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Robustness Analysis of YOLOv9 Object Detection Under Dynamic Illumination Variance for Museum Artifacts

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Abstract

Object detection technology has been widely applied in smart tourism and digital museum systems. However, variations in illumination conditions pose a significant challenge, affecting the visibility of objects and the object localization performance. This study aims to evaluate the robustness of the YOLOv9 model in detecting museum objects under different illumination conditions. To evaluate the model performance, 5-Fold Cross-Validation was used on a multi-class dataset of eleven classes of cultural heritage artifacts from Museum Lampung. To test the effects of illumination variation, testing was done under three different lighting conditions (normal lighting, 50 percent dimmed lighting, and 50 percent brightened lighting). The results show that YOLOv9 can maintain stable detection performance in such conditions, with a mean Average Precision at 50 percent ($mAP@50$) of 0.991 and a mean mAP at 50 to 95 percent ($mAP@50{-}95$) of 0.846. In particular, under normal lighting conditions, the model achieved a $mAP@50$ of 0.995 and a $mAP@50{-}95$ of 0.946. For under 50 percent dimmed and brightened lighting, $mAP@50{-}95$ dropped to 0.928 and 0.933, respectively. These results suggest that illumination variation affects the localization accuracy more under stricter Intersection over Union thresholds than the general object detection performance. Overall, the results of this research work demonstrate that YOLOv9 can maintain stable object detection performance in a museum environment despite variations in illumination conditions.

Keywords : Object Detection, YOLOv9, Dynamic Illumination, Lighting Conditions, Museum Artifacts

1. INTRODUCTION

The rapid growth of computer vision technology has significantly improved the capability of digital systems to interpret and analyze visual information automatically. Object detection is one of the most widely studied applications in computer vision, enabling computers to detect and localize objects in images or video streams. Recent advancements in deep learning based object detection models have shown considerable improvements in detection accuracy and computational efficiency. Among these methods, the YOLO (You Only Look Once) family has gained popularity as one of the most widely used object detection frameworks owing to the trade-off between detection performance and real-time processing [1].

Object detection technology has been used in numerous fields such as intelligent surveillance, autonomous systems, healthcare, industrial automation, and smart tourism applications. In the cultural heritage domain, object detection can be used for the development of interactive museum guide systems that can automatically recognize museum collections by mobile devices or smart cameras [2]. These systems can help boost engagement with visitors and provide more powerful educational experiences. However, there are some problems in the implementation of object detection systems in museum settings. The challenges are largely caused by variations of illumination conditions, reflective display surfaces, cluttered backgrounds, and complexity of objects to be detected.

Variation of illumination is one of the major issues for object detection systems [3], [4]. Changes in the lighting intensity can have a great influence on the image quality, feature extraction and object localization performance. Images captured in low-light conditions often suffer from low contrast, high noise, and significant loss of visual details. These factors cause both false positives and false negatives in object detection models. On the other hand, too much brightness can obscure clarity of features due to overexposure and reflection problems. These are particularly acute challenges in museum settings, where exhibition rooms typically use a variety of lighting arrangements to preserve artifacts and create aesthetically pleasing presentation effects. Thus, the object detection systems applied in museums need to have good detection capabilities to function under various lighting conditions.

Several previous studies investigated the application of object detection methods in the context of cultural heritage and low-light environments. Meyer et al. proposed a museum artwork exploration system based on the Grounded Language-Image Pre-Training (GLIP) for interactive recognition of museum objects. However, the proposed system could not recognize very specific and complex objects [5]. Rizki et al. used Mask R-CNN framework for object detection with a small dataset and achieved promising detection results [6]. However, the system performance was degraded on low resolution images. In another study conducted by Virgiawan et al. , YOLOv3 was combined with an object tracking algorithm to detect the objects in real-time [7]. The results showed that the performance reduced in low-light and visually dynamic environments. Additionally, some studies using YOLOv4-Tiny and improved YOLOv5 architectures demonstrated enhanced detection capabilities in low-light scenarios [8]. However, some of the approaches introduced additional computational complexity that could affect deployment efficiency on devices with limited resources.

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Previous studies have shown that existing work mainly focused on the performance of generic object detection or techniques for improving the low-light performance. There is a lack of studies that specifically evaluate the robustness of recent YOLO architectures for museum object detection under varying illumination conditions. Thus, the stability evaluation of object detection models under different lighting environments is still a prominent research challenge, especially in the practical applications of smart museums.

