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Adaptive Landmine Detection and Recognition in Complex Environments using YOLOv8 Architectures

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ABSTRACT

Landmine detection and recognition represent critical tasks in humanitarian and military operations, aiming to mitigate the devastating impact of landmines on civilian populations and military personnel. Landmine detection and identification using computer vision offers several advantages. Safety is enhanced, given the reduced exposure to humans in dangerous environments. Advanced algorithms are applied to increase the performance of a computer system operating with high accuracy and efficiency in the hidden location. Real-time processing makes Fast detection possible, which is essential for time-sensitive processes. Furthermore, unlike human operators, computer vision can work continuously without getting tired. The efficacy of these systems is further enhanced by their capacity to adapt to various environments. This abstract explores the application of You Only Look Once (YOLO), a state-of-the-art object detection algorithm, in landmine detection and recognition. YOLO offers real-time performance and high accuracy in identifying objects within images and video streams, making it a promising candidate for automating landmine detection processes. By training YOLO on annotated datasets containing diverse landmine types, terrains, and environmental conditions, the algorithm can learn to detect and classify landmines with remarkable precision. Integrating YOLO with unmanned aerial vehicles (UAVs) or ground-based robotic systems enables rapid and systematic surveying of large areas, enhancing the efficiency and safety of demining operations. The YOLOv8 is employed in this research to address the issue of missed detection and low accuracy in real-world landmine detection. For this study, we have assembled a data set of 1055 photos that were shot in various lighting and backdrop situations. This article aims to enhance landmine detection accuracy and efficiency using YOLOv8, overcoming traditional method limitations. In the experiment employing picture data, we obtained outstanding results with mAP = 93.2%, precision = 92.9%, and recall = 84.3% after training the model on the dataset numerous times. According to experimental results, the YOLOv8 has better detection accuracy and recall based on the landmine dataset. By improving the processing of real-time detection, we seek to create an avenue for a much safer and more efficient demining operation-one that could save lives and restore communities.

Keywords: Landmine, YOLO, Detection and Recognition, Computer Vision

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1 Introduction

Landmines persist as a significant threat in regions affected by conflict, causing casualties, hindering development, and preventing the return of displaced populations. Traditional ways of detecting landmines are frequently slow, costly, and prone to errors. Nonetheless, computer vision and deep learning developments provide promising approaches to automate and raise landmine detection and recognition precision.

This research focuses on leveraging the capabilities of YOLOv8, a state-of-the-art object detection algorithm, to detect and recognize landmines in real-world images [1]. The You Only Look Once (YOLO) model's evolution, known as YOLOv8, is well known for its quickness and precision in object detection tasks [2].

The integration of YOLOv8 in landmine detection and recognition offers several advantages. First, it allows for real-time processing of images, enabling swift identification of potential threats in the field. Second, its ability to detect multiple objects simultaneously enhances efficiency, which is crucial in scenarios where landmines may be scattered across vast areas. Third, its accuracy and robustness make it suitable for distinguishing landmines from other objects in complex environments [3].

These conventional landmine detection methods have inefficiencies, safety risks, and limited accuracy. Manual probing and metal detectors are extremely time-consuming and may expose the operators to hazardous conditions [4]. In that respect, YOLOv8 is far more efficient and safe. YOLOv8 can quickly review images and video streams for possible landmine threats using deep learning and computer vision. This reduces exposure risk to humans and other tangible benefits, such as increased accuracy and decreased time required in clearance operations.

In this study, we aim to address the challenges associated with landmine detection by developing a YOLOv8-based model trained on the landmine dataset encompassing various terrains and conditions. We will explore methods to mitigate false positives and enhance the model's ability to discern landmines from similar-looking objects or clutter.

This research's outcomes can potentially revolutionize landmine detection efforts, offering a faster, more accurate, cost-effective solution for identifying and neutralizing these deadly threats. By deploying automated systems equipped with YOLOv8-based algorithms, humanitarian organizations, and demining agencies can enhance their capabilities in safeguarding civilian lives and facilitating post-conflict reconstruction and development.

After numerous training on the dataset, the model got outstanding results: mAP = 93.2%, precision = 92.9%, and recall = 84.3%. The landmine detection system, with a precision of 92.9%, represents a significant advancement in safety and efficiency for mine clearance operations. This level of accuracy indicates that the system can correctly identify a high proportion of landmines while minimizing false positives and negatives. This accuracy rate dramatically reduces risks for personnel involved in mining activities and increases the safety of post-conflict regions.

