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IAES International Journal of Artificial Intelligence (IJ-AI)

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IAES International Journal of Artificial Intelligence (IJ-AI)
ISSN/e-ISSN 2089-4872/2252-8938
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p-ISSN 2089-4872, e-ISSN 2252-8938
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This journal is published by the Institute of Advanced Engineering and Science (IAES).

IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 1, February 2026, pp. 852~860
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i1.pp852-860

Efficient YOLO-based models for real-time ceramic crack detection

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Article Info

Article history:

Received Apr 11, 2025
Revised Dec 29, 2025
Accepted Jan 22, 2026

Keywords:

Ceramic crack detection
Low-memory devices
Object detection
Real-time processing
You only look once

ABSTRACT

The following research work systematically compares four variants of you only look once (YOLO), namely, YOLOv8, YOLOv9, YOLOv10, and YOLOv11 proposed recently, considering the key properties required to perform ceramic surface crack detection tasks with high computational efficiency, real-time inference speed, and low memory usage. A total of 300 images of ceramic surfaces were collected with manually labeled cracks and divided into training, validation, and testing sets in portions of 263, 22, and 15 images, respectively. Each of the four YOLO variants was trained for 50 and 100 epochs, and each was evaluated regarding mean average precision (mAP), inference time, model size, and computational complexity in giga floating point operations per second (GFLOPs). YOLOv9 produced the highest accuracy with mAP values as high as 0.752-0.79 but the highest cost in terms of increased computational complexity. However, among these methods, YOLOv8 can produce the fastest inference (~2-2.3 ms) with a small memory footprint (~6 MB) with an acceptable accuracy of ~0.65-0.67. The results showed that YOLOv8 is the most feasible to deploy in resource-constrained industrial automation environments. By offering this comparative study, the research attempts to provide hints for the selection of appropriate YOLO-based models by practitioners in quality control applications related to ceramic manufacturing.

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1. INTRODUCTION

Ceramic materials are widely utilized, including applications involving electronics to aerospace, owing to their resistance to high temperatures, stability, and strength [1]. Despite the mentioned merits, ceramic materials tend to experience micro-cracking that causes catastrophic failure [2]. It is essential to detect the micro-cracks immediately to ensure that the products are safe and function effectively [3]. A conventional technique to inspect micro-cracking might typically involve human observation and the use of conventional image processing, which tends to be time-consuming and requires precise illumination conditions [4].

However, the emergence of deep learning methods has brought a revolutionary approach to automated defect detection, and convolutional neural networks (CNNs) have proved remarkably successful in image classification and object detection problems [5]–[7]. One of the most popular techniques in the domain of object detection is the you only look once (YOLO) family of algorithms [8]. YOLO is a single-end network used for both the classification and localization of objects; its subsequent versions have adapted a compromise between the accuracy of defect detection and real-time processing, making it an ideal approach for automation in the industry [9], [10].

Recently, improvements in the YOLO method, ranging from YOLOv8 to YOLOv11, have led to highly optimized designs that deliver high values for the average precision metric [11]–[14]. However, these designs can be computation-intensive, which can pose challenges for their use on resource-limited platforms like those on an industry floor [15]. In an industrial inspection system, apart from the accuracy level, low latency rates and memory usage are important for the system to function in an online process [16], [17].

There has been an increasing amount of studies concentrating on the application of deep learning techniques for the detection of ceramic defects. For instance, Yu *et al.* [18] presented an advanced YOLOv5 system for automatic surface defect detection in ceramic tiles through the optimization of the model components and the application of the attention mechanism, leading to higher detection accuracy and faster computing speed. Another example, Alexandru *et al.* [19] presented an innovative method for the detection of ceramic plate defects utilizing YOLO-R, dealing with the difficulties in the presence of different types of ceramic defects and obtaining competitive detection speed. Relatively more recently, there have been studies utilizing the more advanced YOLO models for further improved performance in the detection of ceramic defects. For example, Zhu and Song [20] presented an advanced YOLOv8 model specifically for the detection of small ceramic surface defects utilizing supplementary detection heads and a selective attention module. At the same time, Huang *et al.* [21] utilized deep learning techniques for the establishment of defect detection systems for ceramic substrates based on YOLOv3 models and obtained considerable improvements in both detection accuracy and computing speed.