YOLOv9 has recently gained attention for its progress in feature aggregation and gradient information handling. The architecture includes the Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI) [9], which are designed to improve feature learning ability while keeping the computational efficiency. These features render YOLOv9 particularly well-suited for real-time object detection applications in complex visual environments, including those with varying illumination conditions.

Considering these aspects, the objective of this study is to evaluate the robustness of YOLOv9 for detecting museum objects under low-light, normal-light, and bright-light conditions. We evaluate the model performance with metrics such as Precision, Recall, $mAP@50$ and $mAP@50–95$ to study the impact of illumination variations on the detection accuracy and localization performance. The findings of this study are expected to provide insights into the deployment of illumination-aware object detection systems in smart museum environments.

2. RESEARCH METHODOLOGY

2.1 Research Overview

The study was conducted in several different steps, namely dataset acquisition, annotation, preprocessing and augmentation, model training and evaluation. We first captured images of museum objects using a smartphone camera from different viewpoints under different illumination conditions such as low-light, normal-light and bright-light. The images obtained were then labelled with bounding boxes . The images were then preprocessed and augmented using methods to improve the quality and variability of the dataset. The processed dataset was partitioned into training, validation, and testing sets and used to train the YOLOv9 architecture. Finally, the performance of the trained model was evaluated against precision, recall, and other important metrics to verify the robustness of YOLOv9 in different lighting conditions. The comprehensive research workflow is illustrated in Figure 1.

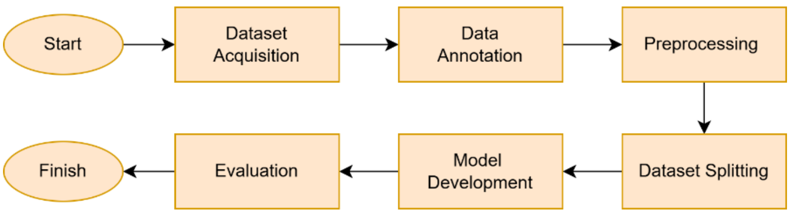

Figure 1. Overall research workflow of the proposed study.

Table 1. Profiles of datasets for lighting variation.

No	Class Label Name	Artifact Category	Measured Intensity	Illumination Profile
1	1_canang	Musical Instrument	185 lux	High
2	2_kendi	Handicraft	176 lux	High
3	3_gamolan_pekhing	Musical Instrument	60 lux	Medium
4	4_arca_folonesia	Cultural Regalia	59 lux	Medium
5	5_payan_kejang	Traditional Weapon	46 lux	Low
6	6_keris_tekhapang	Traditional Weapon	46 lux	Low
7	7_panderang	Traditional Weapon	46 lux	Low
8	8_kain_sinjang	Cultural Regalia	43 lux	Low
9	9_topi_sunat	Cultural Regalia	43 lux	Low
10	91_nampankaki_tudungsaji	Cultural Regalia	43 lux	Low
11	92_kulit_kelapa	Cultural Regalia	43 lux	Low

2.2 Dataset Acquisition

The raw data collection was carried out systematically at the Museum Lampung to get the authentic cultural heritage object in the real exhibition environment. In data acquisition, a smartphone camera sensor was used, namely the Poco M4 Pro, with a resolution of 64 Megapixels, an aperture of f/1.8, and a 26mm wide-angle lens. Phase Detection Auto Focus was employed for visual clarity and to minimize motion blur. All primary targets were recorded at a fixed distance of about 1 m from the display cases of the museum for the sake of consistency in sampling. The recording protocol was

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adapted to the spatial constraints imposed by each artifact's display. For exhibits that were fully accessible, video recordings were taken from multiple spatial perspectives, including front, back, left, and right sides. Vertical variations were also considered by capturing at different camera elevation angles of 0 degrees, 45 degrees and 135 degrees which captured all the geometric and structural features of the artifacts.

2.3 Dataset Annotation

The basic labeling process is the basis for the assignment of a class label to each object in the video recording samples collected during the sample collection. Figure 2 shows an example of this approach. The MP4 video recording samples are first imported into the Roboflow platform [10]. When the video file is imported, it is converted to an image file for each frame. The user is then prompted to select the image file and then open the annotation editor to start creating bounding boxes and assigning labels. In cases where there are no museum objects in the picture, it should be deleted. On the other hand, if a museum object is detected, it is important to assign a suitable bounding box and label to the object. For each image in the dataset this is done in a systematic way.

