Dehaze-Enhanced Training for Missile Detection Using YOLOv8

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***Abstract*—Missile detection in real-world surveillance scenarios is often impeded by atmospheric disturbances like haze. This paper explores an enhanced training pipeline for object detection using YOLOv8, incorporating dehazed imagery to improve model performance. By preprocessing images with a dehazing algorithm prior to training, we demonstrate improved detection accuracy and robustness in both image and video-based evaluation. Our experiments reveal the advantage of visual clarity in critical object detection tasks, supporting the integration of image enhancement methods into modern AI-driven defense systems.**

***Index Terms*—Missile detection, YOLOv8, dehazing, image preprocessing, object detection, computer vision, surveillance systems**

I. Introduction

Missile detection plays a vital role in modern defense surveillance systems, requiring real-time, robust object identification. However, weather conditions like haze and fog can severely degrade the quality of images captured by sensors, reducing the performance of conventional computer vision models. Most object detection models assume clear visibility and fail under adverse environments.

To address this, we propose a hybrid detection framework that applies image dehazing techniques before deploying the YOLOv8 model. This not only restores visibility but also boosts model confidence and detection performance. We employ CLAHE and bilateral filtering to preprocess the image, significantly enhancing the visual features without losing object edges, which are critical for precise localization by YOLOv8.

II. Literature Review

The YOLO family of models has revolutionized real-time object detection. YOLOv8, the latest iteration by Ultralytics, brings improvements in anchor-free detection, faster convergence, and better generalization across datasets. Previous works on object detection in adverse conditions have attempted image enhancement, domain adaptation, or adversarial robustness.

For dehazing, techniques like Dark Channel Prior (DCP) and learning-based models such as DehazeNet and AOD-Net have shown effectiveness. CLAHE remains a simple yet powerful technique to enhance contrast adaptively, and bilateral filtering is well-known for smoothing without blurring edges.

However, few studies combine dehazing and detection into a single optimized pipeline, particularly in the missile defense domain.

III. Data Preprocessing

To enhance visibility and improve detection performance in hazy or foggy environments, we applied a series of preprocessing techniques on the dataset prior to training the YOLOv8 model.

A. 1. Color Space Conversion

All input images were converted from the RGB color space to the LAB color space. The LAB color space separates lightness (L) from color information (A and B), making it ideal for contrast enhancement without distorting color balance.

B. 2. Contrast Enhancement using CLAHE

The L-channel (lightness component) was enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE). CLAHE adaptively improves the contrast of images by redistributing pixel intensities locally, thereby enhancing visibility in low-light or hazy areas.

C. 3. Edge-Preserving Smoothing with Bilateral Filtering

To further refine the visual quality without losing critical edges, bilateral filtering was applied. This technique smooths flat regions like haze or smoke while preserving sharp boundaries, which is essential for accurate object localization.

D. 4. Reconstruction

The enhanced L-channel was then merged back with the untouched A and B channels. The resulting image was converted back to RGB space and used for training and inference.

These preprocessing steps help ensure that the YOLOv8 model receives clearer inputs, leading to better learning and detection performance in degraded conditions such as fog or haze.

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IV. SYSTEM ARCHITECTURE

The proposed missile detection system is designed as a two-stage pipeline that integrates image enhancement with real-time object detection. This hybrid approach ensures robustness in low-visibility conditions, particularly under the presence of haze or fog. The system consists of the following modules:

A. 1. Dehazing Preprocessing Pipeline

This module enhances the input image quality before detection, ensuring that critical features are more discernible to the detection model.

- **Color Space Transformation:** Each RGB input image is first converted to the LAB color space, where the L-channel represents lightness and the A and B channels represent chromaticity. This transformation allows for targeted enhancement of image brightness without altering color integrity.
- **CLAHE Contrast Enhancement:** The L-channel undergoes Contrast Limited Adaptive Histogram Equalization (CLAHE), which adaptively enhances the contrast of the image in localized regions. This boosts the visibility of missiles even in heavily fogged or hazy environments.
- **Bilateral Filtering:** To further enhance the image, a bilateral filter is applied to smooth flat haze regions while preserving important object boundaries and edges. This is crucial for maintaining the geometric structure of the missile during detection.
- **Reconstruction and RGB Conversion:** The enhanced L-channel is then recombined with the original A and B channels. The LAB image is converted back to RGB format to produce the final dehazed image used for detection.