Other research efforts have been devoted to further crafting the detection of defects in ceramics using mobile-friendly vision transformers, superior feature fusion models, and custom loss functions. These include, for example, MCAW-YOLO [22] which integrated a vision transformer into its backbone architecture for global and local context understanding, and another [23] that further boosted the performance of YOLOv5s via anchor structure optimization and the application of the attention mechanism. Other research efforts in [24], [25] have been directed at crafting dense detection algorithms and unique convolutional models for tackling multi-scale and small-target defect detection. The body of research work already presented has primarily targeted the improvement of the detection performance using superior architectural refinement, including improved feature fusion, attention mechanisms, and complex loss functions. While these have already demonstrated success in defect detection, there remain challenges with models characterized by higher computing complexity, larger models, and longer inference times, which remain a concern for industry implementation.

The originality of this current research work is in carrying out a comparative analysis of the performance of four YOLO models: YOLOv8, YOLOv9, YOLOv10, and YOLOv11 for the detection of ceramic cracks performed in a customized dataset of the ceramic material. The research work focuses on addressing the low memory and real-time issues coupled in the ceramic manufacturing process by taking into consideration the trade-offs between the performance of the models in terms of precision, recall, mean average precision (mAP)-50, mAP50–95, and their ability to work within the computational costs of both execution time measured in microseconds, size of the model in megabytes, and giga floating point operations per second (GFLOPs). In this research, both 50 and 100 epoch models are used for analysis of performance. The two models are used for analysis of performance to determine the effects of additional training in terms of performance and utilization of computational resources. The analysis of this research provides a significant milestone in determining the YOLO model that should be used in industrial automation systems for their accuracy and feasibility in real-time automation systems. The research work has contributed to both the accuracy and computational cost areas in detecting defective ceramic products.

2. METHOD

The total experiment procedure for the detection of ceramic breakage is shown in Figure 1. A dataset of 300 images is assembled and split into sets for training, validation, and testing. Image preprocessing tasks like caching and scaling are used for image preparations before training. Then, the model trains for 50 or 100 epochs on all four versions of the YOLO model (YOLO-v8, YOLO-v9, YOLO-v10, and YOLO-v11). Detection performance and resource-related criteria are investigated on computationally intensive parameters like inference timings, model size, and GFLOPs along with crucial detection parameters like precision, recall, mAP50, mAP50-95, and fitness scores.

2.1. Data collection and preprocessing

In total, 300 images were collected from ceramic parts with different crack severities. Each image was manually labeled with bounding boxes for all the visible cracks. The dataset was divided randomly into a training set consisting of 263 images, a validation set of 22 images, and a final test set of 15 images. All images were resized to 640×640 pixels to unify input dimensions. For training, data augmentation was carried out to increase model robustness and to avoid overfitting. Employing augmentation techniques such as blur and median blur simulates minor distortions in images. Grayscale conversion enforces the model to rely on luminance rather than color alone. Contrast limited adaptive histogram equalization (CLAHE) is used to highlight subtle cracks in low-contrast regions.

