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Enhancing Ceramic Tile Production with Advanced Defect Detection: YOLOv7 vs. YOLOv10

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A B S T R A C T

In this research, the performance of two advanced object detection algorithms, YOLOv7 and YOLOv10, was evaluated for accurate defect detection in ceramic tiles. Using a comprehensive dataset of diverse defective tile images, the algorithms were trained and tested on their ability to precisely identify various defects, such as edge chipping, holes, and surface scratches. The results demonstrated that YOLOv10 significantly outperformed YOLOv7, exhibiting a higher capability to detect a broader range of defects. Our findings highlight the substantial potential of deep learning algorithms like YOLOv10 for industrial inspection applications. Compared to traditional inspection methods, which are often time-consuming, costly, and prone to human error, deep learning algorithms can detect defects with remarkable speed and accuracy. This leads to significant reductions in production costs, increased efficiency, and higher product quality. Moreover, early detection of defects by these algorithms prevents more serious issues and associated costs, ultimately improving the overall production process. However, it is important to note that this research focused specifically on ceramic tile defects, and further investigations are needed to generalize the findings to other materials and industries.

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1. INTRODUCTION

Iran ranks among the top 10 global exporters of tiles and ceramics. This significant achievement is attributed to consistent efforts to improve technological infrastructure and optimize its utilization in the production process. Figure 1 illustrates the quantity of tile exports, measured in millions of square meters, for various countries.

As is well known, defects are inevitable in the tile and ceramic industry. Exporting defective products can significantly damage the international reputation of Iran's tile and ceramic sector. Therefore, the implementation of advanced technologies, such as neural networks and image processing algorithms, can play a critical role in the accurate and automated detection of these defects. By leveraging these technologies, defective tiles and ceramics can be removed from the production line before packaging and shipping, or they can be classified into different grades based on the severity of the defects. This approach not only enhances the quality of exported products but also prevents the waste of resources ("FEM and ANN Investigation of A356 Composites Reinforced with B4C Particulates," 2012; Shabani et al., 2018). In summary, investing in research and development and adopting advanced technologies in Iran's tile and ceramic industry is a crucial step towards maintaining and enhancing the industry's position in global markets. The "You Only Look Once" (YOLO) algorithm is a highly popular and widely used method for object detection in images(Sultana et al., 2020).

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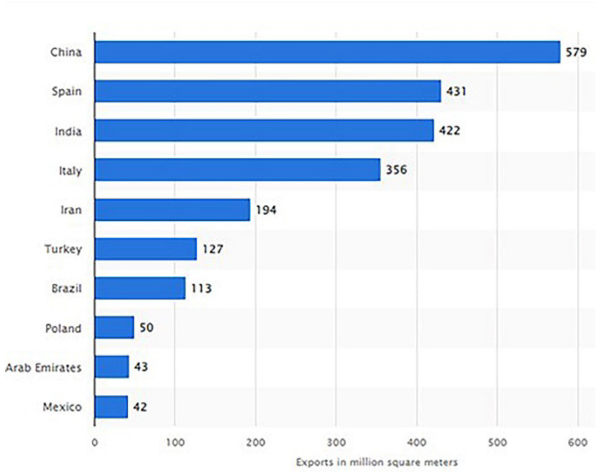

Figure 1. Export volume of tiles from the top 10 exporting countries in million square meters

It is renowned for its speed and accuracy. The first version of YOLO was introduced in 2015, and since then, researchers have developed several improved versions, each adding new features and functionalities. The main versions include YOLOv2, YOLOv3, YOLOv4, and YOLOv5 (Zhiqiang & Jun, 2017).

Single-stage object detection algorithms, such as the YOLO series, simultaneously generate region proposals and classify them in a single step. This approach simplifies network computations and significantly increases detection speed (Redmon et al., 2016).

