IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

REALTIME BATTLEFIELD OBJECT DETECTION USING YOLO ALGORITHM

1Sri N.V. Phani Sai Kumar, G. Praveen Avinash, S. Madhulika, K. Vamsi Viraj, G.N.V Aditya
[1]Assistant Professor, [2345] UG Scholars
[1] Department of electronics and Communications Engineering,
Sagi Rama Krishnam Raju Engineering College, Bhimavaram, Andhra Pradesh, India

Abstract: Automatic target detection holds a pivotal purpose in military operations, involving the recognition of military assets from captured imagery. The core idea in the realm of automatic target detection in warfare is to recognize military assets within the acquired images. To achieve this, efficient utilization of Convolutional Neural Network (CNN) architectures is employed for object recognition in the given images.

Due to legal constraints and security considerations associated with military data usage, we have accessed diverse datasets obtained from platforms such as Kaggle, ImageNet, GitHub, and Roboflow.

To enhance the automatic target detection process, the integration of the YOLO (You Only Look Once) algorithm is employed. YOLO, a real-time object detection algorithm, is utilized efficiently to processes images, allowing for the rapid identification and localization of military objects within the captured scenes. This integration of YOLO algorithm enhances the speed and accuracy of military object recognition, contributing to the overall effectiveness of automatic target detection in war operations.

Training a deep learning model involves feeding it data and adjusting its parameters so that it can make accurate predictions. Train mode in Ultralytics YOLOv8 is engineered for effective and efficient training of object detection models, fully utilizing modern hardware capabilities.

***Index Terms* - object detection, deep learning, convolution neural network, computer vision, Ultralytics, YOLO v8.**

I. INTRODUCTION

In recent years, the widespread use of Imagery obtained through remote sensing in both military and civilian applications have increased due to their rapid data acquisition, speedy update cycles, Wide-angle perspective, and terrain independence. The focus of current research lies in object detection within remote sensing images, with particular emphasis on identifying Military equipment. This research is crucial in military operations for efficient battlefield information gathering and accurate targeting. As a result, the rapid and accurate identification of Armored guns, aircrafts, vehicles, and other related objects in remote sensing imagery is of significant research importance.

Even though deep learning has brought progress to spotting objects, dealing with remote sensing images still has its challenges. Problems like missing things and not being able to work in real-time (where it should be faster than 25 frames per second) are still common. This happens because: (i) objects in remote sensing images are often small, and deep networks struggle to see them with their big view; (ii) the backgrounds in these images are complicated; and (iii) deep neural networks need a lot of computer power, making it tough to do real-time detection on today's devices. So, the important goal of achieving quick object detection, especially in the military, is hard because of these issues.

Within this document, we aim to create an object identification algorithm, specifically designed for instantaneous identification of objects in military related images. We will be building upon the YOLOv8 framework to improve the detection accuracy, focusing on aspects like mAP (mean Average Precision) and fps (frames per second. The layout of this paper is organized as follows: Section II examines relevant previous research, followed by a comprehensive explanation of our proposed methodology in Section III. Subsequently, Section IV demonstrates experimental outcomes and conducts a detailed comparative analysis. Lastly, Section V offers concluding remarks.

II.RELATIVE WORK

Currently, two main categories of deep-learning-based object detection methods exist: One-stage and Two-stage approaches. The RCNN family, including RCNN, Fast RCNN, and Faster RCNN, exemplifies a traditional two-stage algorithm. In a two-stage detection algorithm, the process involves separately determining the object's position and its type. For instance, the Faster RCNN's Region Proposal Networks (RPN) assist in generating candidate boxes that may contain the object. Following this, another network discerns the category of the object within the selected candidate box. While Object detection employing a two-stage approach offers high-precision results, it comes with the drawback of increased computational cost, leading to longer processing times and making real-time detection challenging. This limitation poses difficulties in meeting the demands of rapidly evolving battlefield scenarios.

The one-stage detection algorithm involves simultaneously positioning and identifying object types. Prominent algorithms in this category include SSD and the YOLO series (YOLO, YOLOv2, YOLOv3, and YOLOv4).