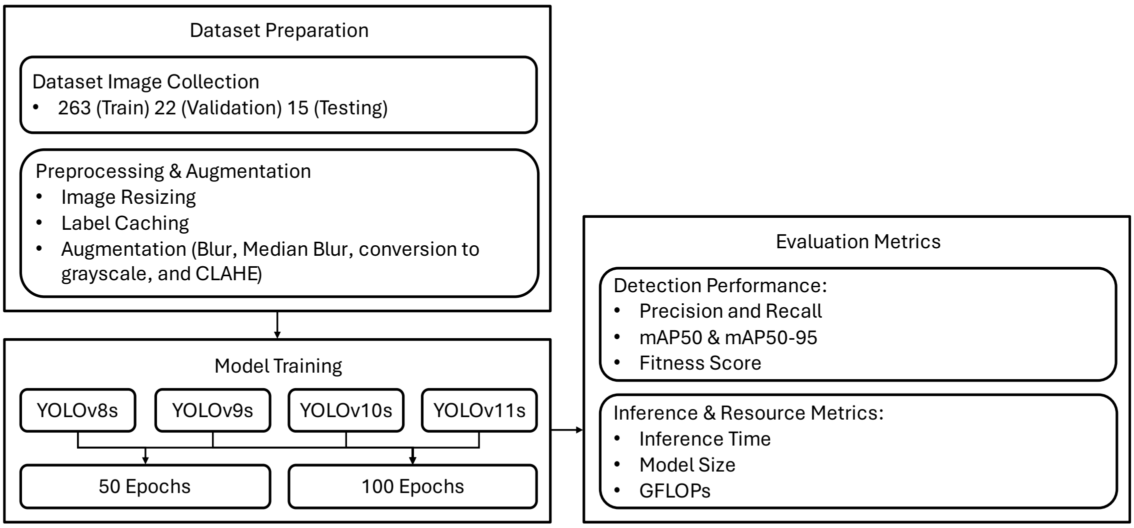

Figure 1. Research overview

2.2. YOLO model variants

Four variations of YOLO were tested in this paper: YOLOv8, YOLOv9, YOLOv10, YOLOv11. In YOLO, there are three overarching tasks in the detection step: bounding box regression, objectness (confidence) prediction, class prediction. For the prediction ($\hat{x}$, $\hat{y}$, $\hat{w}$, $\hat{p}_{obj}$, $\hat{p}_{cls}$) given the corresponding ground truth values (x, y, w, h, pobj, pcls), YOLO loss $\mathscr{L}$ usually computes as shown in (1) [26].

$$\mathcal{L} = \lambda_{box} \times \mathcal{L}_{box} + \lambda_{obj} \times \mathcal{L}_{obj} + \lambda_{cls} \times \mathcal{L}_{cls} \tag{1}$$

Where $\mathcal{L}_{box}$ is the bounding box regression loss, often calculated as a combination of mean squared error or generalized intersection over union (GIoU)/complete intersection over union (CIoU)-based terms; $\mathcal{L}_{obj}$ is the objectness (confidence) loss, penalizing incorrect predictions of background as objects and vice versa; $\mathcal{L}_{cls}$ is the classification loss, here minimized over a single class “damage” in the case of crack detection; and λ_{box}, λ_{obj}, λ_{cls} are hyperparameters that balance the relative importance of each component.

2.3. Training and testing configuration

All the models were trained with Python 3.11.11 and PyTorch 2.5.1, assisted by an NVIDIA Tesla T4 GPU (15 GB VRAM). The batch size was fixed to 16, and the model was trained for 50 or 100 epochs to determine the results after intense training. The optimizer used was the AdamW optimizer, initial learning rate adjusted automatically. Precision and recall as in (2) and (3), mAP as in (4), intersection over union (IoU) as in (5), inference time, model size (in MB), and GFLOPs were the metrics used for evaluation [27].

$$Precision = \frac{TP}{TP+FP'} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{4}$$

$$IoU = \frac{Area\ of\ (B_{pred} \cap B_{true})}{Area\ of\ (B_{pred} \cup B_{true})} \quad (5)$$

After hyperparameter tuning on the validation set, each model was tested on the held out set of 15 images. This final evaluation measured how well the models generalized to unseen data. The results reflected their real-world performance in ceramic crack detection tasks.

3. RESULTS AND DISCUSSION

3.1. Model performance overview

Tables 1 and 2 presents a high-level summary of the results for each YOLO variant at 50 and 100 epochs, focusing on mAP@0.5, mAP@0.5–0.95, inference time, and model size. YOLOv9 and YOLOv11 consistently achieving higher mAP (up to 0.79) but at the cost of larger model sizes (15–19 MB) and slower inference times (~5–6 ms). YOLOv8 maintaining the fastest inference speed (~2–2.3 ms) and smallest model footprint (~6 MB), with slightly lower mAP (0.65–0.67). YOLOv10 providing a middle-ground solution in terms of accuracy and speed, but not significantly outperforming YOLOv8 in resource efficiency.

Table 1. The performance comparison of 50 epochs

Model	mAP50	mAP50-95	Inference time (ms)	GFLOPs	Model size (MB)	Insight
YOLOv8	0.669	0.472	~2.3	8.2	~6.2	Fastest and smallest; acceptable accuracy
YOLOv9	0.752	0.564	~6.0	26.7	~15.2	Higher accuracy but slower and larger
YOLOv10	0.655	0.389	~6.0	24.4	~16.5	Lower accuracy compared to others
YOLOv11	0.704	0.477	~5.1	21.3	~19.2	Moderate accuracy and speed

Table 2. The performance comparison of 100 epochs

Model	mAP50	mAP50-95	Inference time (ms)	GFLOPs	Model size (MB)	Comments
YOLOv8	0.652	0.425	~2.0	8.1	~6.3	Fastest and smallest; slight drop in accuracy
YOLOv9	0.792	0.513	~6.0	26.7	~15.2	Highest accuracy; heavier and slower
YOLOv10	0.741	0.401	~6.3	24.4	~16.5	Good accuracy but larger than YOLOv8
YOLOv11	0.732	0.483	~5.0	21.3	~19.2	Moderate accuracy; slower than YOLOv8

3.2. Influence of training epochs

While increasing epochs from 50 to 100 typically yields an improvement in mAP, the magnitude of this gain varies among models. YOLOv9 benefits the most, with an increase of about 4–5 points in mAP@0.5. YOLOv8's improvement is more modest (about 2–3 points). Given the time and resource constraints in industrial settings, the decision to train for additional epochs depends on whether marginal accuracy gains justify longer training durations.

