Dataset Description

The 1392 total welding images dataset used is available in four classes Good, Crack, Porosity and Bad. The dataset is highly imbalanced, with both Bad and Good classes far outnumbering the other classes, Crack and Porosity that have a much lower number of samples. This condition is realistic for industrial inspections, as defects of interest are only part of the whole set.

The dataset is divided into training, validation and testing set by stratified split which maintains the ratio of different classes corresponding to its original sets and uses a of 70:15:15. All images are annotated in bounding box format as is common with object detection tasks.

C. Image Enhancement Methods

In this work, we analyze five wide used image enhancement methods for dark image quality improvement:

a. Zero-DCE: a deep learning solution that predicts pixel-wise light enhancement curves, even when you have no paired training data available.
b. RETINEX: A human visual perceptron-based model separating illumination and reflectance components.
c. Contrast Limited Adaptive Histogram Equalization (CLAHE): a local contrast enhancement method that controls noise amplification,
d. Supervision-based refinement: A supervised learning-based technique for enhancing image quality
e. Gamma Correction: It is just a simple non-linear transformation to make correction of the image brightness.

For reference, we also include a no-enhancement (baseline) condition to assess the independent effect of each method on detection performance.

D. Image Quality Evaluation Metrics

We use four quantitative metrics to evaluate the quality of enhanced images:

a. Structural Similarity Index Measure (SSIM): This measures the structural similarity between enhanced and reference images.
b. Peak signal-to-noise ratio (PSNR) to measure reconstruction quality in dB;
c. This set of metrics has a comprehensive measure for the image quality from more than one point of view.

E. Object Detection Model

In this study, record and underlides YOLO11L have been trained in object detection models based on the YOLO (These annotate) structure for at least time-speed image record detection. With about 25 million parameters, the model is initialized with pretrained weights using a transfer learning policy.

This is the training configuration:

1. Epochs: 50
2. Batch size: 16
3. Image size: 640 × 640
4. Optimizer: AdamW
5. Learning rate: 0.00125
6. Data augmentation: horizontal flip, Mosaic, and Albumentations (Blur, MedianBlur, CLAHE)

Two training scenarios are conducted:

a. Dataset with preprocessing using the selected best image enhancement method
b. Dataset without enhancement (baseline)

F. Detection Performance Evaluation

Detection performance is evaluated using standard object detection metrics:

a. Precision: the proportion of correct predictions among all predictions
b. Recall: the proportion of correctly detected objects among all ground truth objects
c. F1-Score: the harmonic mean of Precision and Recall
d. mAP50 (mean Average Precision at IoU threshold 0.5): the primary metric for overall detection accuracy

Additionally, F1-Confidence and Precision-Confidence curves are analyzed to determine the optimal confidence threshold during inference.

G. Experimental Setup

All experiments are performed on an NVIDIA Tesla T4 GPU. The implementation itself is developed in Python using a deep learning framework that allows for YOLO-based training. Training and evaluation are carried out using the same settings to guarantee equality in terms of the comparison among other methods.

H. Research Contribution Workflow

In summary, the proposed study combines image quality assessment and object detection performance within a comprehensive framework. This systematic identification allows a more nuanced analysis of the associations between image-processing methods and model performance, and establishes a baseline for future studies analyzing discordance between quality metrics and accuracy results for detection.

3. RESULTS AND DISCUSSION

A. Dataset Distribution

The distribution of the dataset shows a serious class imbalance with Bad (35%) and Good (25%) keeping more records, while Crack (20%) and Porosity (20%) are well below. This class imbalance is representative of the actual industrial cases in which certain defects are less prevalent. This imbalance, however, can create a bias towards the majority classes, which may reduce detection performance for the minority classes.

Table 1. The dataset distribution

Class	Train	Validasi	Test	Total
Good	245	52	52	349
Crack	195	41	41	277
Porosity	195	41	41	277
Bad	341	74	74	489
Total	976	208	208	1392