Tile defects can be categorized into two primary types: surface and aesthetic defects, and internal and structural defects. Surface and aesthetic defects are visible on the tile's surface and affect its appearance. Examples include hairline cracks, pits, stains, and color variations, all of which directly impact the tile's aesthetic appeal. In contrast, internal and structural defects occur within the tile's body and are often not visible to the naked eye. These defects may result from manufacturing issues, such as internal cracks or impurities in the raw materials. While they may not be immediately apparent, they can potentially compromise the tile's durability and longevity (*Use of an Eye-Tracker to Assess Workers in Ceramic Tile Surface Defect Detection | IEEE Conference Publication | IEEE Xplore*, n.d.).

2. MATERIALS AND METHODS

In this research, the specialized "ceramic-tile-defects-14" dataset, sourced from the Roboflow platform, was used to train and evaluate two state-of-the-art object detection models: YOLOv7 and YOLOv10. The images in this dataset, collected under two different lighting conditions, contained three primary defects—cracks (line), holes, and edge-chipping—as shown in Figure 2. After preprocessing and converting the images to JPG format, a dataset comprising 4,956 images was prepared for model training. This dataset was used as the training data for both models (Van Etten, 2018).

Figure 2. Different defects in the database.

To efficiently train the models, images were uploaded to Google Drive, and a powerful T4 GPU within the Google Colab environment was utilized (specifications shown in Figure 3). This setup significantly accelerated the computations and reduced the training time.

```
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
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|   0  Tesla T4                       Off | 00000000:00:04.0 Off |                    0 |
| N/A   45C    P8              10W /  70W |      0MiB / 15360MiB |      0%      Default |
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| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
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Figure 3. Google Colab GPU specifications used for both models

To achieve a precise comparison between YOLOv7 and YOLOv10, both models were trained for 55 epochs using the same T4 GPU and a batch size of 16. This approach was adopted to minimize the influence of external factors on the results and to ensure consistent conditions for both models. After the completion of training, the performance of each model was evaluated on an independent test dataset, and the results were thoroughly analyzed.

