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Effect of Image Pre-Processing Techniques on Object Detection

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Abstract: This work analyses how different image pre-processing techniques affect object detection results. Objects are detected after applying various processing methods, and the outputs are compared. Most existing studies focus on improving object detection models, but there is limited work analysing how individual pre-processing techniques influence detection results. YOLOv8 (You Only Look Once) is used in this study as it is a fast and reliable model pre-trained on the COCO (Common Objects in Context) dataset. The focus of this work is to observe how different techniques affect the number of detected objects and their corresponding confidence scores, which indicate how certain the model is about a detected object and its location. The effects of techniques such as greyscale conversion, histogram equalisation, contrast adjustment, blurring, and edge detection are analysed on real-world images and a subset of the COCO dataset. Approximately 20 images from the coco128 subset are used for controlled analysis. The evaluation is based on a relative comparison of detection outputs using detection count and confidence scores (above a threshold of 0.5). It is observed that different techniques perform differently depending on the image, and no single method consistently provides the best results. This study helps in understanding how pre-processing influences object detection behaviour and supports better selection of techniques based on the input image.

Keywords: Object Detection, YOLOv8, COCO Dataset, Image Pre-processing, Confidence Scores, Histogram Equalisation, Edge Detection

I. INTRODUCTION

A. Background

Object detection identifies the objects present in a given image. Some of the common uses of object detection are surveillance, self-driving cars, and medical image analysis. Earlier, object detection was slow and less accurate, but with improvements in deep learning, it has become faster and more accurate.

YOLO (You Only Look Once) is a commonly used deep learning model based on Convolutional Neural Networks (CNNs) for object detection. It is fast and provides good accuracy, making it suitable for real-world applications.

Image pre-processing involves modifying the raw input image before providing it to the model. Techniques such as greyscale conversion, blurring, edge detection, and contrast adjustment modify image features like edges, brightness, and texture. Due to this, there is an effect on how the model interprets the image and detects the objects. In some cases, pre-processing improves detection, while in others it may reduce performance.

When different pre-processing techniques are applied, detection results can change significantly. This is because each technique modifies image features differently. There is no single technique that works best for all images, as each produces different results depending on the input.

Most existing work focuses on improving object detection models such as YOLO and other deep learning architectures. However, there is not much attention given to analysing how each technique affects the detection results. As a result, the impact of these techniques is not clearly understood, making it difficult to determine which method works best.

B. Objective

This work analyses the effect of a few pre-processing techniques on object detection, such as greyscale conversion, edge detection, contrast adjustment, and blurring. Objects are detected using YOLOv8n [1]. The results are evaluated

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using the average confidence score of detections above 0.5. The performance of different pre-processing techniques is compared to understand how each method affects detection results.

II. LITERATURE REVIEW

Studies exist where models such as YOLO and SSD are compared [2], and efforts are made to improve their performance. Most existing papers focus on model performance, accuracy, and speed, but do not focus on how pre-processing affects object detection. As a result, the impact of pre-processing techniques on detection performance is not clearly studied.

In many cases, pre-processing techniques are used as a basic step before detection but are not analysed in detail. They are mainly applied to improve input quality without studying how each technique affects results. They are compared to evaluate which model is faster (in terms of speed) and more accurate (in terms of detection correctness). They are evaluated based on detection confidence, speed, and accuracy.

Pre-processing is mentioned but not analysed in detail. Since most papers focus on improving the model, pre-processing is treated as a basic step and not analysed. Image pre-processing affects detection, as it changes the image slightly. This can either increase or decrease visibility, which affects how the model sees and detects the object.

For example, blur might blur the main object, making detection incorrect, or it might affect only the background, increasing focus on the main object and improving detection. Another example is greyscale conversion, which reduces RGB channels to a single channel. In this work, different pre-processing techniques are compared to analyse how they affect object detection using the YOLO model. YOLO is chosen as it is a widely used object detection model known for its speed and accuracy. The number of objects detected with confidence above 0.5 is used for evaluation.

III. METHODOLOGY

A. Model Used

YOLO (You Only Look Once) is a deep learning model used for object detection. It is based on Convolutional Neural Networks (CNNs), which extract features from images such as edges, shapes, and textures.

Unlike traditional methods, YOLO performs detection in a single step by processing the entire image at once. It divides the image into regions and predicts bounding boxes, object labels, and confidence scores for each region. The confidence score indicates how certain the model is about the detected object.