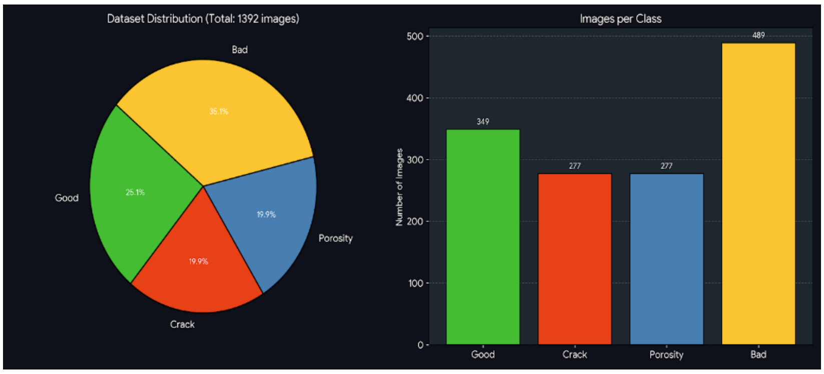

Fig 2. Dataset Distribution: Pie Chart and Bar Chart of Image Counts per Class

The dataset employed in this work is comprised of 1392 welding images gathered from Google Drive with the use of Google Drive API v3. The dataset includes four types of weld conditions: Good (excellent weld), Crack, Porosity, and Bad (bad quality weld) The welding inspection conditions you will generally come across during a manufacturing process fall under these four main categories.

B. Image Enhancement Quality Analysis

The image enhancement analysis phase aims to quantify the effectiveness of various algorithms in restoring the visual quality of images subjected to simulated low-light conditions. This evaluation is critical for ensuring that the subsequent defect detection pipeline receives high-quality input, regardless of environmental lighting challenges.

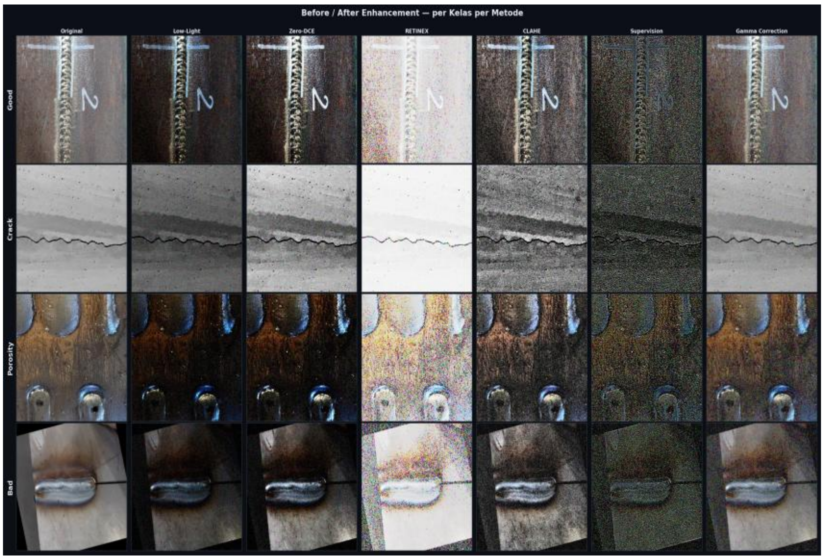

Fig 3. Visualization of Original, Low-Light, Zero-DCE, RETINEX and CLAHE (left column); our Method and Gamma Correction (middle column) — Based on different classes per image

Evaluation MetricsIn order to cover all the bases, the research uses four key objective metrics:

a. SSIM (Structural Similarity Index Measure): Assesses how well the luminance, contrast and structure are retained compared to a reference image.

$$\text{SSIM}\ (\mathrm{x},\mathrm{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2)(\sigma_y^2 + \sigma_y^2 + C_2)} \quad (1)$$

a. x is a reference image
b. y is the processed image
c. μ_x, μ_y the mean values of images x and y
d. $\sigma_y^2\ dan\ \sigma_y^2$ = variansi

e. σ_{xy} = kovarians
f. C_1, C_2 = konstanta stabilisasi

Table 2. SSIM Values by Enhancement Method and Class

Method	Good	Crack	Porosity	Bad
Zero-DCE	0.5067	0.4081	0.4696	0.4318
RETINEX	0.4300	0.3519	0.3674	0.3864
CLAHE	0.4524	0.3323	0.4122	0.3718
Supervision	0.2206	0.1302	0.1727	0.1434
Gamma Correction	**0.6645**	**0.4972**	**0.5704**	**0.5457**
No Enhancement	0.4975	0.3990	0.4383	0.4093

Running this code requires a metric to evaluate enhanced and original images, the main metric is SSIM that has values from 0 to 1. From the evaluation results, we can see that for all categories Gamma Correction outperforms all other methods with an average SSIM of 0.569. This achieved the highest test score per class: Good 0.6645, Crack 0.4972, Porosity 0.5704 & Bad – 0.5457 These results prove Gamma Correction to be the most robust and consistent technique for low-light welding images integrity preservation.