3. RESULTS AND DISCUSSION

The performance of the trained models was evaluated using the following metric: Mean Average Precision (mAP), as shown in Equation (1). mAP is a comprehensive indicator of model performance that considers the average precision of predictions across all classes (*Mean Average Precision (mAP) in Object Detection*, 2022). It reflects how accurately, on average, the model detects objects in an image, and the corresponding results are presented in Table 1.

$$\mathrm{mAP} = \frac{1}{n} * \Sigma(\mathrm{AP}) \tag{1}$$

where n represents the total number of classes or categories the model is trained to detect, and Σ AP the summation of "Average Precision" (AP) for all classes.

TABLE 1. Performance evaluation of YOLOV10 and YOLOV7 using Mean Average Precision (mAP)

mAP@0.5	edge-chipping	Hole	line	All classes
YOLOv7	42.2%	65.5%	12.0%	39.9%
YOLOv10	46.7%	58.8%	26.7%	44.1%

The primary evaluation metric in this table is mAP@0.5, representing the mean Average Precision at an IoU threshold of 0.5. Overall, YOLOv10 outperforms YOLOv7 and achieves a higher mAP@0.5 value, indicating that YOLOv10 is better at accurately detecting defects (*Tianchi Competition-Alibabacloud Tianchi*, n.d.).

The second evaluation metric used in this study is the F1-score. The F1-score is the harmonic mean of precision and recall, providing a balanced metric that considers both the model's ability to correctly identify positive instances (precision) and its ability to find all relevant instances (recall). Figure 4 shows that YOLOv7 achieves an average F1-score of 0.44 for all classes at a confidence threshold of 0.152. This means that, on average, when YOLOv7 is 15.2% confident in a detection, there is a 44% chance that the detection is correct. In comparison, YOLOv10 achieves a higher average F1-score of 0.48 for all classes at a lower confidence threshold of 0.111. Therefore, YOLOv10 demonstrates greater accuracy at a lower confidence threshold than YOLOv7.

The F1-score is calculated using equations (2), (3), and (4), where Recall is defined by equation 2, Precision by Equation 3, and the F1-score by Equation 4. To calculate the F1-score, it is necessary to define the following metrics:

True Positives (TP): The cases where the model correctly predicted the positive class.

True Negatives (TN): The cases where the model correctly predicted the negative class.

False Positives (FP): The cases where the model incorrectly predicted the positive class (a "false alarm").
