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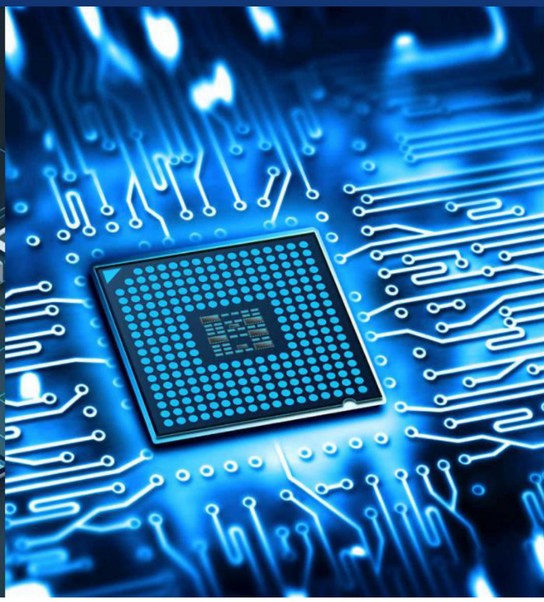


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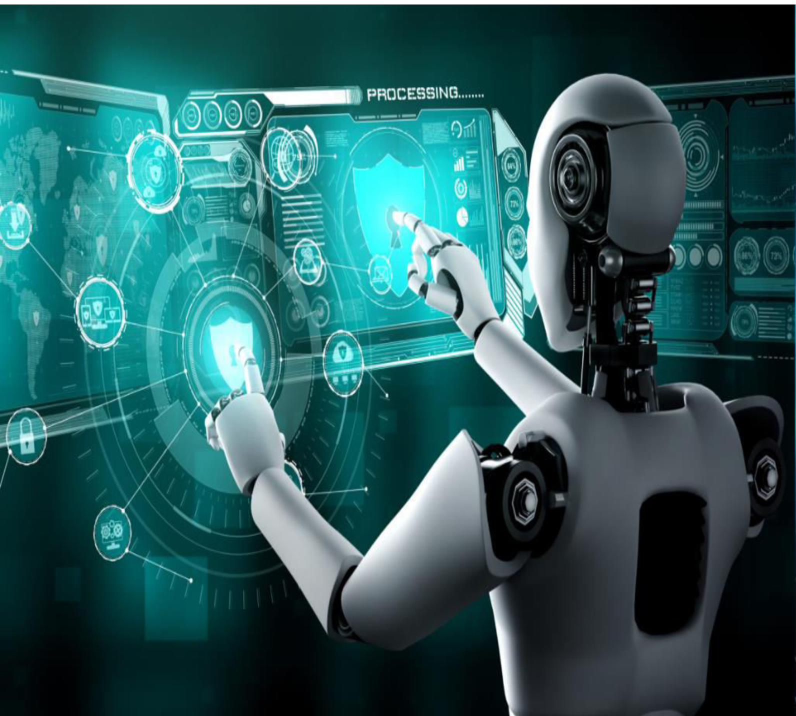

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Real-Time Aircraft Detection using Deep Learning

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ABSTRACT: The research work explores advanced techniques in object detection frameworks, specifically focusing on Faster R- CNN and YOLOv8, to enhance the accuracy of military aircraft detection. Leveraging the multi-stage Faster R-CNN architecture, we investigate the impact of adjusting anchor ratios, systemati- cally evaluating their influence on the model's ability to detect objects with diverse shapes. Departing from the conventional anchor-based approach, YOLOv8 introduces anchor-free detec- tion, eliminating predefined anchors and increasing robustness to object scale variations. Our experimentation includes anchor ratio configurations and explores the innovative components of YOLOv8, such as the CSPDarknet53 backbone and the C2f module.It aims to contribute insights into optimizing military aircraft detection accuracy, catering to the dynamic and critical nature of aerial threats. By providing a comparative analysis of Faster R-CNN and YOLOv8, we shed light on their strengths and weaknesses, offering valuable considerations for deployment in military contexts. The paper's findings contribute to the continual advancement of computer vision applications in national security, emphasizing the importance of automated detection for efficient and timely threat identification.