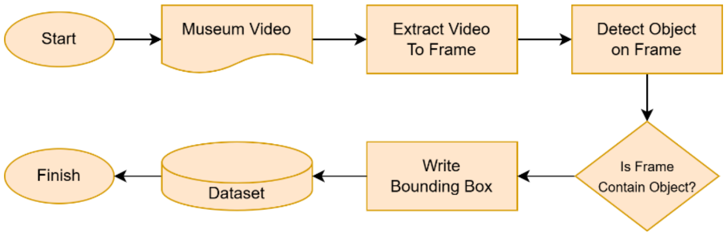

Figure 2. The workflow of labelling process on dataset.

Afterward, the primary data was collected in high-definition video formats, namely MP4, to effectively capture continuous interactions with the environment. We ran a sequential temporal extraction pipeline to produce a discrete image dataset for deep learning training. The pipeline processed the raw MP4 video streams into separate digital images, one image per video frame, in JPG format. The extracted images were uploaded to the Roboflow computer vision platform for centralized data management and annotation. In the Roboflow Annotation Editor interface, a complete process of manual labeling and localization was performed. The workflow included drawing precise spatial bounding boxes around every artifact and labelling them with their ground-truth class among 11 different classes of cultural heritage objects like traditional weapons, musical instruments and historical relics. The dataset has evident multi-label characteristics with a single frame often containing overlapping objects from multiple target classes due to the complex visual composition of the museum displays.

2.4 Dataset Preprocessing

Preprocessing and augmentation are key steps to improve the dataset, by introducing variations using techniques like oversampling. The purpose of these variations is to help the model to learn to recognize objects from different perspectives and reduce the chances of overfitting [11], [12]. These steps of preprocessing and augmentation are performed on the Roboflow platform, as shown in a structured flow in Figure 3. The user is taken to the versions menu from the annotation editor menu to create a dataset. Users need to choose the images that they want to include in the menu to create the dataset. After that, users need to go to the preprocessing option and then in the augmentations option to improve the dataset further.

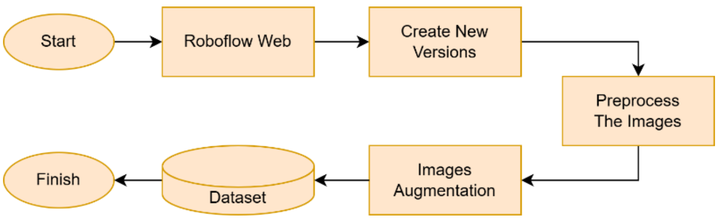

Figure 3. The workflow of preprocessing and augmentation on dataset.

To mitigate spatial distortion and enhance computational convergence during the deep learning training phase, a standardized preprocessing pipeline was implemented for the collected dataset utilizing the Roboflow platform. The initial stage of geometric preprocessing involved reshaping all heterogeneous digital images to a uniform resolution of 640x640 pixels. This alignment was essential to meet the native input layer requirements of the YOLOv9 model. Subsequent to the resizing procedure, data augmentation techniques were systematically employed to avert overfitting and to bolster the model's generalization capacity across diverse spatial configurations. These transformations were

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applied in a randomized manner and included alterations in spatial orientation as well as geometric oversampling, compelling the network to learn resilient feature representations that are independent of the artifacts' orientation or positioning within the museum showcases. The results of this stage can be seen in Table 2.

Table 2. The data used in the study, after preprocessing and augmentation.

No	Nama label kelas	Num. of Data
1	1_canang	156
2	2_kendi	134
3	3_gamolan_pekhing	132
4	4_arca_folonesia	129
5	5_payan_kejang	36
6	6_keris_tekhapang	54
7	7_panderang	87
8	8_kain_sinjang	87
9	9_topi_sunat	99
10	91_nampankaki_tudungsaji	114
11	92_kulit_kelapa	81
	Total	**1109**

2.5 Illumination-Based Dataset Generation

In addition to employing geometric oversampling, a rigorous conditional preprocessing framework was implemented to simulate a variety of environmental illumination conditions. This approach facilitated a thorough robustness analysis of the results. Prior to the simulation of exposure, Contrast Limited Adaptive Histogram Equalization (CLAHE) [13] was utilized on the test set to standardize localized contrast boundaries across the diverse lighting profiles present within the museum chambers. Subsequently, a script-driven baseline analysis was performed using Python to extract the statistical luminous properties of the consolidated test scenes. The empirical calculations revealed a global baseline mean brightness ($\mu_{\text{brightness}}$) of 111.54, an estimated gamma value of 1.1930, and a mean luminance channel (L^*) of 118.68 within the CIELAB color space.