In general, when comparing different versions of YOLO, newer versions often aim to address limitations, improve accuracy, and enhance performance. Developers typically iterate on the models to make them more robust and suitable for a wider range of applications.

Here is a brief history of the YOLO Algorithm

- YOLO (You Only Look Once), a seminal model for object detection and image segmentation, originated from the collaborative efforts of Joseph Redmon and Ali Farhadi at the University of Washington in 2015.
- YOLOv2, released in 2016, improved upon the original model by incorporating characteristics like like batch normalization, anchor boxes, and fine-grained feature maps for better localization
- YOLOv3, released in 2018, Further boosted both speed and accuracy through a more powerful Darknet-53 backbone, residual connections, and multi-scale outputs for varying object sizes.
- YOLOv4, released in 2020, brought innovations like Mosaic data augmentation, a detection head devoid of anchors, along with a new loss function.
- YOLOv5 leverages the pre-trained YOLOv3 models and offers a well-documented API, making it accessible for developers seeking a fast and easy-to-use real-time object detection solution.
- YOLOv6, open-sourced by Meituan in 2022, is utilized in the company's autonomous delivery robots.
- YOLOv7 (2022) refines real-time detection. Its custom YOLOv7-CSPDarknet53 backbone boosts accuracy, while the Focus module improves spatial information. This translates to significant accuracy gains over YOLOv4 without sacrificing real-time speed.
- YOLOv8, the most recent release by Ultralytics, succeeds YOLOv7, inheriting its accuracy improvements but with a focus on model size reduction. This makes YOLOv8 particularly attractive for applications with limited computational resources. The key to this efficiency lies in the YOLOv8-CSPDarknet53 backbone, which utilizes efficient building blocks for faster feature extraction during object detection. Additionally, YOLOv8 incorporates Bottleneck CSP, a technique that further reduces.

III. METHODOLOGY

Deep learning, drawing inspiration from the structure and functionality of the human mind, and often implemented through artificial neural networks, forms the foundation of this project focusing on real-time battlefield object detection using the YOLO algorithm . This project uses the latest advanced deep learning methods, especially convolutional neural networks, known for their outstanding performance in this domain. Both classification and localization of specific objects within frames are essential components of the methodology. Through experimentation, the most effective algorithms were identified to handle the challenges posed by small objects amidst complex backgrounds.

Various datasets were gathered from diverse sources such as Kaggle, Roboflow, ImageNet, and GitHub. Following careful consideration of project requirements, the datasets deemed most suitable were selected from Roboflow to ensure they align closely with the project's objectives and specifications. Object recognition encompasses both object classification and detection. Classification assigns labels to objects within an image or video, while detection goes further by not only identifying objects but also determining their spatial locations. By combining classification and localization, detection provides both the class name and the region where the object is located within the frame. This combined approach is essential for addressing various detection challenges across different domains.

A. OBJECT RECOGNITION

Object recognition involves accurately determining the category or class to which an image belongs by assigning a high probability to the correct class. The YOLO algorithm is often employed to efficiently carry out this process. Many advanced classification and detection algorithms employ CNN as a foundation to perform their work.