The eight precision-recall (PR) curves in Figure 2 likely represent four YOLO variants trained at 50 and 100 epoch: YOLOv8 as in Figures 2(a) and 2(b), YOLOv9 as in Figures 2(c) and 2(d), YOLOv10 as in Figures 2(e) and 2(f), and YOLOv11 as in Figures 2(g) and 2(h). Each curve plots precision on the y-axis against recall on the x-axis, illustrating how well a model balances these two metrics across varying confidence thresholds. As the threshold for predicting a "damage" detection change, precision and recall shift accordingly lower thresholds typically boost recall but reduce precision, while higher thresholds improve precision but often lower recall.

In general, a more "bowed" PR curve that stays toward the top-right corner indicates better performance, meaning the model maintains high precision at higher recall levels. The label mAP@0.5 on each plot refers to the mAP at a 0.5 IoU threshold, which is a single-value summary reflecting the area under the PR curve. The higher the mAP@0.5, the better the ability to handle a wide range of recall levels, which maintains a high precision while getting most of the cracks.

When comparing the various versions of the YOLO, the PR curves of the YOLOv9, or the YOLOv11, are generally higher, indicating improved detector performance. However, the memory requirements as well as the inference time are relatively larger. On the other hand, the YOLOv8 aims for improved speed, which might translate to a slightly decreased mAP but can still be effective in a real-time setting. As for the YOLOv10, it generally lies in between, promising improvements over the YOLOv8 but not entirely on the level of the YOLOv9.

To compare 50 versus 100 epochs, longer training (100 epochs) tends to help stabilize and marginally advance the curve in terms of precision versus recall, implying more model convergence and optimization. However, incremental gains differ for different versions of the YOLO model: certain versions report large benefits for longer training times, although diminishing returns also tend to be associated with extended training for certain versions. Generally, which model to be used for ceramic crack detection, conditional upon application needs, is as follows: for real-time needs combined with limited graphics processing unit (GPU) resources, the relative weakness in precision for YOLOv8 appears inconsequential. For applications stressing overall precision for tasks requiring large computation resources, YOLOv9 or YOLOv11 for 100 epochs might be preferable.