KEYWORDS: Object Detection, Faster R-CNN, YOLOv8, Mil- itary Aircraft Detection, Anchor-free Detection, CSPDarknet53 Backbone, Comparative Analysis, Computer Vision, National Security, Automated Detection.

I. INTRODUCTION

In an era characterized by evolving geopolitical landscapes and emerging security threats, the need for robust and efficient military aircraft detection technologies has never been more critical. The ability to swiftly and accurately identify airborne threats plays a pivotal role in ensuring national security and safeguarding strategic assets. As advancements in artificial intelligence and computer vision continue to reshape the landscape of defense technology.

The ability to accurately identify and track airborne objects is paramount for safeguarding borders, monitoring airspace, and ensuring the safety of nations. As technology continues to evolve, the field of computer vision has emerged as a powerful tool in automating the detection process. This paper delves into two prominent object detection frameworks, Faster R- CNN and YOLOv8, exploring their capabilities and proposing strategies to enhance their accuracy in the context of military aircraft detection.

Faster R-CNN, a Region-based Convolutional Neural Net- work framework, stands at the forefront of contemporary object detection methodologies. Leveraging a multi-stage ap- proach, Faster R-CNN utilizes a pretrained Convolutional Neural Network for feature extraction. The subsequent inte- gration of the Region Proposal Network (RPN) further refines object localization, offering unparalleled accuracy in detecting military aircraft.
evolving threats.

YOLOv8, a revolutionary object detection architecture that redefines how we perceive and execute precision in identifying objects within images. Built upon the powerful CSPDarknet53 backbone, YOLOv8 introduces innovations such as CSP and SPP, crucial for capturing multi-scale features essential in the diverse landscape of military aircraft. With its anchor-free detection approach and the unique C2f module, YOLOv8 not only advances the precision of detection but also enhances adaptability to varying object scales, making it a compelling solution for military

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applications.

This research delves into an exploration of these frame- works, with a specific focus on the impact of adjusting anchor ratios within the Faster R-CNN framework. The objective is to enhance object detection accuracy, particularly in the context of military aircraft, by systematically modifying anchor ratios. It contributes to the overarching goal of fortifying national security through advancements in technology, ensuring that the vanguard of defense remains vigilant, precise, and adaptable in the face of.

II. LITERATURE SURVEY

The paper by Ajay Kumar Goud et al[1] focuses on the critical need for military aircraft detection in strategic mil- itary decision-making, especially with challenges posed by stealth aircraft. The proposed approach utilizes the YOLOv5.

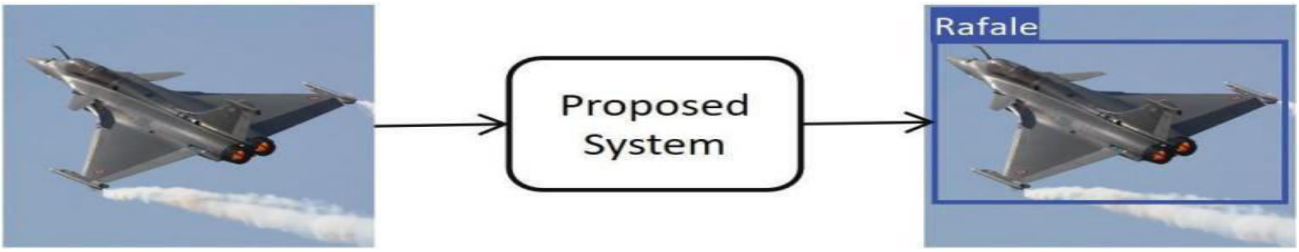

Fig. 1. Proposed Detection system [16]