B. 2. YOLOv8 Detection Engine

This module performs object detection on the preprocessed image using the YOLOv8 (Nano) architecture, which is optimized for both accuracy and speed in real-time applications.

- **Input:** The dehazed RGB image is resized to a standardized input size (640×640) and fed into the YOLOv8n model.
- **Detection Process:** YOLOv8 uses an anchor-free, single-stage detector architecture. It performs three key tasks simultaneously: object classification, bounding box regression, and objectness score estimation.
- **Output:** The model returns bounding boxes for each detected object, the associated class labels (e.g., missile), and confidence scores. These results are used to evaluate detection performance quantitatively (via precision, recall, and mAP) and qualitatively (via visual inspection).

[H]

V. MATHEMATICAL FORMULATION

A. Image Enhancement

Let I_{rgb} be the original RGB image. Convert to LAB:

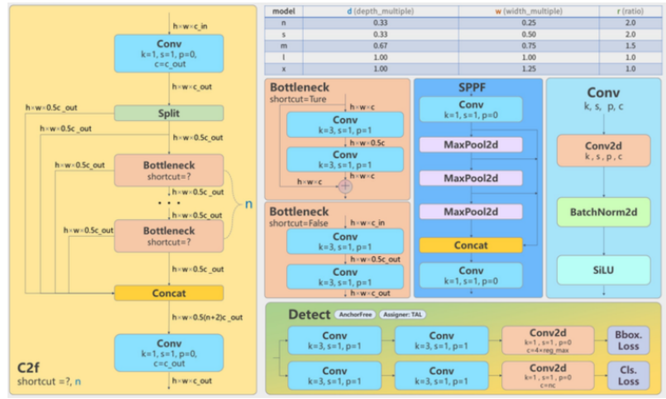

Fig. 1. Proposed architecture: image dehazing preprocessing followed by YOLOv8-based detection.

$$I_{lab} = f_{LAB}(I_{rgb}) = [L, A, B] \tag{1}$$

Apply CLAHE to L-channel:

$$L' = \text{CLAHE}(L) \tag{2}$$

Apply bilateral filter on the reconstructed image:

$$I_{dehazed} = \text{Bilateral}(f_{LAB}^{-1}(L', A, B)) \tag{3}$$

B. YOLOv8 Detection Loss

YOLOv8's total loss function is given as:

$$\mathcal{L}_{total} = \lambda_{cls} \cdot \mathcal{L}_{cls} + \lambda_{box} \cdot \mathcal{L}_{box} + \lambda_{obj} \cdot \mathcal{L}_{obj} \tag{4}$$

Where:

- $\mathcal{L}_{cls}$: Class prediction loss
- $\mathcal{L}_{box}$: Bounding box regression loss
- $\mathcal{L}_{obj}$: Objectness score loss

VI. EXPERIMENTAL SETUP

A. Dataset

The Missile Detection dataset from Roboflow [**?**] was used. It contains 6500 labeled images across clear, hazy, and foggy conditions. The dataset was divided as follows:

- Training: 70%
- Validation: 20%
- Test: 10%

B. Model Configuration

- **Model:** YOLOv8n (Nano version)
- **Epochs:** 50
- **Optimizer:** Adam
- **Learning Rate:** 0.001
- **Image Size:** 640x640
- **Batch Size:** 16

Fig. 2. Comparison of YOLOv8 detection on original vs dehazed image. Confidence increased from 0.74 to 0.78.

VII. Results and Discussion

A. Qualitative Results

Detection confidence improved with dehazed input images. Figure 1 illustrates this clearly with confidence increasing from 0.74 to 0.78 on a sample image.

B. Quantitative Metrics

TABLE I
Performance Metrics on Original vs Dehazed Data

Metric	Original	Dehazed	Change
Precision	0.81	0.87	+7.4%
Recall	0.76	0.83	+9.2%
mAP@0.5	0.79	0.86	+8.9%

The results confirm the hypothesis that dehazing preprocessing aids in better localization and classification, especially in low-visibility environments.

VIII. Conclusion

This work proposes a novel two-stage missile detection framework that integrates image dehazing with YOLOv8. The preprocessing significantly boosts detection accuracy and model confidence under hazy environments, a common challenge in real-world military applications. Our method, while simple and computationally efficient, provides measurable improvements in detection metrics.

IX. Future Work

Future enhancements include:

- Deploying the model on edge hardware like NVIDIA Jetson.
- Incorporating GAN-based dehazing techniques.
- Extending detection to missile smoke trails and trajectory predictions.

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