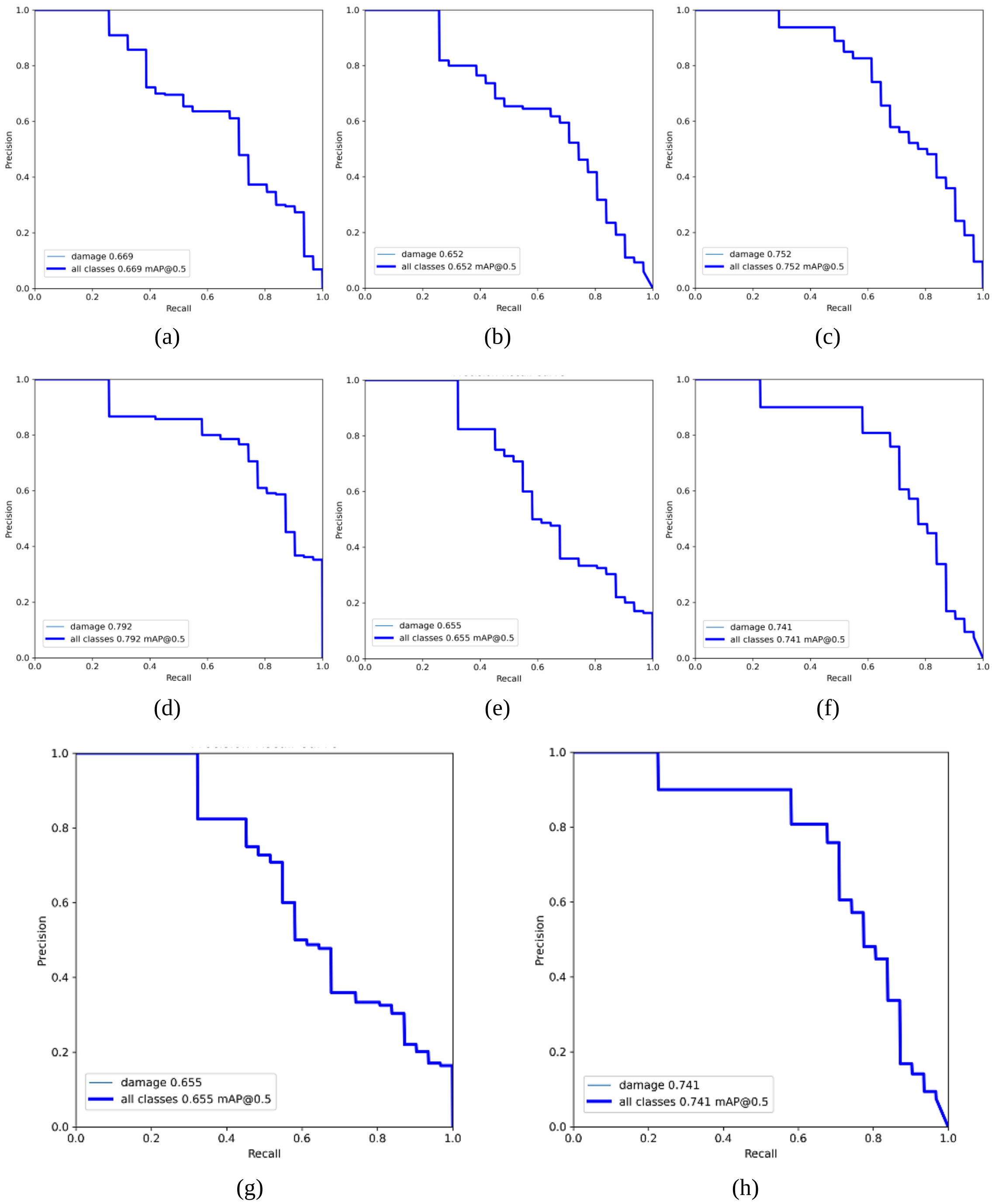

Figure 2. The PR curve comparison for: (a) YOLOv8–50 epoch, (b) YOLOv8–100 epochs, (c) YOLOv9–50 epoch, (d) YOLOv9–100 epochs, (e) YOLOv10–50 epoch, (f) YOLOv10–100 epochs, (g) YOLOv11–50 epoch, and (h) YOLOv11–100 epochs

Figure 3 shows 15 detection results with different bounding boxes labeled "damage" on the various surfaces of ceramics; each of these has a confidence score ranging approximately from 0.45 to 0.84. The scores are a probability-like measure of the model's confidence that a certain region contains a crack. In general, the higher the score, such as 0.84 or 0.77, the stronger the belief in actual damage, while a lower score, such as 0.45 or 0.52, indicates more uncertainty. On some images, the model might produce multiple bounding boxes if it detects several regions which are distinct from a crack or when subtle visual cues cause a single crack to be segmented into parts.