method and a PyTorch army aircraft dataset to recognize different types of airplanes independently of class or orienta- tion. By employing computer vision and object identification, the model aims to detect military aircraft, offering potential applications in border security, air force, and marine force operations. Ferhat Ucar et al.[2] proposed a deep learning- based model for stationary aircraft detection in airport satellite images using Google Earth data. The model employs a custom CNN for initial learning and utilizes Regions with Convolu- tional Neural Network (RCNN) for precise aircraft bounding box detection. With a large dataset of aircraft images, the model achieves high performance, showcasing a 92.4% test accuracy for the classifier network and successful identification of stationary aircraft with matched bounding boxes in test images. Yanfeng Wang et al.[3] introduces TransEffiDet, an aircraft detection method for aerial images, combining the EfficientDet algorithm with Transformer modules to address challenges such as poor environmental conditions and vast sky backgrounds. The proposed model achieves a mean Average Precision (mAP) of 86.6%, surpassing EfficientDet by 5.8%, demonstrating improved robustness. Kiyak E et al.[4] intro- duces four deep learning tracking models (DCNN, DCNNFN, TLDCNN, FNDCNNTL) for autonomous aircraft, focusing on collision prevention and target tracking. FNDCNNTL, results ranging from 89.4% to 95.6%. The study highlights the ef- fectiveness of the proposed model in enhancing tracking algo- rithms for autonomous aerial systems. The paper[5] introduces Aircraft-YOLOv4, a real-time aircraft object detection method in remote sensing images, which enhances the YOLOv4 algorithm by incorporating depthwise separable convolutions, ELU activation functions, and SE modules. The proposed model achieves a detection mAP of 86.92% and a frame-per- second (fps) rate of 29.62, outperforming YOLOv4 by 2.82% and 7.01, respectively. Tested on the UCAS-AOD dataset, Aircraft-YOLOv4 demonstrates improved performance and generalization, making it more suitable for military applica- tions in aircraft object detection in remote sensing imagery. The paper[6] proposes an aircraft recognise scheme combining corner clustering and CNN in remote sensing images. The approach generates candidate regions using mean-shift clus- tering on corner-detected binary images, followed by CNN for feature extraction and classification. Compared to classical methods like SS+CNN, Edgeboxes+CNN, and HOG+SVM, the proposed scheme demonstrates higher accuracy and effi- ciency, automating feature learning and reducing the number of candidate regions.

The paper[7] introduces an aircraft detection algorithm for spaceborne optical remote sensing images, addressing the challenge of small sample sizes. The proposed method achieves a high f1 score of 90.44%, demonstrating effective and efficient detection of weak and small aircraft objects, contributing to enhanced military object detection and early warning capabilities. The paper[8] introduces an aircraft detection algorithm for spaceborne optical remote sensing im- ages, addressing the challenge of small sample sizes. The pro- posed method achieves a high f1 score of 90.44%, demonstrat- ing effective and efficient detection of weak and small aircraft objects, contributing to enhanced military

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object detection and early warning capabilities. The paper[9] introduces DPANet, a two-stage aircraft detection method for remote sensing images, combining Deconvolution operation and Position Attention mechanism. DPANet enhances structural feature representation by capturing external characteristics with deconvolution and addressing complex backgrounds through position attention, resulting in improved accuracy and reduced error detections in aircraft detection from top-down perspective remote sensing images. The paper[10] discusses the importance of aircraft detection in satellite imagery for operational intelligence and proposes a CNN-based methodology achieving a 95% accu- racy in detecting aircraft from remote sensing images. The second paper introduces DPANet.

PRELIMINARIES

A**. Dataset Information**:

Our primary sources for acquiring military aircraft data include Kaggle and GitHub repository. Initially, we collected information from these platforms to compile a comprehensive dataset. Additionally, Figure (2) in our project displays a selection of randomly chosen photos from this gathered collection.