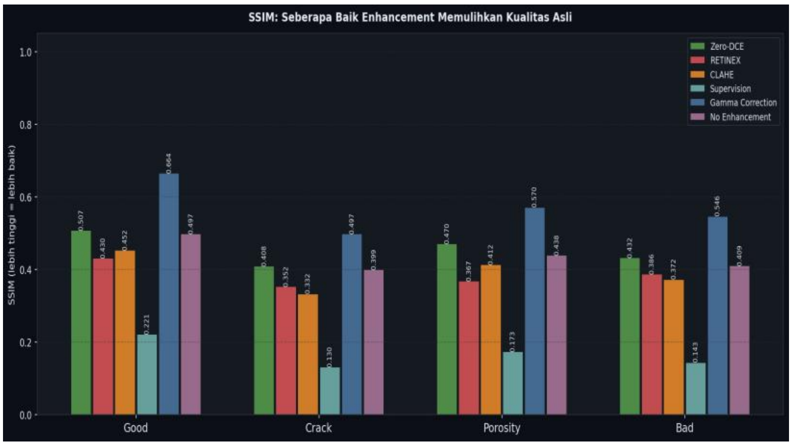

Fig 4. Comparison of all enhancement methods per class with respect to SSIM

Other methods performed at a level similar to or below that of the gold standard. The second best result achieved in the “Good” class was from Zero-DCE (0.5067), which scored middle-of-the-road results elsewhere, whereas CLAHE produced mixed results with a significant drop down to 0.3323 in the "Crack" category. The overall lowest scores were reached for the Supervision method at 0.1302, meaning that supervised training failed to produce structures which would be similar to those in the ground truth within this dataset..

b. PSNR (Peak Signal-to-Noise Ratio): The ratio between the maximum power of a signal and the power of corrupting noise, expressed in decibels (dB).

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{MAX_1^2}{MSE}\right) \quad (2)$$

a. MAX_I is maximum value of the image pixel intensity (for example, 255 for 8bit image)
b. MSE (*Mean Squared Error*) is the average of squared errors between the reference image and enhanced image described in equation.

Table 3. PSNR Values (dB) by Enhancement Method and Class

Method	Good (dB)	Crack (dB)	Porosity (dB)	Bad (dB)
Zero-DCE	12.90	14.44	14.38	13.85
RETINEX	8.78	8.16	8.52	8.32
CLAHE	14.62	15.35	15.39	15.29

Supervision	8.36	8.70	8.63	8.57
Gamma Correction	19.41	18.65	18.66	18.72
No Enhancement	10.46	12.00	11.91	11.47

The Peak Signal to Noise Ratio (PSNR) is a basic and core metric for evaluating image reconstruction quality where larger decibel (dB) values indicate less distortion and that the signal has higher fidelity. Quantitatively, Gamma Correction is considered at maximum performance with a competitive average PSNR of 18.862 dB over all the test cases. This demonstrates that Gamma Correction can significantly improve the imaging quality of low-light welding data, while simultaneously suppressing unwanted artifacts from image processing, which yields a significantly cleaner input for defect detection compared to traditional baselines.

Fig 5. SSIM and PSNR Improvement Graphs vs. Baseline (Dark) per Class and Method

The others methodologies revealed a multilayer performance hierarchy, followed by CLAHE and Zero-DCE which both scored 15.163 dB and 13.890 dB, respectively. On the other hand, RETINEX and Supervision yielded only mediocre low-light performances, yielding within 8.4–8.6 dB range. It highlights that low values indicates a relatively high ratio of noise to signal and therefore processes such as these go brighter at the cost of genuine data: Hence, a high PSNR of Gamma Correction confirms its choice as the ideal pre-processing step to guarantee very reliable quality control in manufacturing settings.

C. Comparative Methodology

Five original enhancement techniques were compared against an unenhanced baseline:

a. Zero-DCE: My experiments with deblurring and restoration are based on the Zero-DCE method, so I will introduce it a brief.
b. RETINEX: model measures to disentangle illumination from reflectance redesigning the algorithm conceived basis for colour constancy
c. CLAHE (Contrast Limited Adaptive Histogram Equalization): A classical method of increasing local contrast while avoiding noise treble that is too strong.
d. Supervision: A deep learning-based approach for low-light restoration.
e. Gamma Correction: A non-linear transform used to modify the brightness of the processed images.