YOLO also removes overlapping detections by keeping only the most relevant bounding box, which helps avoid duplicate detections. In this project, YOLOv8n is used as it is lightweight, fast, and suitable for testing multiple pre-processing variations.

B. Dataset

The dataset used in this work is coco128, which is a subset of the COCO (Common Objects in Context) [3] dataset and contains 128 images. From this dataset, approximately 20 images were selected for analysis without any specific ordering. These images include a variety of real-world objects, which helps in observing how different pre-processing techniques affect object detection in different scenarios.

C. Pre-processing Techniques

Different image pre-processing techniques are applied before object detection. These techniques modify the image in different ways and can affect how the model detects the objects. The techniques used in this project are:

Original: No changes are made to the image.

Greyscale: The provided image is converted from multi-coloured to a single channel. This reduces colour information but retains structural details.

Greyscale with Histogram Equalisation: Image is converted to greyscale, then contrast is enhanced using histogram equalisation. This helps in improving visibility in low-contrast regions.

Histogram Equalisation: Contrast of images is enhanced by redistributing pixel intensities.

Blurred (Gaussian): Smoothing filter to reduce noise in the image. Helps remove small variation but may also remove important details.

Median Blur: Noise is reduced by replacing each pixel with the median of surrounding pixels. Removes salt-and-pepper noise while preserving edges.

Brightened: Brightness of the image is increased. Objects can be more visible in darker regions.

High Contrast: The difference between light and dark regions is increased. Enhances object boundaries and features.

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Sharpened: Edges and fine details are enhanced. Makes object boundaries clearer.

Edge Detection: Only edges are highlighted. Removes most colour and texture information, focusing only on outlines.

The pre-processed images were passed to the model for detection. These techniques were selected as they are commonly used in image processing and they modify important features such as brightness, contrast, and edges, which can influence how the model interprets the image.

D. Workflow

The system allows both sample images and user-uploaded images as input. For each input, the selected pre-processing techniques are applied, and the processed image is then passed to the YOLOv8 model for object detection. The model returns object labels, bounding boxes, and confidence scores. For this project, labels and confidence scores are primarily used. Labels indicate the object detected, while confidence scores represent how certain the model is about each detection. The number of detected objects and their corresponding confidence scores are used to compare the different pre-processing techniques. The same image is processed using all selected techniques, and the outputs are compared to observe the effect on object detection results.

E. Evaluation

The evaluation was done using the output provided by the YOLOv8 model. The model returns bounding boxes, object labels, and confidence scores for each detected object. In this work, object labels are used for identification and counting the number of objects detected. The confidence scores indicate how certain the model is about the detected objects.

The performance of each pre-processing technique is evaluated based on the number of objects detected and the average confidence score. These values are used to compare how different image pre-processing techniques affect object detection results. A technique is considered the best in this system if it gives a higher number of detections and provides higher average confidence scores; however, this depends on the methods and the input image. For confidence scores, only detections with a score above 0.5 are considered; the rest are ignored.

F. Database

1) MySQL: To improve efficiency, a MySQL database is used to avoid re-processing the same image multiple times. This reduces repeated computation and improves efficiency when the same image is used again.

2) Hashing: To support efficiency, once an image is loaded, it is hashed, creating a unique ID based on its pixel values. Since file names can be changed, either intentionally or unintentionally, relying on file names is not reliable. However, changing the file name does not affect the pixel values, allowing the image to match the previously generated hash. If a matching hash is found and the requested pre-processing result is already stored in the database, the stored data is retrieved.

IV. RESULTS AND OBSERVATIONS

The overall behaviour of different pre-processing techniques is summarised in Table I.

TABLE I SUMMARY OF OBJECT DETECTION BEHAVIOUR ACROSS DIFFERENT IMAGE PRE-PROCESSING TECHNIQUES

Preprocessing Method	General Observation	Confidence Trend	Object Detection Trend
Original	Best / Consistent	High	Stable
Greyscale	Very Good	Slightly lower than original	Stable
Greyscale + Histogram Equalisation	Good	Moderate to high	Slight variation
Histogram Equalisation	Variable	Moderate	Sometimes increases count
High Contrast	Variable	Moderate	Can increase detections
Brightened	Moderate	Slightly reduced	Minor variation

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Sharpened	Moderate	Reduced in some cases	Stable
Blurred	Poor	Low	Reduced reliability
Median Blur	Poor	Low	Reduced detection consistency

** The observations in Table I are based on a relative comparison of detection outputs, considering detection count and confidence scores across multiple images.*

As shown in Table I, different pre-processing techniques produce slightly different detection results. The detected object remains the same (car) in most cases, but the confidence scores vary. It can be observed that techniques such as greyscale, brightening, and high contrast provide slightly higher confidence compared to the original image. Only detections with confidence above 0.5 are displayed; therefore, some techniques are not visible in the figure.