False Negatives (FN): The cases where the model failed to predict the positive class (a "miss") (Ceramic Tile Surface Defect Detection Based on Deep Learning - ScienceDirect, n.d.)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{3}$$

$$\text{F1} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{4}$$

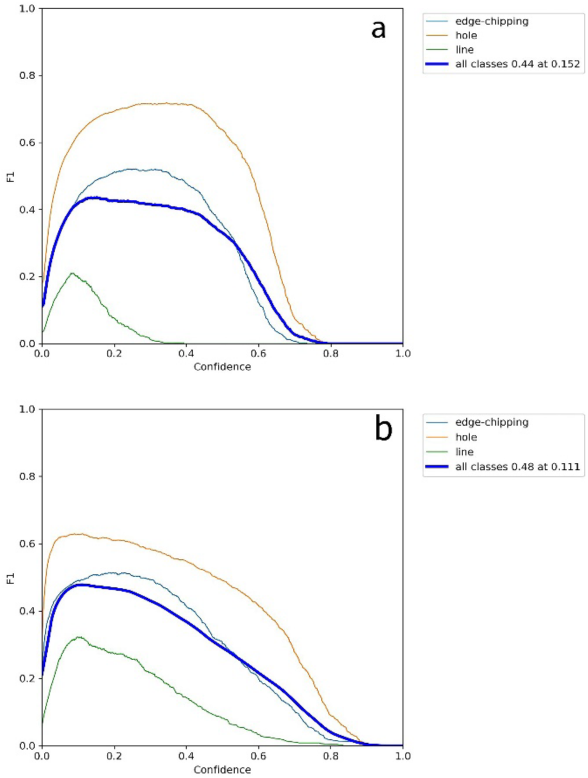

Figure 3. F1 Score diagram for two models a) yolov7 and b) yolov10

In this analysis, YOLOv7 achieves an average F1 score of 0.44 for all classes at a confidence threshold of 0.152. This means that, on average, when YOLOv7 is 15.2% confident in a detection, there is a 44% chance that the detection is correct. However, YOLOv10 achieves a higher average F1 score of 0.48 for all classes at a lower confidence threshold of 0.111. Therefore, it can be concluded that, on average, YOLOv10 attains a higher accuracy of 48% at a lower confidence threshold compared to YOLOv7 (*F1 Confidence, Precision-Recall Curve, Precision-Confidence Curve, Recall Confidence Curve and Confusion Matrix · Issue #7307 · Ultralytics/Ultralytics*, n.d.)

Figure 5 presents the Precision-Recall curve, which illustrates the trade-off between precision and recall at various threshold values. Precision measures the proportion of correct positive identifications, while recall measures the proportion of actual positives correctly identified. Ideally, both precision and recall should be as close to 1 as possible. The closer a model's plotted points are to the upper-right corner of the graph, the better its performance. However, considering the mAP@0.5 values provided for YOLOv7 and YOLOv10, it is apparent that the higher mAP of YOLOv10 indicates its superior ability to detect more objects with greater accuracy (Ultralytics, n.d.).

This capability is highly beneficial in various applications such as surveillance systems, autonomous vehicles, and robotics. Figure 6 illustrates the accuracy of two object detection models, YOLOv7 and YOLOv10, at varying confidence thresholds. Both models demonstrate improved accuracy as the confidence threshold increases. However, as shown in the figure, YOLOv10 exhibits more stable performance with lower fluctuations, indicating greater reliability in maintaining accuracy across different confidence levels ("Performance Evaluation of YOLOv5 and YOLOv8 Models in Car Detection," 2024) . Figure 7 presents the normalized confusion matrix, which shows the number of samples assigned to each class and aids in analyzing the model's errors. The confusion matrix is expressed as a percentage and indicates the model's performance in identifying each class. The results demonstrate that the YOLOv10 model outperformed YOLOv7 in detecting line defects (*Mean Average Precision (mAP) in Object Detection*, 2022).