2 Material and Method

This study used the YOLOv8 model, a machine learning-based algorithm. The system was implemented using Google Colaboratory, Ultralytics, and the Python Library.

2.1 Object Detection

Rescue operations, face detection, pedestrian detection, visual search engines, computation of objects of interest, brand detection, and many other areas are available for object detection applications. Deep learning techniques are frequently used in object detection algorithms, which try to detect and classify things in images automatically [8]. The region-based convolutional neural network (R-CNN) family of algorithms is a popular solution since it generates region proposals and classifies them using a convolutional neural network [9]. Another popular approach is the You Only Look Once (YOLO) model, which divides the input image into grid cells and predicts bounding boxes and class probabilities straight from them [10]. Other prominent algorithms include Single Shot MultiBox Detector (SSD) and Faster R-CNN, which enhance speed and accuracy [11]. These methods have considerably expanded the area of object identification, allowing for reliable and efficient detection of objects in various real-world circumstances. So, in this study, we will evaluate the performance of the well-known YOLOv8 in terms of detecting landmines in real-world images. Figure 1 shows the object detection and recognition by using Yolo.

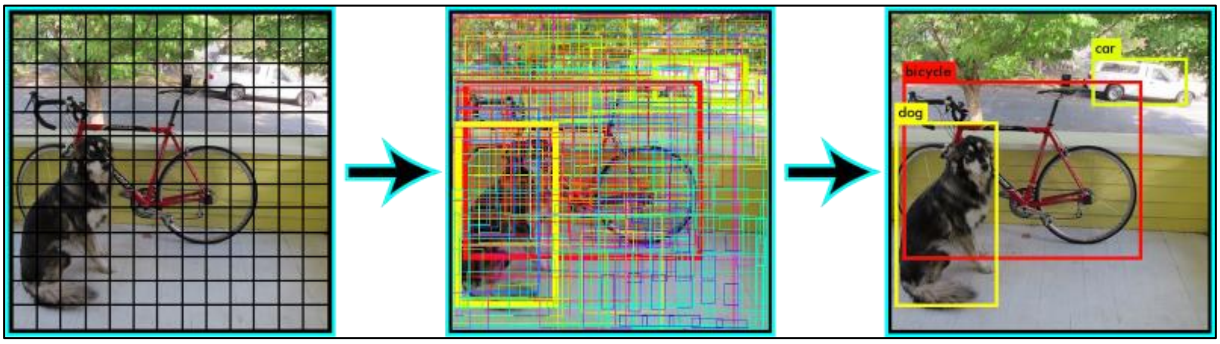

Figure 1: Object Detection and Recognition [12]

2.2 YOLOv8 (You Only Look Once) deep learning model

YOLOv8, also known as You Only Look Once version 8, is a convolutional neural network (CNN) architecture used for object detection in images and videos. It is an evolution of the YOLO (You Only Look Once) series of models, which are famous for their real-time object detection capabilities [13,14].

YOLOv8 builds upon the concepts introduced in earlier versions of YOLO, incorporating improvements in terms of accuracy and speed. One evaluation uses a single neural network to predict bounding boxes and class probabilities for objects directly from full images. This approach contrasts with other object detection methods that involve multi-stage processes [15].

YOLOv8 typically consists of a backbone network (often based on Darknet or another CNN architecture), followed by detection layers that predict bounding boxes and class probabilities. The model is trained on labeled datasets using gradient descent and backpropagation techniques to learn to recognize objects in various scenes [16].

YOLOv8 has been widely used in computer vision tasks such as autonomous driving, surveillance, and robotics, where real-time or near real-time object detection is essential. Researchers in the field continue to improve upon it, with each iteration aiming to enhance performance and efficiency [17,18].

The two primary components of the convolutional neural network used by YOLOv8 are the head and the backbone. YOLOv8 is an effective model for real-time object detection because of its design: a strong backbone for feature extraction, a sophisticated neck for feature aggregation, and a practical head for prediction. Integrating contemporary methodologies and optimizations guarantees its ability to identify objects with exceptional precision and swiftness [19,20]. Figure 2 shows YOLOv8 architecture.