To systematically evaluate the localization and detection stability of YOLOv9 under extreme photometric shifts, the baseline indices were mathematically modified by a factor of plus or minus 50 percent to establish two independent illumination subsets. The 50 percent Dimmed Scenario, or Low-Light Simulation, was designed to assess feature extraction degradation under low-contrast conditions. In this scenario, the parameters were structurally compressed to achieve a target brightness of 55.77, a target gamma of 0.5965, and a target L^* channel of 59.34. Conversely, the 50 percent Brightened Scenario, referred to as overexposure simulation, was configured to examine the model's resilience against color saturation and glare. In this case, the luminance thresholds were expanded to a target brightness of 167.31, a target gamma of 1.7895, and a target L^* channel of 178.02. The comparative evaluation of these distinct subsets provides a comprehensive baseline for determining the operational limits of the single-shot detector when deployed in visually unpredictable environments.

2.6 Dataset Splitting

Given the highly skewed distribution of the target classes outlined in the preceding section, wherein dominant classes such as 1_canang significantly outnumber minority classes like 5_payan_kejang, the implementation of a standard random data splitting technique presents a substantial risk of validation bias and extreme cross-validation variance. To mitigate the effects of this pronounced class imbalance while accurately preserving the architectural multi-label integrity of the samples, a systematic validation framework was established utilizing a 5-Fold Multi-Label Stratified Cross-Validation approach. Dividing the dataset statistical balance effectively reducing evaluation bias without introducing unnecessary computational complexity during the cross-validation cycles [14].

In contrast to single-label stratification methods that solely manage uniform single-category distributions, this framework employs an iterative stratification algorithm specifically designed for complex multi-label constraints. The mathematical foundation of the algorithm iteratively prioritizes minority labels, dynamically assigning images to specific validation folds based on the strict discrepancy between the current fold label frequency and the ideal expected uniform distribution. This mechanism ensures that the relative frequency and proportion of all eleven target classes remain entirely consistent and structurally balanced across both the training and validation sub-matrices for each cross-validation iteration.

2.7 Model Development

The object detection model architecture employed in this study is founded on YOLOv9, an advancement that signifies a considerable technical progression in comparison to its predecessor. The YOLOv9 architecture was meticulously

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designed to address the information bottleneck commonly observed in deep neural networks. In dynamic environments, such as museum exhibition spaces characterized by unpredictable fluctuations in lighting, the retention of spatial information emerges as a vital parameter that ensures the model's capacity to accurately localize artifacts.

To attain this level of robustness, the model development phase of this research incorporated two essential architectural innovations from YOLOv9: the Generalized Efficient Layer Aggregation Network and Programmable Gradient Information. The synergistic integration of the structural flexibility inherent in the Generalized Efficient Layer Aggregation Network and the gradient conditioning mechanism provided by Programmable Gradient Information equips the YOLOv9 model to extract features of Lampung cultural artifacts that remain invariant despite variations in lighting distribution. This innovative gradient tracking architecture, alongside a comparative feature extraction scheme, served as the fundamental basis prior to evaluating the model using Stratified K-Fold Cross-Validation.

3. RESULTS AND DISCUSSION

In this section, provided the experimental results and discuss the performance of the YOLOv9 model under different illumination conditions in the museum environment. The evaluation is based on the analysis of detection capability, localization performance, and computational latency in normal, 50 percent dimmed, and 50 percent brightened lighting conditions. We evaluate the model performance using metrics like Precision, Recall, mean Average Precision at IoU 0.50 ($mAP@50$), and mean Average Precision at IoU 0.50 to 0.95 ($mAP@50–95$) to understand the impact of lighting variation on object detection accuracy and bounding box localization. Furthermore, a computational latency analysis is performed in order to assess the feasibility of the model for the purposes of interactive museum object detection applications.

3.1 Training Performance

The training process demonstrated that the YOLOv9 model learned the visual characteristics of the museum items well under different lighting conditions. The training loss and the validation loss gradually decreased during the training process and converged to a stable value eventually. This result indicates that the model fitted well to the dataset without facing significant overfitting problems. Preprocessing and augmentation techniques were applied to increase the variability of the dataset and to keep the model performance stable during the validation.

Table 3. The Cross-validation performance metrics baseline at optimal epochs.