1. Number of images: 92k
2. Number of categories: 46
3. Image size: Varies, but most are around 256x256 pixels
4. Split: Training set (1600 images per category), test set (400 images per category)

III. METHODOLOGY

System Architecture

In the proposed aircraft detection workflow in Figure 3. The first phase entails acquiring data from Kaggle and GitHub repositories, followed by a meticulous data preprocess- ing stage. This crucial step involves various transformations, such as resizing images to a standardized format, adjust- ing brightness and contrast for consistency, and cropping or padding to focus on relevant regions. These enhancements aim to eliminate noise, amplify key features, and ensure the model receives high-quality, uniform data to optimize learning and overall performance. Subsequently, the preprocessed dataset is segregated into training and testing sets, enabling the inde- pendent evaluation of machine learning models' performance on one subset while assisting their training on another.

Fig. 2. Sample Dataset Images

This method is useful for evaluating the model's ability to gener- alise well to data that hasn't been seen before, especially when it comes to using the Faster R-CNN and YOLOv8 algorithms for aircraft identification and then figuring out which algorithm performs best based on estimation metrics.

Faster RCNN

An efficient method for detecting objects in photos is the Faster R-CNN framework which can be seen in figure 4, it is made up of a number of linked networks. To extract high-level characteristics from the input image, a pretrained Convolutional Neural Network (CNN), especially ResNet101, is used first. The final fully-connected layer of the CNN yields these features, which together make up the image feature map and capture crucial aspects of the image like as shapes and edges.The next stage pertains to RPN, which is an essential component of the Faster R-CNN architecture. Operating on the created feature map, the RPN integrates a classifier and a regressor. Potential regions containing objects can be proposed using anchors, which are defined bounding boxes with various sizes and ratios. In order to improve the suggested bounding boxes, the RPN produces regressed coordinates and a target score that shows how likely it is that an object will be present in each suggested zone. The RPN's versatility is increased by using preset anchor ratios and scales, which enable it to adjust to a variety of object sizes and shapes in the input data.

we propose an exploration into the impact of adjusting the anchor ratio in the Faster R-CNN framework as a means to enhance object detection accuracy. Anchors play a pivotal role in guiding the region proposal network, influencing the aspect ratios of bounding boxes over the convolutional feature map. By systematically modifying the anchor ratio, which defines the width-to-height ratio of these bounding boxes, we aim to investigate its influence on the model's ability to detect objects with diverse shapes and proportions. It involves experimenting with different anchor ratio configurations such as [0.5, 1, 0.7], [0.5, 1, 3] and [0.5, 1, 2]. Departing from the conventional defaults with anchor size multiples anchorScaleV=[8,16,32] , to discern whether a tailored anchor setting can yield improve- ments in accuracy.

The Faster R-CNN architecture shown in figure 4 comprises two pivotal layers.The Fast R-CNN Layer and the Region Proposal Network (RPN). A loss function that combines bounding box regression and classification losses is defined for each layer. In order to jointly optimise the model for accurate object detection through exhaustive training and a two-fold loss evaluation method as equations 1 and 2, the RPN suggests candidate regions, and the Fast R-CNN Layer refines these ideas.

YOLOv8

The YOLOv8 architecture shown in figure 5, leverages the powerful CSPDarknet53 as its backbone, a modified version of the Darknet53 used in earlier YOLO models. This back- bone features Cross-Stage Partial Connections (CSP), which efficiently channel information between layers, and Spatial Pyramid Pooling (SPP), capturing multi-scale features crucial for detecting objects of diverse sizes.Its design combines fully linked layers for object detection with deep convolutional layers for feature extraction.

Backbone and Feature Extraction: At the core of YOLOv8 lies the CSPDarknet53 backbone, a refined version of the Darknet53 used in earlier YOLO models. This backbone leverages Cross-Stage Partial Connections (CSP) to facilitate efficient information flow across layers, while Spatial Pyramid Pooling captures multi-scale features crucial for detecting objects of varying sizes.