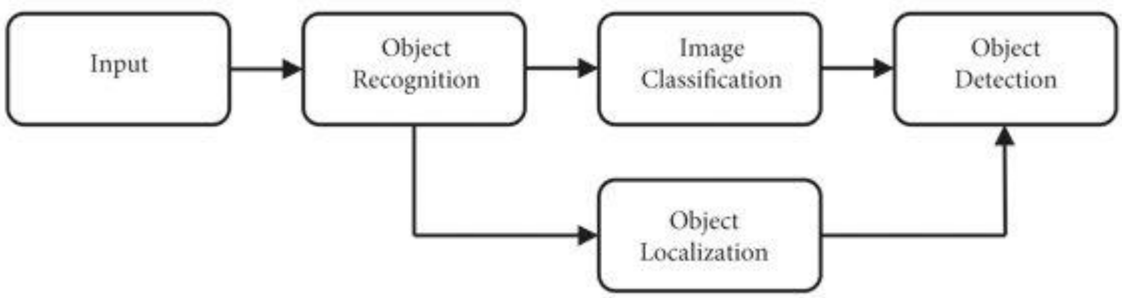

FIGURE 1. Implementation steps of object detection and classification

A1. Image Classification: The Initial Characterization

The initial stage acts as a foundational step, providing a broad understanding of the image content. Convolutional Neural Networks (CNNs) are powerful algorithms employed for this purpose. CNNs work like a series of filters, meticulously dissecting the image into smaller features and progressively building a complex understanding. These filters analyze aspects like edges, shapes, and textures. Finally, the system outputs a list of potential classifications for the objects present, along with corresponding confidence scores (e.g., car with high confidence, person with moderate confidence).

A2. Object Detection: Identifying Candidates of Interest

Building upon the classifications from image recognition, object detection steps in like a subsequent analytical stage. Techniques like Region-based CNNs (R-CNNs) or You Only Look Once (YOLO) leverage the classifications to pinpoint object locations. These methods act like targeted tools, drawing bounding boxes, rectangular areas around the identified objects. Bounding boxes offer an initial approximation of where objects might be located in the image.

A3. Object Localization: Precise Coordinate Determination

Object localization acts as a refinement stage, further enhancing the information obtained. Techniques like key point estimation come into play, identifying specific points on objects (e.g., corners or key features). This meticulous analysis results in more accurate location data, often represented by a set of coordinates, pinpointing the exact position of each object within the image.

The multi-stage approach to object recognition and location empowers machines to analyze and interpret visual information with increasing accuracy. This unlocks a wide range of applications across various domains. By continuously evolving algorithms and exploring new functionalities, the future holds immense promise for machines to not only see but also truly understand the visual world around them.

B. CLASSIFICATION AND DETECTION APPROACH

Object detection models operate by taking an image and generating bounding box proposals for areas likely to contain objects. While these proposals may not perfectly encapsulate the object, they include one that corresponds closely to the original target object. These models analyze patches within the image, identifying regions most probable to belong to a particular category. The region with the highest score is then proposed as the object's location.

The YOLO series stands out among contemporary object identification/detection models. In contrast to other techniques that depend on region proposals, YOLO partitions the input image into a grid of SxS. subsequently it predicts probabilities and bounding boxes for objects located within each grid cell's center.

C. MODEL DEPLOYMENT FLOWCHART

Figure 2 illustrates the standard approach used in model deployment. It starts with gathering the required dataset, applying the data-cleaning methods, performing model training, and finally integrating the resultant model in military applications.

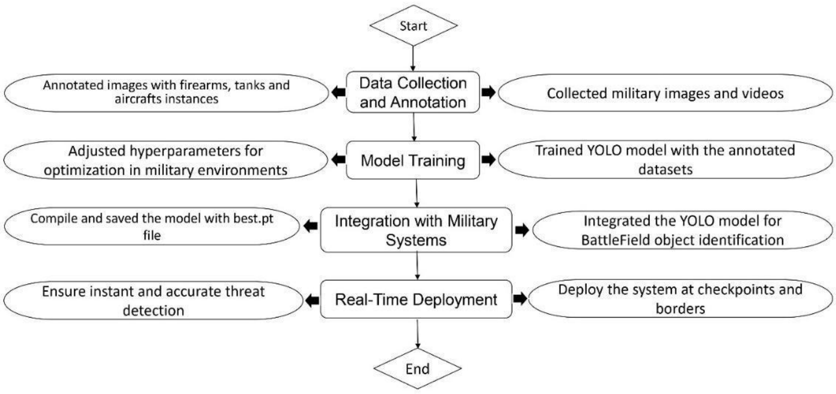

Figure 2. Classification and detection Methodology

D. ASSEMBLING THE DATASET, ANNOTATING AND PREPARING THE DATASET

The process of constructing and collecting the dataset was crucial and challenging due to the absence of a benchmark dataset for this task. Various datasets were gathered from diverse sources such as Kaggle, Roboflow, ImageNet, and GitHub.