Validation Fold	Precision	Recall	mAP@50	mAP@50–95
Fold 1	0.98094	0.99000	0.99218	0.85951
Fold 2	0.98670	0.98818	0.98904	0.83545
Fold 3	0.98568	0.98065	0.99088	0.85778
Fold 4	0.98510	0.98095	0.99043	0.84102
Fold 5	0.98024	0.97620	0.99137	0.83476
Mean (μ)	0.98373	0.98320	0.99080	0.84570
Std. Deviation (σ)	0.00294	0.00570	0.00120	0.01208

The results of validating the five-fold evaluation process are shown in Table 3. From the experimental results, the mean Precision of the model is 0.98373 and the mean Recall is 0.98320. These numbers show that the model was able to detect most museum objects consistently, with a relatively low number of false detections. The model achieved a mean $mAP@50$ value of 0.99080 in localization performance which shows good detection performance at common IoU thresholds. Furthermore, the mean $mAP@50–95$ value obtained is 0.84570, which indicates that the model is relatively stable in localization even at stricter IoU thresholds.

Moreover, the low values of standard deviation for all evaluation metrics suggest that the performance of the model was consistent for different validation folds. The standard deviation values of 0.00294 for Precision, 0.00570 for Recall, 0.00120 for $mAP@50$ and 0.01208 for $mAP@50–95$ indicated that the trained model had stable detection performance for different validation subsets. These results, taken together, demonstrate that YOLOv9 can provide reliable performance for museum object detection under varying illumination conditions.

3.2 Detection Performance under Different Illumination Conditions

To assess the robustness of the YOLOv9 model in the face of illumination variation, an analysis of object detection performance was conducted across three distinct lighting scenarios: normal illumination, 50 percent dimmed lighting, and 50 percent brightened lighting conditions. Each scenario was strategically designed to replicate the lighting variations that might be encountered in actual museum environments, encompassing conditions of low light and excessive illumination resulting from reflections or overexposure. The evaluation employed various metrics, including Precision, Recall, Mean Average Precision at 50 ($mAP@50$), and Mean Average Precision from 50 to 95 ($mAP@50\text{-}95$), to comprehensively analyze both the object detection capabilities and the localization performance across different levels of

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illumination. Furthermore, a class-level analysis was undertaken to ascertain the impacts of illumination changes on the detection performance of various categories of museum artifacts.

3.2.1 Performance under Normal Illumination Scenario

To establish a baseline for the detection performance of the YOLOv9 model, it was first evaluated under normal museum lighting conditions. In this context the dataset had a mean brightness of 111.54 and a mean luminance (L^*) of 118.68 in the CIELAB color space. Based on the evaluation results, the model achieved a macro-average $mAP@50$ score of 0.995 and an $mAP@50\text{-}95$ score of 0.946. The results show that the model was able to detect and locate museum objects with very high accuracy under standard lighting conditions.

Table 4. Performance metrics under normal illumination scenario

Class ID	Target Artifact Class Name	Precision	Recall	mAP@50	mAP@50–95
1	1_canang	0.963	1.000	0.995	0.957
2	2_kendi	0.977	0.985	0.994	0.942
3	3_gamolan_pekhing	0.978	1.000	0.995	0.946
4	4_arca_folonesia	1.000	0.991	0.995	0.962
5	5_payan_kejang	0.941	1.000	0.995	0.947
6	6_keris_tekhapang	1.000	1.000	0.995	0.955
7	7_panderang	0.977	1.000	0.995	0.954
8	8_kain_sinjang	1.000	1.000	0.995	0.932
9	9_topi_sunat	0.977	1.000	0.995	0.954
10	91_nampankaki_tudungsaji	0.949	1.000	0.995	0.937
11	92_kulit_kelapa	0.984	0.992	0.995	0.916
	Macro Average (μ)	0.977	0.997	0.995	0.946

For further evaluation of the model performance, the object detection results were analyzed on eleven target classes. The experimental results showed that a few object categories such as 1_canang, 3_gamolan_pekhing and 4_arca_folonesia consistently yielded high precision and recall values. Objects with clear structural patterns and distinctive visual features were generally detected with higher accuracy than objects with more complex textures or irregular shapes. Moreover, the conventional lighting conditions allowed the model to keep the details of the objects and reduce the impact of shadows and reflections during the detection. The detailed detection performance for each object category in the normal illumination scenario is summarized in Table 4.