ReLU Activation and Alternating Convolution Layers: YOLOv8 utilizes the Rectified Linear Unit (ReLU) activation function in each hidden layer. ReLU simply outputs the maximum value between its input and 0, promoting spar- sity and improving training efficiency. The final output is achieved through alternating convolution layers that progres- sively shrink the feature space extracted from earlier layers. This step refines the extracted features, ultimately leading to more precise object detection.

C2f Module and Decoupled Head: Departing from tradi- tional YOLO necks, YOLOv8 introduces the C2f module. This novel element seamlessly channels high-level features with contextual information from lower levels, enriching the feature representation. The decoupled head further enhances flexibility by separating prediction branches for bounding boxes, class probabilities, and confidence scores.

Anchor-Free Detection and Multi-Scale Prediction: YOLOv8 ditches pre-defined anchors, a staple in earlier YOLO models. This ”anchor-free” approach makes the model more robust to object scale variations, leading to better perfor- mance on diverse datasets. Additionally, YOLOv8 employs five dedicated detection modules, each focusing on different object scales. This multi-scale prediction strategy tackles the challenge of identifying objects of varying sizes within the same image.

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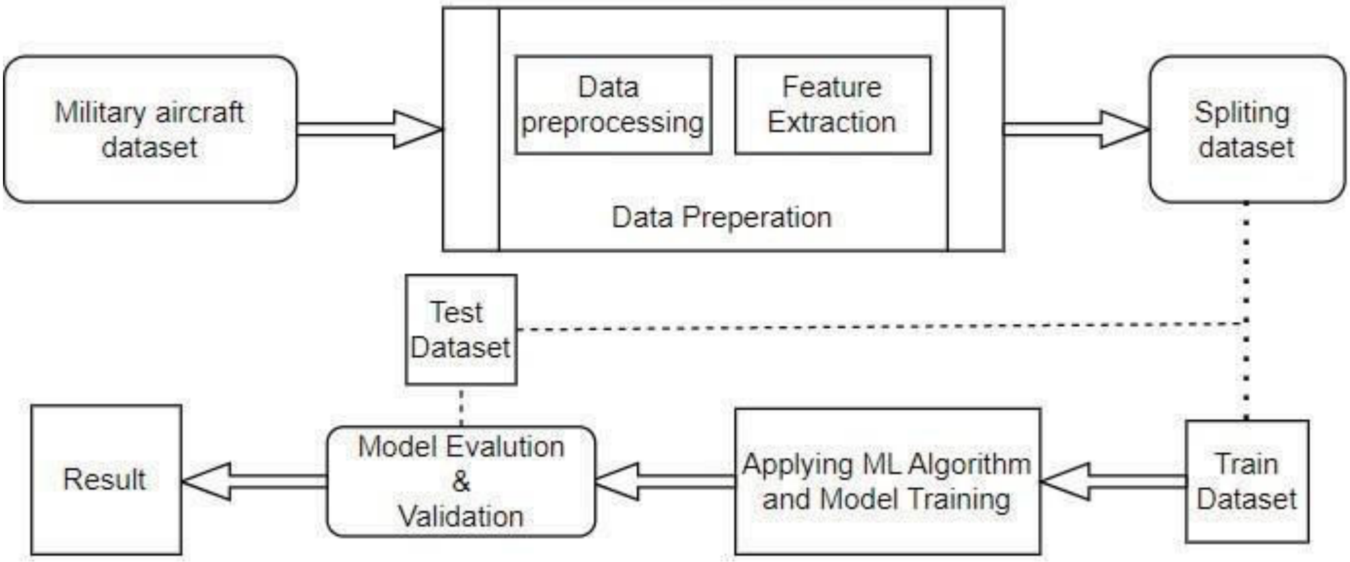