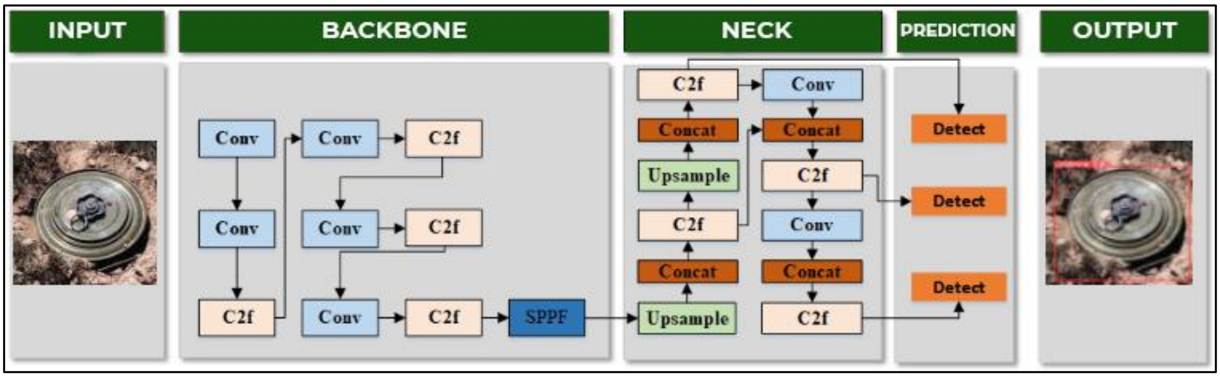

Figure 2: YOLOv8 Architecture

2.3 Landmine Bomb Dataset

The images in the dataset for YOLO models are annotated with bounding boxes and class labels to describe the items in the images. The YOLO model must be trained and performed well; hence, the dataset must be appropriately prepared and formatted. To do this, various images must be gathered, correctly annotated, and formatted appropriately before the dataset is divided into training, validation, and testing sets [21,22].

Data gathering, which involves obtaining a sizable image dataset that includes landmines, is required for this phase. This can be accomplished by collecting images from open sources, including news websites and social media, or taking pictures with specialized equipment. The dataset must be appropriately curated, duplicates removed, and landmine presence or absence tagged using manual or automated labeling techniques. A wide variety of landmine situations, including both tiny and large landmines and low- and high-light settings, are included in the collection. There are 1055 images in the dataset, which feature various kinds of landmines. The dataset has 923 training, 44 testing, and 88 validating entries.

Preparation of data and gathered landmine image collection is ready for training and testing of the landmine detection system at this stage. This entails manually annotating the images with bounding boxes surrounding the landmines using a tool known as Roboflow. After labeling the data, it is divided into training and testing sets to make sure each set is representative of the complete dataset. It might also be required to perform further pre-processing operations like data normalization or scaling. Having a sufficiently large and well-balanced dataset that can generalize well to new data is the aim.

The model choice to train the landmine detection model at this stage entails choosing the proper object detection algorithm. Some algorithms are available, each with pros and cons, including YOLOv8, Faster R-CNN, and SSD. The selected algorithm should function well on the gathered dataset and be able to manage various landmine situations based on the specifications of the landmine detecting system. Because of its accuracy and quickness, YOLOv8 is the best option. YOLOv8 is an efficient architecture, hence appropriate for optimized processing on UAVs and other mobile platforms. It has established itself to deal with complex, variable detection scenarios under harsh environmental conditions, therefore suitable for real-time applications needing fast and reliable detection.

The YOLOv8 model is trained on the labeled dataset prepared. Model training involves teaching the deep learning model to recognize the features of landmine images accurately. Figure 3 shows an example of a landmine image in the dataset.

Figure 3: Example landmine image in the dataset

3 Experimental Results and Discussion

Using the YOLO technique, a system was created in this work to identify and locate landmines in real-world images automatically. Randomly chosen landmine images from Google were submitted to the system, and their performance was examined for various images to assess the effectiveness of the suggested system. Images with multiple situations, including illumination, terrain, and occlusion levels, were included in the dataset. When tested, the system functioned as intended. Using YOLOv8, we trained the model over 110 epochs on the landmine data set. Standard criteria were taken into account when testing the performance. The precision, recall, and mAP criteria showed that the YOLOv8 was successful based on the results. Figure 4 illustrates the system's improved accuracy and decreased average loss.