3.2.2 Performance under 50% Dimmed Light Scenario

To evaluate the robustness of the YOLOv9 model under low-light conditions, an evaluation was performed on the images with fifty percent reduced brightness. In this case, the dataset showed an average brightness value of 55.77, with an estimated gamma value of 0.5965, and a mean luminance (L^*) value of 59.34. The evaluation results revealed a marginal decline in the macro-average mean Average Precision at IoU threshold 0.50 ($mAP@50$) from 0.995 in the standard lighting to 0.994 in the dimmed lighting conditions. At the same time, the $mAP@50\text{-}95$ score dropped from 0.946 to 0.928. This means that the decrease in illumination had a clear impact on the localization precision at more strict Intersection over Union (IoU) thresholds.

Table 5. Performance metrics under 50% dimmed illumination scenario.

Class ID	Target Artifact Class Name	Precision	Recall	mAP@50	mAP@50–95
1	1_canang	0.971	0.985	0.994	0.944
2	2_kendi	0.976	0.977	0.994	0.916
3	3_gamolan_pekhing	0.981	0.994	0.994	0.932
4	4_arca_folonesia	0.984	0.994	0.994	0.946
5	5_payan_kejang	0.963	1.000	0.994	0.941
6	6_keris_tekhapang	1.000	0.944	0.994	**0.827**
7	7_panderang	0.976	0.994	0.994	0.946
8	8_kain_sinjang	0.976	0.981	0.994	0.933
9	9_topi_sunat	0.973	0.991	0.994	0.942
10	91_nampankaki_tudungsaji	0.975	0.985	0.994	0.925
11	92_kulit_kelapa	0.976	0.991	0.994	0.951
	Macro Average (μ)	0.977	0.985	0.994	0.928

As shown on Figure 4, at the level of individual classes the effect of low-light conditions was dependent on the visual properties of the objects involved. Some object categories like 4_arca_folonesia and 5_payan_kejang had relatively

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stable detection performance with $mAP@50\text{-}95$ value of more than 0.94. On the other hand, the biggest decrease in performance was in the 6_keris_tekhapang class, where the $mAP@50\text{-}95$ value decreased to 0.827. Results show that objects with thin structure, complex contour or low visual contrast were more difficult to localize accurately in low-light conditions. Despite these challenges, the overall macro-average Precision remained stable at 0.977, confirming that the model showed consistent object detection performance even in the face of illumination reduction. The detailed performance results of each object category in the fifty percent dimmed lighting scenario are shown in Table 5.

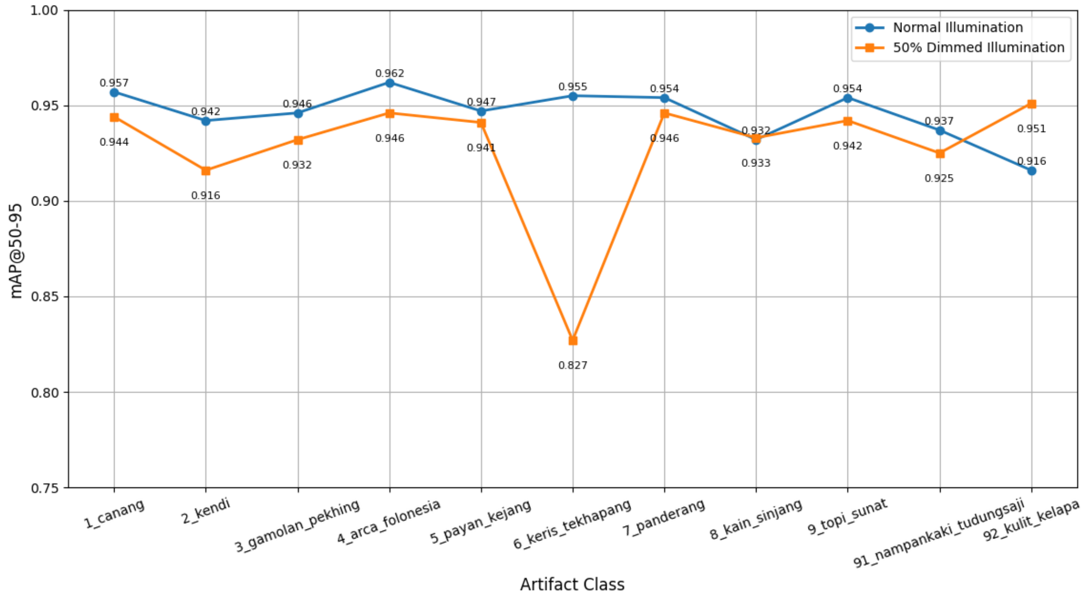

Figure 4. Comparion of under normal and 50% dimmied illmunination.

