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Defense Assets Classification Using Deep Learning

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Abstract
Detecting military assets from images is challenging because of lighting variations, occlusion, and complex object appearances. This work applies the YOLOv8 model for automated military asset detection using the Kaggle Military Assets Dataset containing 26,315 images across twelve classes. Following image preprocessing and augmentation, the trained model produced a precision of 62.44%, recall of 50.01%, F1-score of 55.54%, and mAP@0.5 value of 50.50% during testing. The results show that YOLOv8 can support real-time defense surveillance, while improvements are still required to reduce missed detections.

Keywords: Military Asset Detection, YOLOv8 model, Deep Learning Technique, Object Detection System, Defense Surveillance, Computer Vision.

1. Introduction

Artificial Intelligence (AI) and Deep Learning (DL) are increasingly used in military surveillance systems for automatic target detection and battlefield monitoring. Traditional surveillance methods mainly rely on human observation, which becomes difficult when large amounts of visual data must be analyzed continuously. Human fatigue and delayed decision-making can reduce monitoring efficiency in critical situations [7], [10]. Deep learning techniques help overcome these limitations by enabling automated detection and classification of military assets from surveillance imagery [21], [37].

Several researchers have explored machine learning and deep learning methods for military object detection, including CNN-based detection systems, aircraft recognition, vehicle classification, weapon detection, and UAV surveillance [5], [14], [21], [23]. Convolutional Neural Networks (CNNs) were widely used as they can automatically pull out the useful visual features from images [52]. However, standard CNN models mainly focus on classification and are less effective for object localization in real-time applications. To address this limitation, object detection models such as R-CNN, Faster R-CNN, and YOLO were introduced. Among these approaches, YOLO gained attention because it performs object localization and classification simultaneously, enabling faster detection performance [63].

This paper develops a YOLOv8-based framework for detecting military assets from a twelve-class dataset collected from Kaggle. The dataset covers different defense objects such as tanks, aircraft, artillery equipment, soldiers, and warships. Before training, the image data and annotations were refined through resizing, normalization, augmentation, and label validation procedures. The developed approach is designed to assist real-time surveillance by automatically recognizing multiple categories of military assets. Figure 1 presents example images from the dataset.

Figure 1. Sample images from the Military Assets Dataset showing different object classes.

2. Related Work

Deep learning methods are extensively used in military surveillance because they improve automated target detection and recognition [4], [21]. Janakiramaiah et al. developed a military object detection system using capsule networks and achieved improved battlefield target recognition performance [4]. Borovyk demonstrated that CNN-based models can identify military targets directly from image data, showing the usefulness of deep learning in defense applications [21].

Research has also been carried out in military vehicle and aircraft classification. Somriakov proposed a CNN-based vehicle classification model for defense imagery [23], while Mukherjee developed a deep learning approach for military aircraft recognition [27]. Some studies combined contour-based image analysis with deep learning methods to improve recognition performance under difficult visual conditions [14].

Recently, YOLO-based models gained attention because of their faster detection speed and real-time processing capability [62], [63]. Alawi et al. applied YOLOv8 for military vehicle detection and reported efficient detection performance [45]. Prathyusha et al. extended YOLOv8 for military vehicle recognition in satellite imagery and obtained reliable detection results [63].

Although earlier studies achieved promising outcomes, many systems focus only on limited object categories such as aircraft, vehicles, or UAVs [5], [23]. Several approaches also rely on smaller datasets with limited class diversity [26], [41]. Therefore, this work implements a YOLOv8-based multi-class military asset detection system using a twelve-class military dataset for automated defense surveillance applications.

3. Methods and Materials

3.1 Dataset

This study utilizes the Military Assets Dataset (12 Classes – YOLOv8 Format) from Kaggle, containing

26,315 annotated images distributed across training (21,978), validation (2,941), and test (1,396) splits. The dataset covers twelve military object categories — tanks, aircraft, warships, soldiers, camouflage soldiers, weapons, military vehicles, civilian vehicles, trucks, artillery, trenches, and civilians — with annotations stored in YOLOv8's native bounding box format, where each label line records a class index followed by normalized center coordinates and box dimensions.