D1. Classes in the weapon dataset:

The categories within the real-time weapon detection dataset are as follows**:**

- Shotgun
- Riffle
- Pistol
- Machine Gun

D2. Classes in the Military vehicles

The Military vehicles data set images for instantaneous armed vehicle detection is segmented among the following categories

- Military Tank
- Mine-Resistant Ambush Protected
- Mobile Artillery Transport
- Light Anti-Tank Weapon
- High-Mobility Transport

- Heavy Armored Weapon

D3. Classes in Aircrafts

The Aircraft dataset images are segmented into the following categories

- Mirage
- Rafale
- Tornado
- Vulcan
- YF23

Data quality is crucial for effective machine learning models. Preprocessing, which includes cleaning, standardization, and feature extraction, is vital. It involves steps like image scaling and data augmentation. Annotation, localization, or label of objects in images is also essential. Bounding box coordinates are stored in formats like XML or CSV. Overall, preprocessing enhances model training by ensuring data uniformity and increasing dataset diversity.

IV. RESULTS AND ANALYSIS

In our project, we have successfully identified various types of weapons, military vehicles, and aircraft. To achieve this, we employed YOLO v8, a state-of-the-art model, to train on diverse datasets encompassing multiple classes. Our evaluation of the model's performance has been comprehensive, incorporating analyses such as confusion matrix assessments and the examination of different loss curves. These metrics provide valuable observations and perspectives into the model's ability to accurately classify and localize objects of interest within the input images. By leveraging advanced techniques and rigorous evaluations, we have been able to achieve robust performance in detecting and categorizing a wide range of military asset than APT.