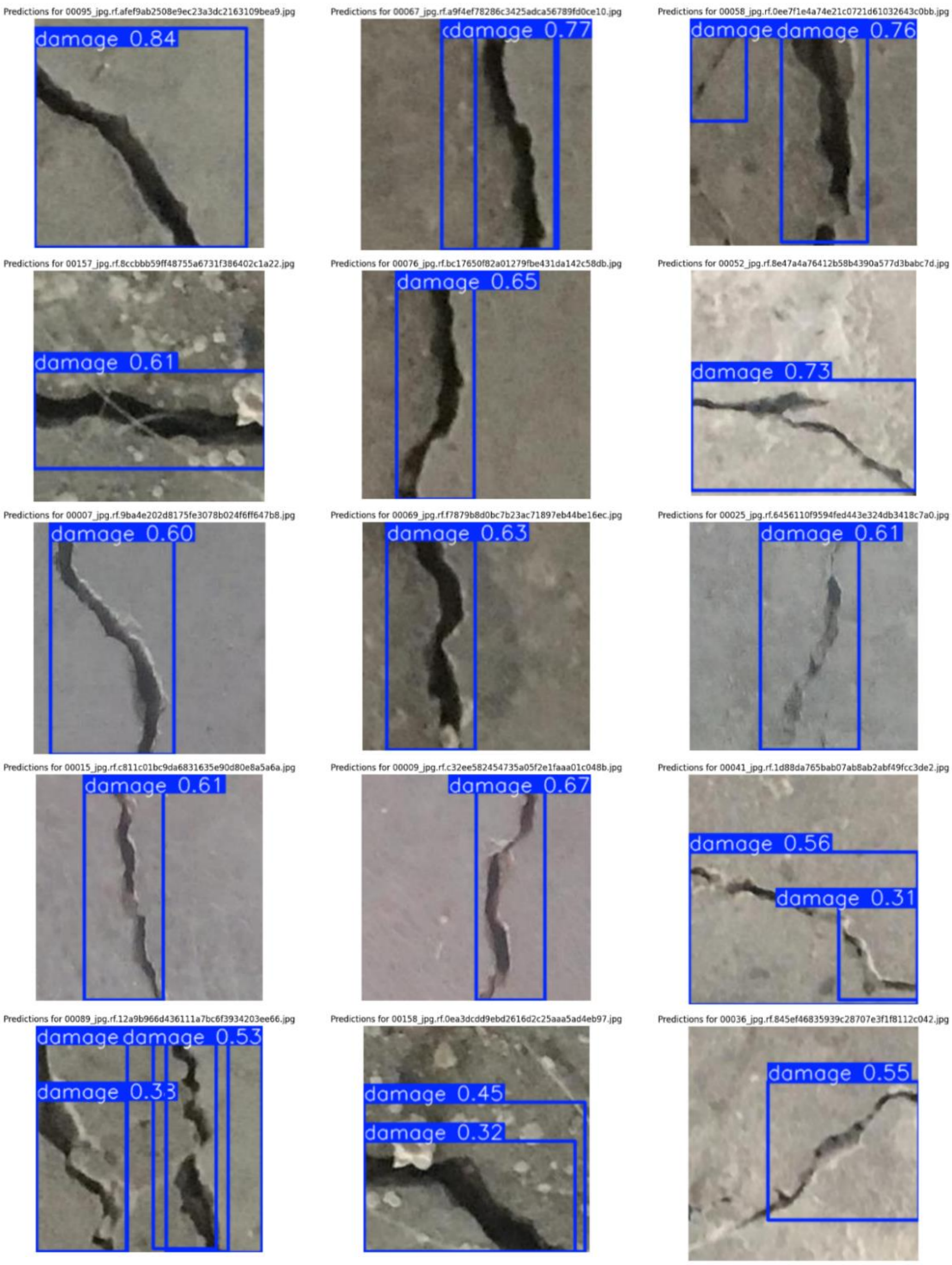

Figure 3. YOLOv8 ceramic crack detection results

The bounding box fits well with visibly clear cracks at relatively high confidences above 0.70, reflecting the ability of the model to identify well-defined crack features. Conversely, for many cases with a moderate or lower confidence score, the crack is quite light, thin, or partially obscured by lighting conditions and background textures. Poor contrast or uneven patterns in ceramics, among other environmental factors, make it difficult for the model to detect cracks with reliability, hence the fall in confidence.

These differences in confidence highlight how important context is when gauging the predictions of the model. Adjusting the detection threshold can help in tailoring performance to suit the needs of a particular application. A higher threshold does reduce false positives, ensuring only the most surefire detections remain under consideration, by removing boxes with lower confidence. A smaller threshold risks admitting more false alarms but may be able to detect minor or borderline breaches. The optimal threshold thus depends on whether, for a particular manufacturing or quality-control situation, it is more critical to miss a crack (false negative) or to falsely signal an intact area (false positive).

4. CONCLUSION

This study compared four variants of YOLO for real-time ceramic crack detection, including YOLOv8, YOLOv9, YOLOv10, and YOLOv11, with a focus on fast inference and low memory usage. YOLOv9 and YOLOv11 result in a higher detection accuracy while substantially increasing the computational cost. Thus, they are not suitable for resource-constrained environments. Eventually, YOLOv8 turns out to be optimal in an industrial context, offering an excellent compromise between detection performance, inference speed, and model compactness. These findings underline the potential of YOLOv8 for practical applications in automated ceramic defect inspection and thus improve quality control efficiency in an industrial environment.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Suan Sunandha Rajabhat University and Rajamangala University of Technology Thanyaburi for their valuable support and encouragement throughout this research project.

FUNDING INFORMATION

Authors state there is no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SK], upon reasonable request.

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