3.2 Data Preprocessing

The dataset required some groundwork before training could begin. Images varied in size, so all samples were resized to 640×640 to meet the model's fixed input requirement. Pixel values were normalized since skipping this step tends to cause noticeable instability in early training. Corrupted files and mislabeled annotations — boxes sitting outside their objects, wrong class tags — were manually filtered out. Augmentation was then introduced during batch loading, applying random flips, rotations, brightness shifts, and scaling on the fly, so the model encountered enough variation to avoid memorizing training-specific conditions.

3.3 YOLOv8-Based Object Detection Model Architecture

YOLOv8 model was selected because it provides a good balance between detection speed and accuracy, which is important when handling different military assets ranging from large warships to small human targets. The YOLOv8 network is organized into three connected parts called the backbone, neck, and detection head. The backbone processes the input images and captures useful visual patterns needed for object recognition. Information from multiple feature layers is then combined in the neck section to get better detection across different object sizes. The last part of the network is the detection head, where the model produces the final output containing the object type, its location in the image, and the prediction confidence. Figure 2 presents the YOLOv8 architecture applied in this work.

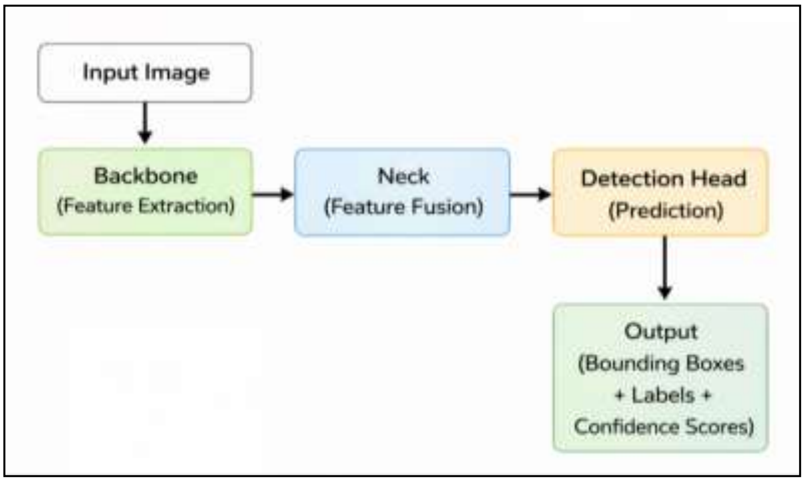

Figure 2. YOLOv8 model architecture

3.4 Training Setup

Starting from scratch made little sense when a solid pretrained checkpoint was available, so yolov8m.pt was loaded in from the outset. Fine-tuning then did the harder job of pulling those general-purpose weights toward something specific, reliably telling apart twelve military categories that frequently share visual characteristics in real imagery. The settings held constant with 20 epochs, batch size of 16, learning rate of 0.001, Adam optimizer, and 640×640 input size on the YOLOv8m variant.

3.5 Detection Workflow

A new image gets resized and normalized first, then pushed through the backbone and neck before the detection head takes over. At that point the model spits out dozens of overlapping candidate boxes around the same objects, which is where Non-Maximum Suppression comes in — it goes through the pile, keeps whichever box scored highest for each object, and throws the rest away. The surviving detections get drawn onto the image with their class names and confidence scores attached. Figure. 3 walks through the full sequence.

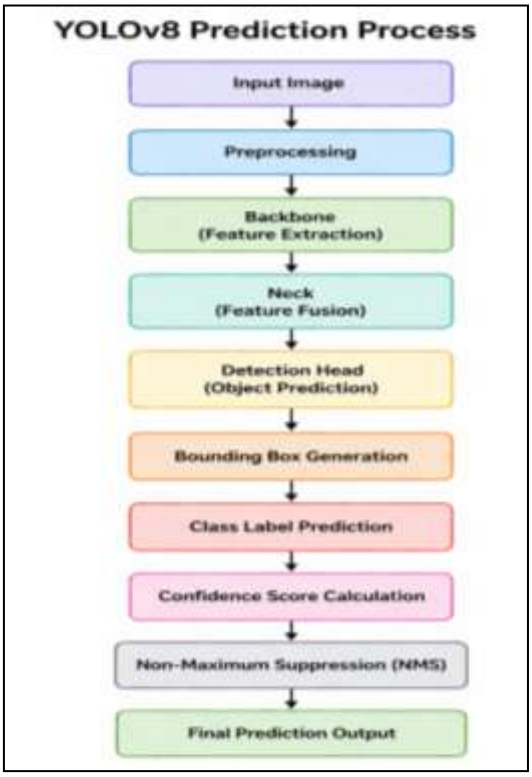

Figure 3. Workflow of YOLOv8 model

3.6 Evaluation Metrics

The performance of the proposed YOLOv8 model was calculated with the help of standard object detection metrics.