3.2.3 Performance under 50% Brightened Light Scenario

The final evaluation step was performed under a lighting condition which was brightened by 50 percent to analyze the performance of the YOLOv9 model in an overexposed environment. In this case, the dataset had an average brightness value of 167.31, an estimated gamma value of 1.7895 and an average luminance (L^*) value of 178.02. The evaluation results present that the macro-average mean Average Precision at 50 percent Intersection over Union ($mAP@50$) score is steady at 0.995. This result shows the model still detected object categories with increased illumination conditions with consistent detection.

Table 6. Performance metrics under 50% brightened illumination scenario

Class ID	Target Artifact Class Name	Precision	Recall	$mAP@50$	$mAP@50\text{-}95$
1	1_canang	1.000	0.932	0.995	0.936
2	2_kendi	0.986	1.000	0.995	**0.882**
3	3_gamolan_pekhing	0.983	1.000	0.995	0.995
4	4_arca_folonesia	0.981	1.000	0.995	0.970
5	5_payan_kejang	0.934	1.000	0.995	0.995
6	6_keris_tekhapang	0.996	1.000	0.995	**0.855**
7	7_panderang	0.938	1.000	0.995	**0.885**
8	8_kain_sinjang	0.983	1.000	0.995	0.995
9	91_nampankaki_tudungsaji	0.976	1.000	0.995	0.974
10	92_kulit_kelapa	0.978	1.000	0.995	0.904
11	9_topi_sunat	0.985	1.000	0.995	0.869
	Macro Average (μ)	0.976	0.994	0.995	0.933

However, as shown on Figure 5, the $mAP@50\text{-}95$ score was reduced to 0.933 compared with the performance under normal illumination conditions. This reduction suggests that the effect of excessive brightness on localization accuracy was more significant with stricter Intersection over Union thresholds. The effect of excessive illumination was different for different object categories at the class level. There are some classes such as 2_kendi, 6_keris_tekhapang and 7_panderang which have reflective surfaces or relatively uniform colors and these classes have significant decreases in $mAP@50\text{-}95$ values which are recorded at 0.882, 0.855 and 0.885 respectively. On the other hand, object categories with more apparent visual patterns and different texture properties, such as 3_gamolan_pekhing and 8_kain_sinjang, retained high localization performance with $mAP@50\text{-}95$ values of 0.995.

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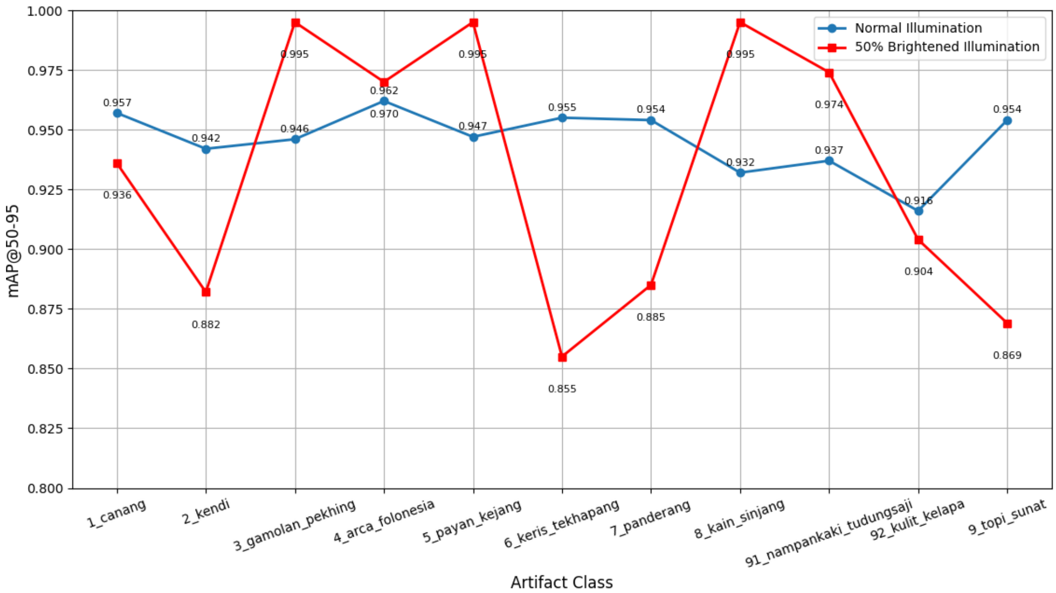

Figure 5. Comparison of mAP@50-95 Under Normal and 50% Brightened Illumination.