Fig. 3. Proposed Work Flow

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{box}}$$

$$\mathcal{L}(\{p_i\},\{t_i\}) = \frac{1}{N_{\text{cls}}}\sum_i \mathcal{L}_{\text{cls}}(p_i,p_i^*) + \frac{\lambda}{N_{\text{box}}}\sum_i p_i^* \cdot L_1^{\text{smooth}}(t_i - t_i^*) \quad (1)$$

$$\lambda_{\text{coord}}\sum_{i=0}^{S^2}\sum_{j=0}^{B} \mathbb{1}_{ij}^{obj}\left[(a)^2+(b)^2+(c)^2+(d)^2\right] \quad (3)$$

$$L_{cls}\left(p_i,p_i^*\right) = -p_i^*\log p_i - \left(1-p_i^*\right)\log\left(1-p_i\right) \quad (2)$$

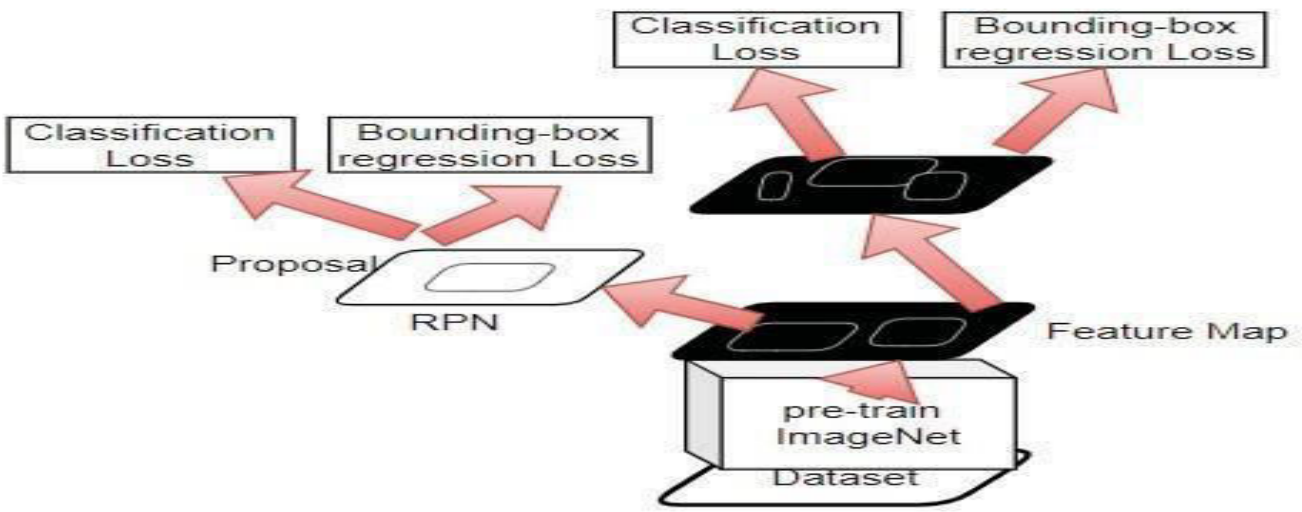


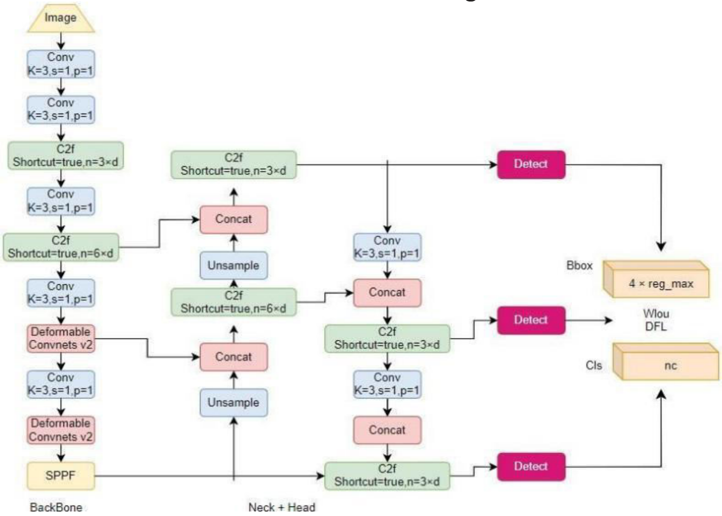
Fig. 4. Fast R-CNN structure

The loss computed as a combination of three individual loss components:
Localization Loss: The accuracy of the bounding box containing the object is measured by the localization loss. Mathematical equation can be seen in equation 3 .
Confidence Loss: The objectness prediction, which indi-cates whether or not an object is available in a specific grid