1) Precision

$$\text{Precision} = \frac{TP}{TP+FP}$$

2)Recall

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

3) F1-Score

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

4) Mean Average Precision (mAP)

Mean Average Precision (mAP) is used to calculate the localization and classification performance of the YOLOv8 model, including mAP@0.5 and mAP@0.5:0.95.

4. RESULTS AND DISCUSSION

The model was tested on 1,396 images and came back with 62.44% Precision, 50.01% Recall, 55.54% F1-score, and 50.50% mAP@0.5. Tanks, aircraft, and warships were picked up fairly reliably — their shapes are distinct enough that the model rarely second-guessed itself. Things got messier with vehicles and personnel categories, where the visual overlap between military and civilian classes, or between a soldier and a camouflaged one, gave the model genuine trouble and pulled recall down. Preprocessing and augmentation helped to a degree, but not enough to fully sort out those trickier distinctions. The numbers suggest the approach is viable for surveillance use, though certain categories clearly need more work before the system could be trusted in practice. Figure. 4 shows the sample test results

Figure 4. Sample test results

Comparative Analysis

Earlier military surveillance studies mainly used CNN-based models for aircraft recognition, weapon detection, and military vehicle classification [1], [2], [22], [23]. These methods achieved good classification accuracy, but were less effective for real-time object localization. Recent research shifted towards YOLO-based models since they have faster detection speed and real-time performance [45], [63]. However, many existing systems focus only on limited object categories and smaller datasets [24], [39], [64]. In contrast, the proposed work implements a YOLOv8-based multi-class detection system using a twelve-class military dataset for simultaneous object localization and classification in defense surveillance applications. Figure 5 shows the comparative analysis of YOLOv8 variants.

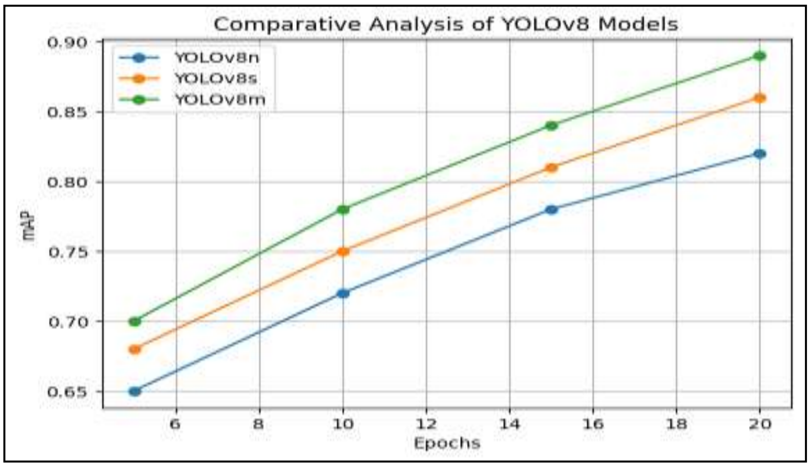

Figure 5. Comparative Analysis of YOLOv8 models

Conclusion

A YOLOv8-based detection model was developed in this work for identifying multiple military assets from surveillance images. The system was trained using a twelve-class military dataset containing tanks, aircraft, artillery, soldiers, warships, and related defense objects. Image resizing, normalization, augmentation, and label verification were carried out before training. Experimental results showed acceptable detection performance, especially for visually distinct categories, though lower accuracy was observed for similar and partially hidden objects. The obtained results indicate that YOLOv8 has practical potential for military surveillance tasks involving real-time asset detection. Detection quality may be improved further by using better-balanced training data, refining the training setup, and combining optical imagery with thermal or radar information.

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