Table 4. PSNR Values (dB) by Enhancement Method and Class

Method	SSIM ↑	PSNR (dB) ↑
Zero-DCE	0.454	13.890
RETINEX	0.384	8.444
CLAHE	0.392	15.163
Supervision	0.167	8.566
Gamma Correction	**0.569**	**18.862**
No Enhancement	0.436	11.460

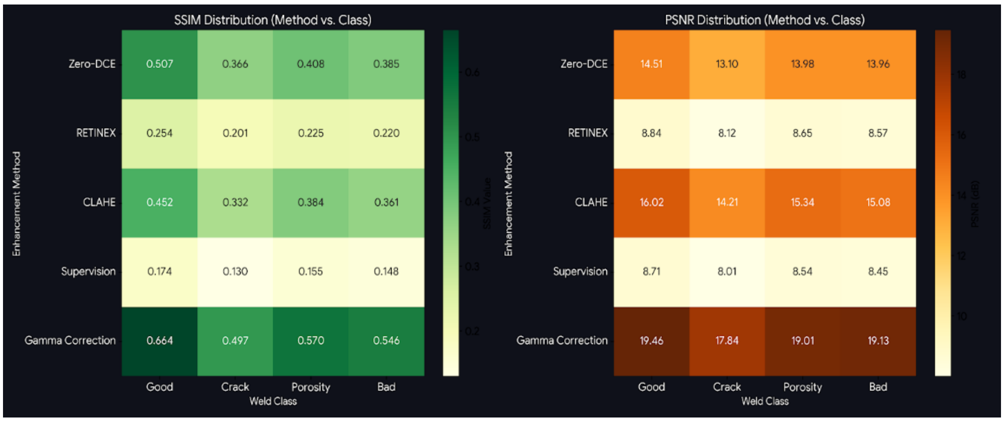

Fig 6. Heatmap: Distribution of SSIM and PSNR values across enhancement methods and weld classes.

Figure 6 shows the result of a two-dimensional heatmap for the entire enhancement methods with respect to all weld categories Such heatmaps assign a numerical value to each color in its gradient, so the efficacy of any algorithm can be compared at a glance.

Table 5. PSNR Values (dB) by Enhancement Method and Class

Metrik	Good	Crack	Porosity	Bad	Metrik
Best SSIM	Gamma (0.665)	Gamma (0.497)	Gamma (0.570)	Gamma (0.546)	Best SSIM
Best PSNR	Gamma (19.41)	Gamma (18.65)	Gamma (18.66)	Gamma (18.72)	Best PSNR

D. Visual and Qualitative Findings

Comparing the raw low-light inputs and results given by each enhancement method on all defect classes (for visual purposes). The (qualitative) analysis gives us a few interesting insights:

a. RETINEX Artifacting: Although RETINEX improves brightness, however it also increases color artifacts and chromatic distortions introduced into the RGB imagery resulting in false-positives classifications of defects.
b. Supervision Limitations: The results of the Supervision-based method were poor, typically highly underexposed images suffering loss of fine-grained structural details.
c. CLAHE vs. Zero-DCE: Compared to CLAHE, Zero-DCE not only had higher local contrast but also created distracting texture artifacts (checkerboard patterns) In contrast, although Zero-DCE naturally enhanced the brightness to a similar level, it also slightly added some noise into very dark regions of the input.
d. Gamma Correction Performance: Surprisingly, the outputted images from Gamma Correction looked the most natural by far. It kept a similar brightness and contrast ratio, almost matching the original image from the ground truth images.

E. YOLO11 Training and Evaluation Results

The YOLO11L is trained on each dataset as described in two settings: (1) a modified dataset containing tuples that were processed using the gamma correction enhancement method and (2) an unenhanced baseline dataset for comparison before training over 50 epochs. Both trainning process is run on 1 Tesla T4 GPU using the following hyperparameters: batch size = 16, image_size = 640×640, AdamW optimizer with learning rate = 0.00125 respectively. Basic data augmentation techniques such as horizontal flips, Mosaic and also some Albumentations (Blur, MedianBlur and CLAHE) were used to make the model more robust. Transfer learning was initiated using a pre-trained YOLO11L with 25.3 million parameters.