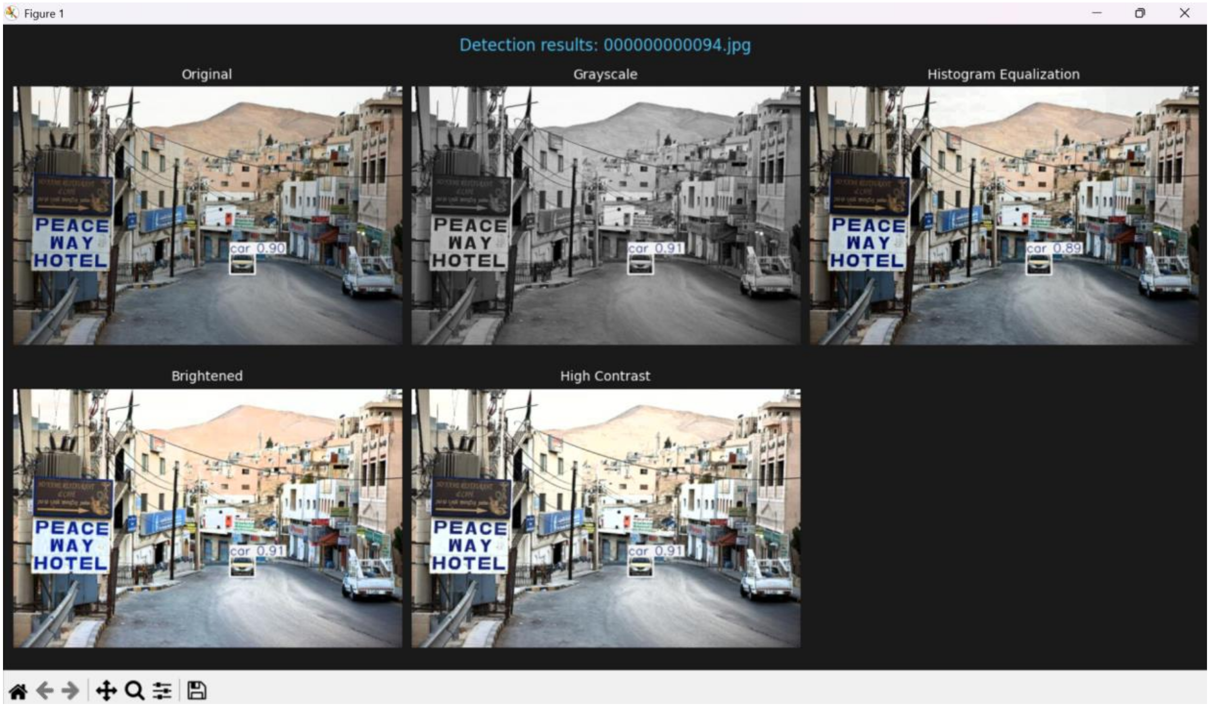

Fig. 1. Comparison of object detection results

The numerical results obtained for different techniques on a single test image are shown in Table II.

TABLE II DETECTION RESULTS FOR DIFFERENT PRE-PROCESSING TECHNIQUES ON A SINGLE IMAGE

Method	**Object Detected**	**Confidence**
Original	Car	0.8956
Greyscale	Car	0.9071
Histogram Equalisation	Car	0.8891
Blurred	None	0.0000
Brightened	Car	0.9139
High Contrast	Car	0.9076
Edge Detection	None	0.0000

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As shown in Table II, techniques such as brightening, greyscale, and high contrast produce higher confidence scores compared to the original image. On the other hand, techniques such as blurring and edge detection do not detect the object, resulting in zero confidence. This shows that certain pre-processing techniques may remove important features required for object detection.