These findings imply that over-illumination and over-reflection could be detrimental to the localization accuracy of certain types of objects, especially those with smooth surfaces or low visual contrast. However, the macro-average Precision and Recall overall remained relatively stable at 0.976 and 0.994 respectively, indicating that the model was still able to maintain consistent detection performance under bright lighting conditions. The detailed performance results for each object category under the 50 percent brightened lighting are presented in Table 6.

3.3 Computational Latency and Real-Time Feasibility Analysis

In addition to the assessment of detection accuracy and localization performance, a detailed analysis of computational latency was carried out to evaluate the inference time of the YOLOv9 model in different illumination conditions. Latency measurement accounted for the full processing time of image preprocessing, feature extraction and object prediction in the inference stage. We ran all illumination test subsets on a fixed hardware configuration for evaluation. The detailed latency results are presented in Table 7.

Table 7. End-to-end inference latency performance across photometric scenarios.

Illumination Testing Subset	Minimum Latency	Maximum Latency	Core Dense Interval	Real-Time Feasibility Status
50% Dimmed Scenario	408 ms	520 ms	430 ms – 480 ms	Feasible (*Near Real-Time*)
Baseline Normal Scenario	415 ms	600 ms	420 ms – 490 ms	Highly Optimal (*Real-Time*)
50% Brightened Scenario	475 ms	605 ms	500 ms – 550 ms	Acceptable Bounds

Experimental results indicated that the normal illumination scenario presented the most stable inference performance with processing times mainly in the range of 420 milliseconds to 490 milliseconds. For the 50% dimmed lighting condition, the inference performance of the model was relatively stable with processing times generally found between 430 milliseconds and 480 milliseconds. The results show that the effect of reduced illumination on the computational processing time during object detection was limited.

In contrast, the 50 percent brightened lighting scenario resulted in increased inference latency compared to other testing conditions. For this scenario, most inference times were between 500 and 550 milliseconds, with maximum latency at 605 milliseconds. This increase in latency might be caused by high brightness and reflection effects that add visual complexity to the detection process. However, overall inference times remained within acceptable limits for interactive museum guide applications and practical object detection scenarios. In general, the results indicate that the YOLOv9 model can maintain stable detection performance with relatively consistent computational latency under various illumination conditions.

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4. CONCLUSION

This paper evaluates the robustness of the YOLOv9 model in the context of museum object detection under different illumination conditions, including normal lighting, 50 percent dimmed lighting, and 50 percent brightened lighting scenarios. The experimental results show that the model has good detection performance under normal illumination with a macro-average mean Average Precision at IoU threshold 0.50 ($mAP@50$) of 0.995 and mean Average Precision across IoU thresholds from 0.50 to 0.95 ($mAP@50\text{-}95$) value of 0.946. The results show that YOLOv9 can reliably detect and localize museum objects under normal environmental lighting. For the 50% dimmed lighting condition, the model still maintained a relatively stable detection performance, with the macro-average $mAP@50$ only slightly decreased to 0.994 and the $mAP@50\text{-}95$ decreased to 0.928. In the 50% brightened lighting condition, the model also held a $mAP@50$ value of 0.995 and the $mAP@50\text{-}95$ value was reduced to 0.933. The results demonstrate that changes in illumination have a greater impact on the localization accuracy at higher Intersection over Union (IoU) thresholds than on the general object detection performance. In particular, objects with thin structures, mirrored surfaces or low visual contrast suffered from large drops in localization performance under extreme lighting conditions. In terms of computational performance, the latency evaluation validated the relatively consistent inference times of the model under different illumination conditions. The inference times ranged from 420 ms to 490 ms on average for normal lighting conditions, with the highest latency observed for the 50 percent brightened case with a maximum processing time of 605 ms. The improved illumination meant an increased computational cost, but this was compensated by the overall good processing speed, which was fast enough for the interactive museum guide applications and the practical object detection applications. Finally, the experimental results show that the YOLOv9 model can achieve stable object detection performance under different lighting conditions in the museum environment. The results of this work contribute to the design of illumination-aware object detection systems for smart museums and cultural heritage applications.

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