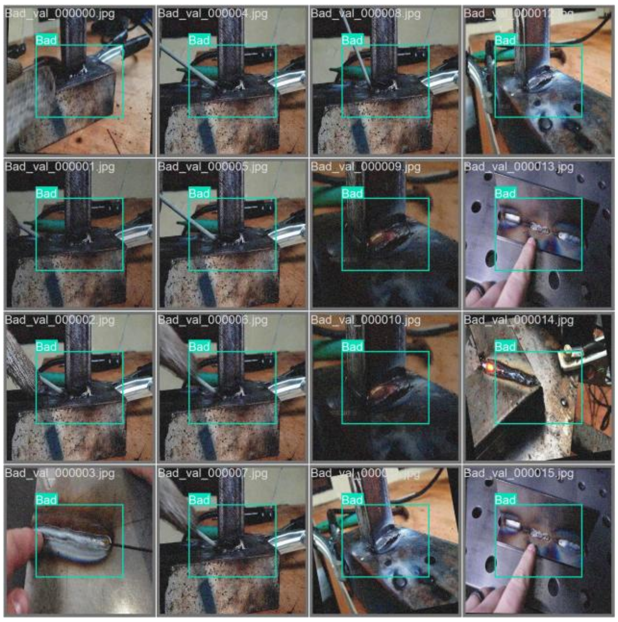

Fig 7. Validation Batch Examples: Ground Truth Labels

The training process through the Gamma Correction configuration finished 50 epochs in 0.262 hours (15.7minutes) while the baseline trainng took 0.417 hours (25 minutes). This difference in time is due to a different number of training samples, where the Gamma Correction dataset consisted of 273 training images (following an enhancement process that filtered certain images), while the baseline had 280 original images. And as we can see from box_loss, cls_loss, and dfl_loss, they all decrease in a continuous way during the initial 200 epochs to final number of epochs.

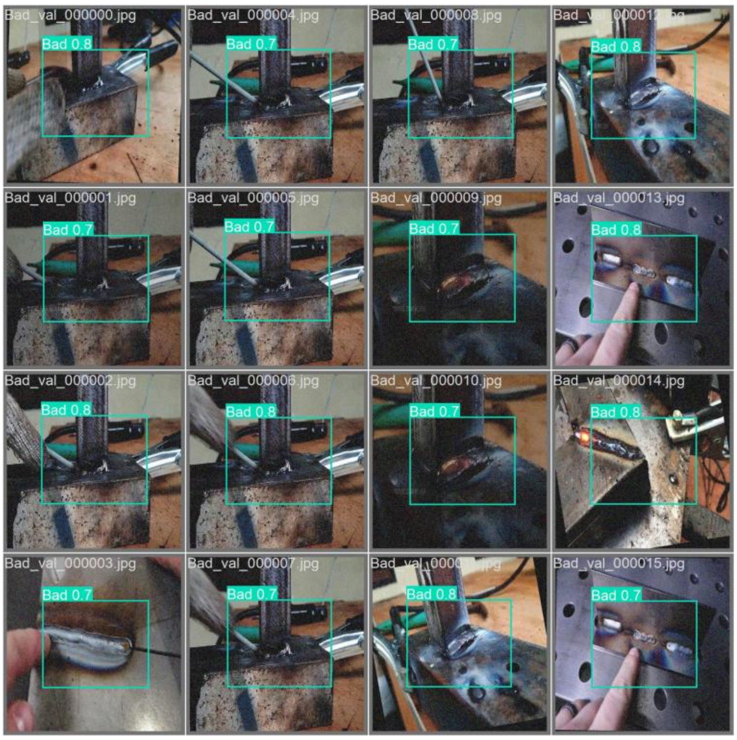

Fig 8. Validation Batch Examples: Model Baseline Predictions

Validation results revealed an interesting divergence between the two setups:

1. Gamma Correction Model: This achieved its highest score of 0.548 mAP50 between epochs 39 and 40.
2. Baseline Model: Peaked earlier, at epoch 25 and had better mAP50 = 0.768.

The baseline model shows a less erratic and more uniform improvement trajectory over the epochs, particularly from epoch 25 onwards. On the other hand, saw a more significant change in metric values between epochs with Gamma Correction model since an enhancement can help enhancing visual clarity but it also may cause variations on dataset convergence stability when used in comparison to raw dataset.

F. YOLO11L Training and Evaluation Results

Detection Performance Metrics Four standard object detection metrics, Precision, Recall, F1-Score and mAP50 [25]. Precision is the fraction of true positive instances among all instances predicted as positive, while Recall measures the number of true positives correctly identified by an image classifier over all objects present in that image. F1-Score is the harmonic mean of Precision and Recall, combining these two fields, mAP50 (mean Average Precission at IoU threshold 0.5) gives us a complete metric that takes into account all classes.