However, the bar chart of the sample distribution in Figure 8 reveals that the number of samples for the line defect class is lower compared to the other two classes. This imbalance in the data may have caused the weight of one sample to be heavier than that of another during training, potentially leading to the model's poorer performance in detecting line defects.

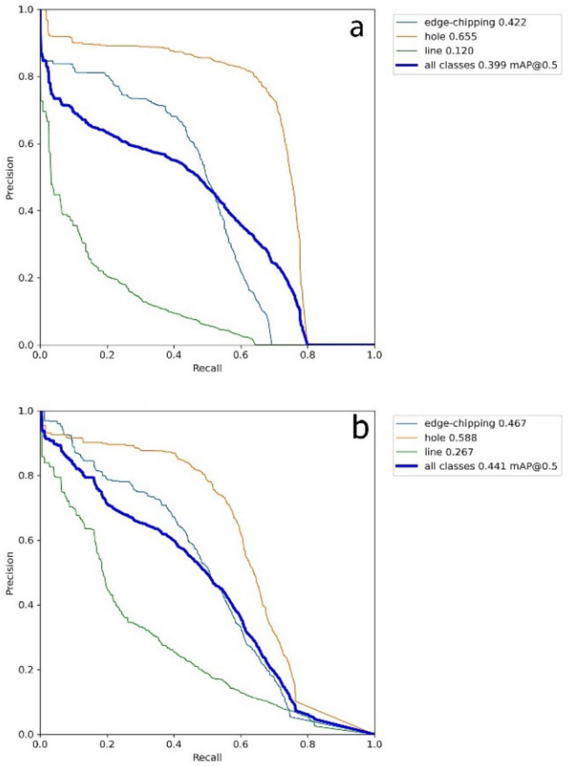

Figure 4. Precision-Recall diagram for two models a) yolov7 and b) yolov10

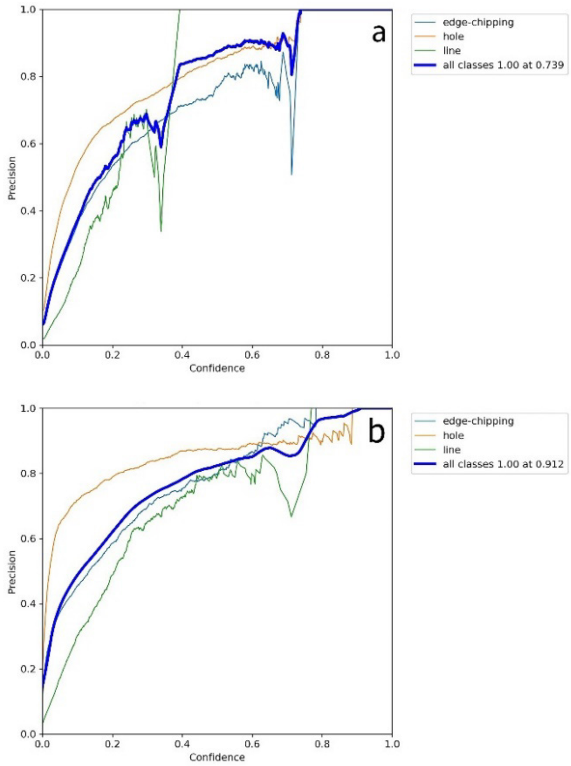

Figure 5. Precision-Confidence diagram for two models: a) yolov7 and b) yolov10

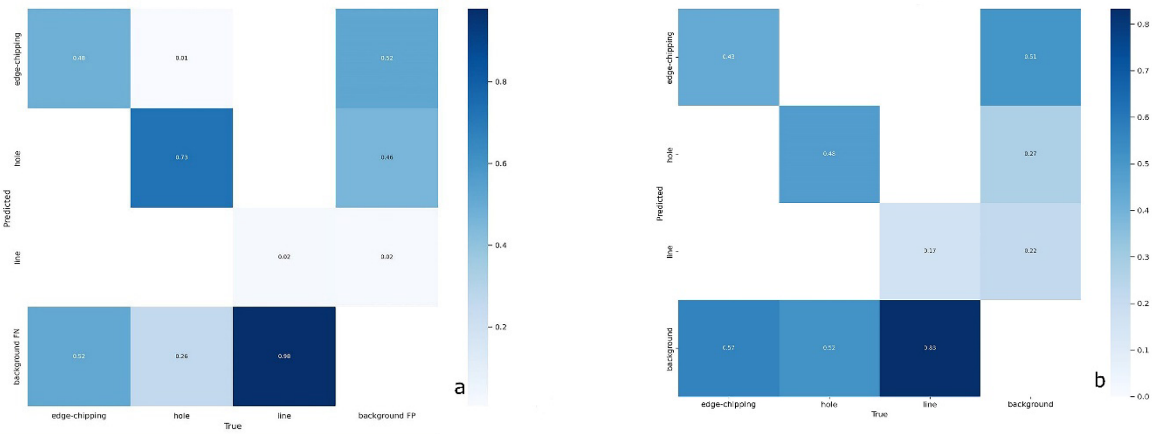

Figure 6. Normalized Confusion Matrix for two models: a) yolov7 and b) yolov10

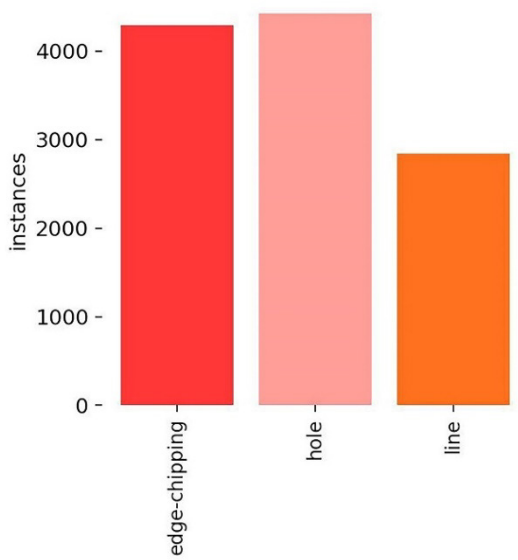

Figure 7. Bar chart of sample distribution across three defect classes

As illustrated in Figure 9, the proposed model demonstrated exceptional performance in surface defect detection. Even with a limited number of training iterations, the model was able to accurately identify defects.

Figure 8. Image of the model's performance in defect detection

4. CONCLUSION

In conclusion, the YOLOv10 model demonstrated superior performance in ceramic tile defect detection compared to the YOLOv7 model. This superiority was evident across multiple evaluation metrics, including mean average precision (mAP), F1-score, precision-recall curve, and normalized confusion matrix.

The YOLOv10 model exhibited a greater ability to accurately identify defects, particularly in the case of line defects. This improved performance can be attributed to its enhanced capability to balance precision and recall, as indicated by the higher F1-score. Additionally, the YOLOv10 model demonstrated greater stability in maintaining accuracy at higher confidence thresholds, as evidenced by the precision-recall curve.

However, the analysis of the sample distribution revealed that the training data contained fewer samples for the line defect class compared to other defect classes. This imbalance in the dataset may have contributed to the relatively poorer performance of both YOLOv7 and YOLOv10 in detecting line defects.

Future research could focus on addressing the data imbalance issue by collecting more samples for the line defect class or by employing techniques like data augmentation to artificially increase the dataset size. Additionally, exploring other advanced object detection models and techniques could further enhance the accuracy and efficiency of ceramic tile defect detection.

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