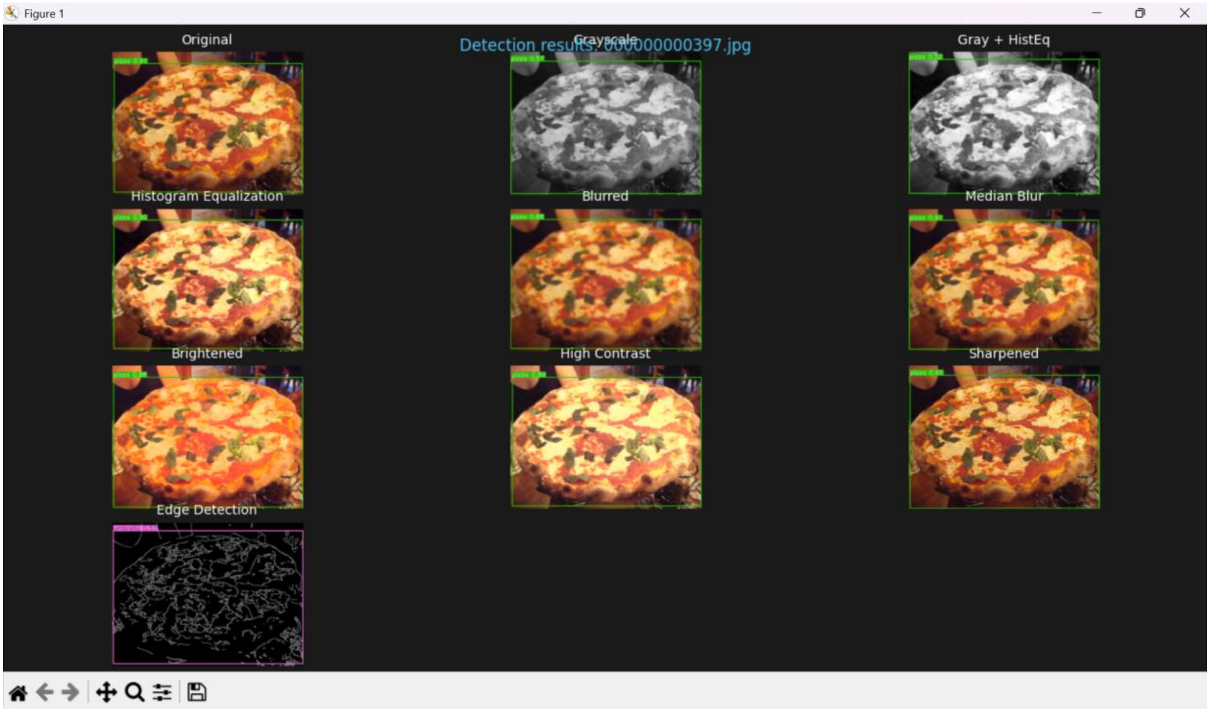

Fig. 2. A second image with different pre-processing applied and the objects detected

The numerical results obtained for different techniques on the second test image are shown in Table III.

TABLE III DETECTION RESULTS FOR DIFFERENT PRE-PROCESSING TECHNIQUES

Method	Object Detected	Confidence
Original	Pizza	0.9053
Greyscale	Pizza	0.5704
Greyscale + HistEq	Pizza	0.5228
Histogram Equalization	Pizza	0.8982
Blurred	Pizza	0.8828
Median Blur	Pizza	0.9053
Brightened	Pizza	0.8825
High Contrast	Pizza	0.89
Sharpened	Pizza	0.6461
Edge Detection	Umbrella	0.5066

As shown in Table III, techniques such as brightening and greyscale provide higher confidence scores, while techniques such as blurring and edge detection may lead to incorrect detections or reduced reliability. Overall, the results show that different pre-processing techniques affect detection behaviour differently, and no single technique works best for all cases.

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V. CONCLUSION

This work analysed how different image pre-processing techniques affect object detection using YOLOv8. Techniques such as greyscale conversion, histogram equalisation, blurring, and contrast adjustment were used, and the resulting changes in detection outputs were observed.

From the results, it can be seen that different techniques affect detection in different ways. Techniques such as brightening and high contrast slightly improved the confidence scores, while others such as blurring and edge detection reduced detection reliability or failed to detect the object.

It was also observed that there is no single pre-processing technique that works best for all images. The results depend on the input image and how each technique alters its features. In future work, a larger set of images can be tested, and additional techniques can be explored to better understand their effect on detection.

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