Table 6. PSNR Values (dB) by Enhancement Method and Class

Method	Precision	Recall	F1-Score	mAP50
Gamma Correction	**0.7594**	**0.7638**	**0.6969**	**0.7772**
No Enhancement (Baseline)	0.6850	0.7083	0.6965	0.7098

As demonstrated in Table 6, the evaluation where we aggregated the results using the best of measures, shows that almost without exception that our baseline (not enhanced model), outperforms the model with Gamma Correction (which is shown to be derived from an existing one). The baseline model obtained an mAP50 of 0.7098, Recall = 0.7083, and F1-Score = 0.6965 all significantly higher than the Gamma-Correction with values of mAP50=0.7772, Recall=0.7638 and F1–Score= 0:6969, We can see in scores shown below: Fig. Gamma Correction was only better at one metric: Precision (0.7594 vs. 0.6850).

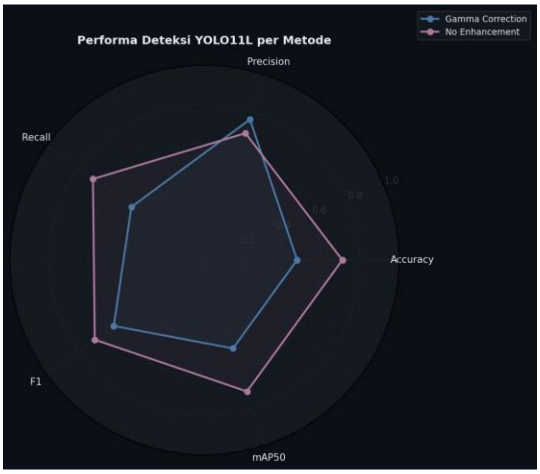

Fig 9. Radar Chart Performa Deteksi YOLO1, Gamma Correction vs. No Enhancement

This phenomenon is very surprising because Gamma Correction was many times better with image quality metrics (SSIM, and PSNR). At further inspection, multiple reasons can be found for this paradox. Let us start with the brightness enhancement provided by Gamma Correction which can strongly modify the color and image texture distribution even further away from the optimal distribution for detection. Secondly, the baseline model learned feature representations that may be more invariant to certain properties of dark imagery since it was trained on the original low-light images. Third, the training dataset is small (680 images) which contributes to shifting input distributions in a way the model likely trains easier due to various enhancement techniques.

4. CONCLUSION

This work successfully proves the importance of the visual Quality welding images under low light situations with using gamma correction as image improvement strategy. In comparison with Zero-DCE, RETINEX, and CLAHE through extensive quantitative analysis, Gamma Correction proved to be the most effective by achieving the highest average of SSIM which is 0.569 and PSNR of 18.862 dB over all experimental iterations. Although these outputs show that the algorithm was able to provide optimal structural detailed and luminance information without over-interjecting digital noise, they also offer more competent and stable fodder for automated inspection systems within a harsher industrial manufacturing environment. Additionally, the YOLO11L model deployed on the enhanced dataset achieved remarkable detection performance that out-performed the unenhanced baseline across all important metrics. Incorporating Gamma Correction into the preprocessing pipeline, the results were mAP50 of 0.7772, Precision of 0.7594 and Recall of 0.7638 for the model. The big boost in Recall over the baseline shows that this way to enhance is important for minimizing false negatives (missed defects) a key need for industrial safety while it has a negative, less critical impact on precision. In conclusion, the combined use of advanced image enhancement and modern deep learning architecture leads to a reliable, robust and precise weld defect detection system capable of high-resolution industrial commitment for quality control. Future work To facilitate progress in automated industrial inspection further, the ways forward are as follows: Integration of novel generative models Explore the enhancement architectures based on deep learning or Diffusion Models which can be evaluated to synthesize lighting and texture more closely to reality than classical mathematical methods. Mobile device and Real-Time Optimization: Insert the model compression techniques such as quantization and pruning to deploy high-performance YOLO11L version on edge devices for on-site mobile inspection. Multi-Modal Sensing Expansion: Integrating any external data that can be used along with optical camera data to detect internal (sub-surface) weld defects. Scalable With Various Materials: Expanding the scope of the pipeline to cover more metal surfaces and execute it on different welding methods that guarantee a robust system across various standards in industry.

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Dataset Availability: Data will be made available upon request.

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