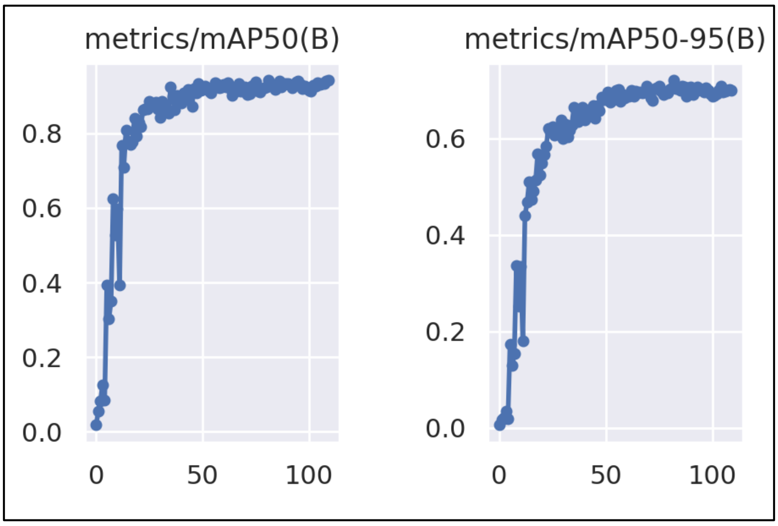

Figure 4: Accuracy of the system

Table 1 summarizes the YOLOv8 model's performance on the test set. Precision is the measure of exactness about how well the model made positive predictions. It gives the ratio of true positive predictions within the set of all the positive predictions of true and false positives and also shows the precision formula in Equation 1 [19].

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

TP = True positive.

FP = False positive.

Recall, sensitivity, or true positive rate is a metric estimating the model's capability of detecting all relevant instances of interest. It is the ratio of true positive predictions to all actual positive cases [19].

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

FN = False Negatives.

Mean Average Precision is an overall metric that calculates a model's precision at various recall thresholds. It's very helpful for multi-class object detection tasks [1].

$$mAP = \frac{1}{C} \sum_{i=1}^{C} APi \quad (3)$$

C = Number of classes.

APi = Average Precision for class i.

Table 1: *The performance of the YOLOv8 model on the test*

Metric	**Value**
Precision	92.9%
Recall	84.3%
mAP	93.2%

The YOLOv8 model achieved a high precision of 92.9, indicating that the model is very accurate in identifying true positives. The recall of 84.3 shows that the model is also effective in detecting most of the landmines in the images. The mAP of 93.2 suggests that the model is highly effective in detecting landmines when considering a moderate overlap criterion, indicating that the model maintains reasonable performance even under stricter localization requirements. The performance of YOLOv8 can be further dissected by examining the individual components of the loss function used during training: box loss and class loss. These losses provide insight into how well the model is learning to localize objects, classify them correctly, and detect the presence of objects.

Box Loss: Measures the accuracy of the predicted bounding boxes against the ground truth [23]. It combines localization errors regarding the bounding boxes' position, size, and shape. The box loss result equals 0.4922; Figure 5 shows it.

Class Loss: Evaluate how well the model classifies the detected objects into the correct categories (in this case, identifying objects as landmines) [24]. The class loss result equals 0.3232, as shown in Figure 5.

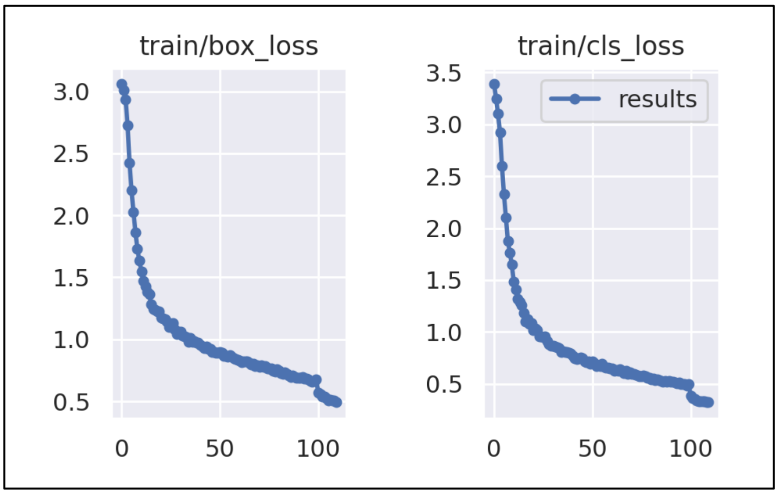

Figure 5: Box loss and Class loss

The model performed remarkably well, accurately detecting landmines in every situation. This successful identification demonstrates the model's resilience and capacity to manage various landmine detection scenarios, making it a valuable resource for automated landmine detection applications in practical contexts. We used the model to analyze several images, and the findings for two sample images are displayed (Figure 6).