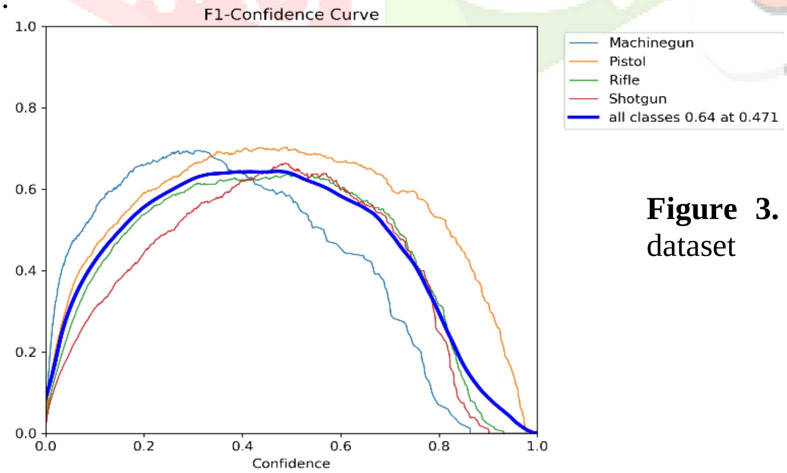

Figure 3. F1 Confidence Curve for Weapon dataset

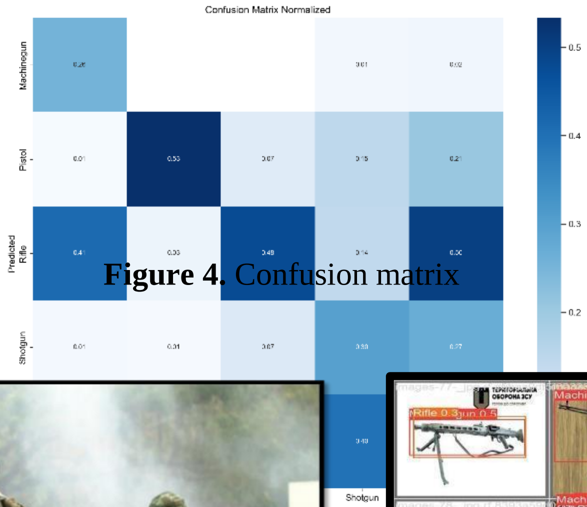

Figure 4. Confusion matrix

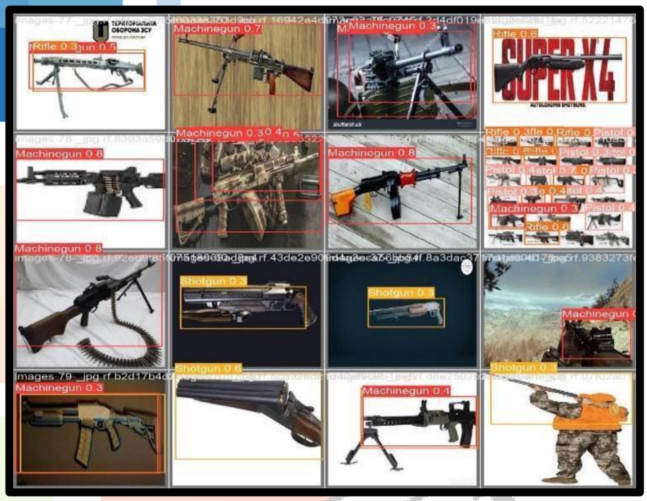

Figure 5. Detection Results of Weapons in Real-time Combat. **Figure 6**. Detection Results of Weapon using bounding Boxes and confidence.

Figure 7. Detection Results of Military vehicles using bounding boxes

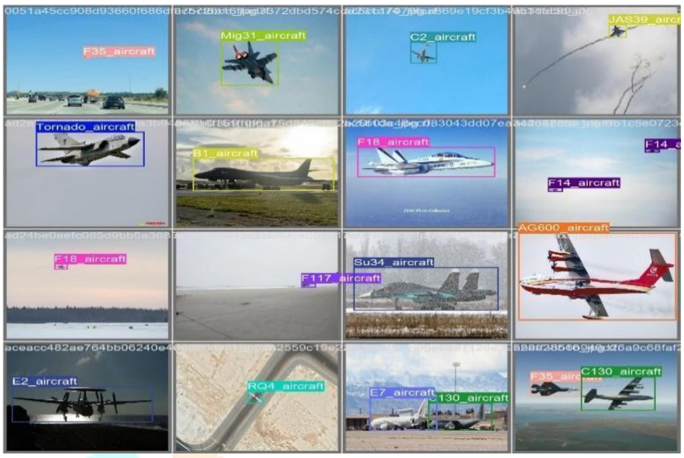

Figure 8. Detection Results of Aircrafts using bounding boxes

V CONCLUSION AND FUTURE WORK

This study introduces a groundbreaking real-time automatic threat detection system, designed for both monitoring and control applications. The implementation of this system is poised to significantly enhance security measures and contribute to the maintenance of law and order. The implications extend to the betterment and safety of humanity, particularly benefiting nations that have endured the repercussions of violent activities. Furthermore, the deployment of such a system promises to yield positive economic effects by instilling confidence among stakeholders and visitors, who prioritize security as well as safety when considering destinations for investment or travel. Various deep learning models were explored to achieve good f1 score, precision, recall and accuracy. After, training different deep learning models it is determined that YOLOv8 have demonstrated superior performance, yielding more successful outcomes.
Future endeavors will concentrate on reducing both false positives and negatives, recognizing the imperative for ongoing improvement. Moreover, there is a potential consideration for broadening the range of classes or objects, with the core goal remaining the augmentation of precision, recall, accuracy and FLscore.

REFERENCES

[1] “Vehicle Detection Under UAV Based on optimal Dense OLO Method”, by Z. Xu, H. Shi, N. Li, C. Xiang, and H. Zhou, pp.407-411, 2018.

[2] "Faster r-CNN: Towards real-time object detection with region proposal networks" by S. Ren, K. He, R. Girshick and J. Sun, pp. 91-99, 2015.

[3] "You only look once: Unified real-time object detection", by J. Redmon, S. Divvala, R. Girshick and A. Farhadi, Proc. IEEE CVPR, pp. 779-788, 2016.

[4]” Deep learning approach for car detection in UAV imagery” by Ammour, N.; Alhichri, H.; Bazi, Y.; Benjdira, B.; Alajlan, N.; Zuair, M,2017.

[5] "Convolutional neural network method for aircraft target classification of remote sensing images", by Zhou Min, Shi Zhenwei and Ding Huoping, Journal of Image and Graphics of China, vol. 22, no. 5, pp. 702-708, 2017.

[6] ” Image processing and its military Applications”, by V.V.D shah, Journal of Military college of Telecommunication engineering.