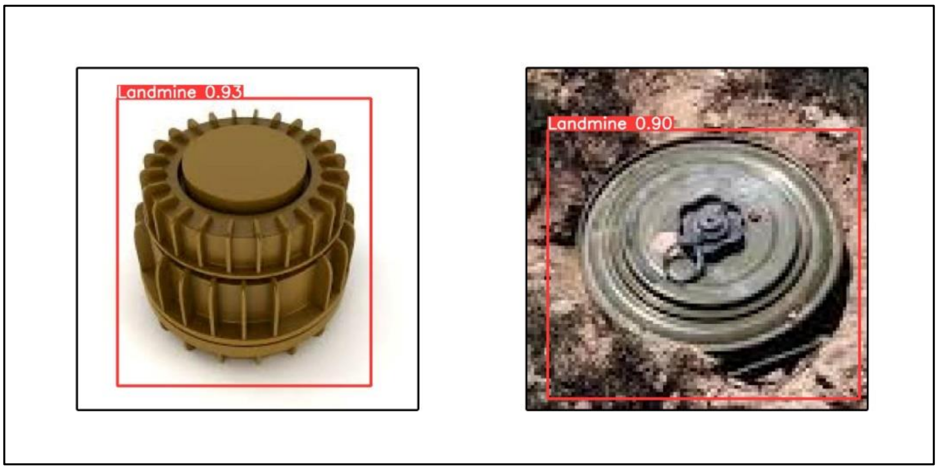

Figure 6: Detection and Recognition of Landmine

The training of YOLOv8 was completed over 110 epochs, achieving a balance between high accuracy and processing efficiency. Utilizing a Tesla T4 GPU, the model was trained on 88 validation images, detecting 115 instances with notable results: a precision of 92.9%, recall of 84.3%, and mean Average Precision (mAP) scores of 0.932 at IoU 0.5. The model's fast inference time of 11.9 ms per image highlights its real-time suitability, demonstrating YOLOv8's potential for effective landmine detection in diverse environments. The training summary for YOLOv8 is shown in Table 2.

Table 2: *Training summary for the YOLOv8 model.*

Parameter	**Value**
Epochs Completed	110
Model Version	YOLOv8.0.0
Python Version	3.10.12
Torch Version	2.3.1+cu121
CUDA Device	Tesla T4
Model Layers	218
Total Parameters	25,840,339
GFLOPs	78.7 GFLOPs
Instances Detected	115
Box Precision (P)	92.9 %
Recall (R)	84.3 %
mAP	93.2 %
Inference Time	11.9 ms per image
Pre-process Time	0.5 ms per image
Post-process Time	4.7 ms per image

4 Conclusion

The study motivation is the urgent need for more accurate and efficient landmine detection methods to ensure the safety of both operators and affected communities.

This study focused on developing an automated system for detecting and recognizing landmines using the YOLOv8 object detection algorithm. The dataset, comprising 1055 images, was collected from diverse sources, including news websites and specialized equipment. It included various landmine scenarios with different sizes and lighting conditions.

YOLOv8 was selected for its balance of accuracy and speed, suitable for real-time detection tasks. The model was trained on the labeled dataset for 110 epochs, employing gradient descent and backpropagation to optimize performance. The training process aimed to teach the model to recognize and localize landmines in varied conditions accurately.

The model's performance was evaluated using a test set of images from Google, representing different lighting, terrain, and occlusion levels. Key metrics indicated high precision (92.9%), recall (84.3%), and mean average precision (mAP) (93.2%). These results demonstrated the model's capability to accurately identify true positives and effectively detect most landmines in the images.

A detailed analysis of loss functions provided further insights. The box loss metric showed significant improvements, indicating accurate localization of landmines. The class loss metric confirmed the model's effectiveness in correctly classifying detected objects as landmines.

The high precision, recall, and mAP underscore YOLOv8's reliability and robustness in real-world conditions, making it suitable for applications requiring real-time detection, such as autonomous driving, surveillance, and robotics. The study suggests that YOLOv8 can significantly enhance object detection systems' performance in challenging environments with proper dataset preparation and training.

Future work could expand the dataset to include more diverse scenarios, fine-tuning the model's hyperparameters and exploring advanced techniques such as transfer learning or leveraging pre-trained models. These improvements could enhance the model's accuracy and efficiency, making YOLOv8 an even more powerful tool for landmine detection and related applications.

Finally, this research highlights the effectiveness of YOLOv8 in landmine detection, providing a solid foundation for future advancements. The successful implementation of YOLOv8 opens up new possibilities for enhancing safety and efficiency in landmine detection, contributing to critical fields like autonomous navigation and security operations.

5 Declarations

5.1 Competing Interests

There is no conflict of interest in this study.

5.2 Authors’ Contributions

Ahmed AL-SLEMANI: Developing ideas for the research and article, planning the materials and methods to reach the results, and supervising.

Govar A.OMAR: Organizing and reporting the data, taking responsibility for explaining and presenting the results.

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