cell, is linked to the confidence loss.Mathematical equation can be seen in equation 4.
Classification Loss: The classification loss measures how well the model predicts the class of the object within the bounding box.

IV. MILITARY AIRCRAFT DETECTIION RESULTS

Two informative graphs in Figure 7 illustrate the val mAP and val precision dynamics of our YOLOv8-based model. It show the evolution of the training loss as well as the as- sessment metrics, Average Precision (AP) and Mean Average Precision (mAP), across 100 epochs. The training loss's shown in figure 5 trend shows that it peaked at the 100th epoch and then sharply declined, falling 15th epoch. Later periods saw a slow decrease that eventually converged to an astonishingly low value that was almost zero. This trend in the training loss



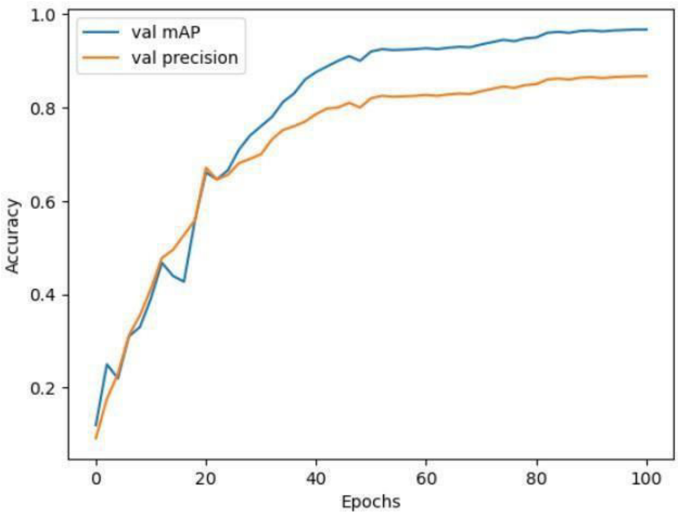
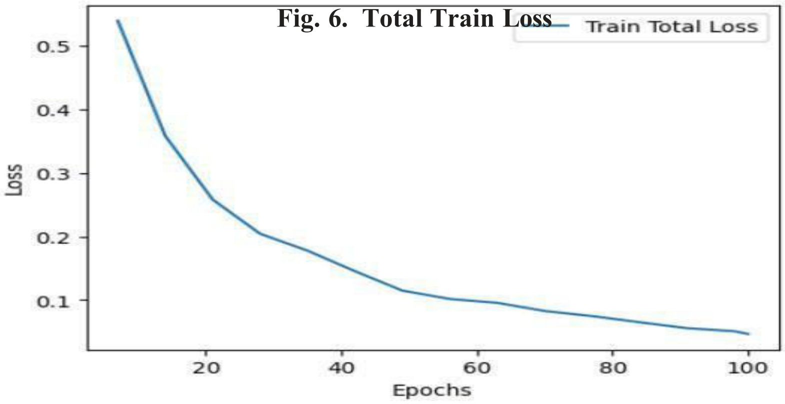


Fig. 5. YOLOv8 proposed Architecture

that we saw throughout the training phase points to a quick convergence of our YOLOv8-based model, which is a sign of effective learning and dataset adaption.Two crucial parameters, mAP and AP, were added to the model during validation in order to assess its efficacy. The AP was depicted by the precision-recall curve (PR curve), which displayed variations as opposed to a steady ascent. The model performed well; at the end of 100 epochs, the AP was greater than 0.91.

Fig. 6. Total Train Loss



In addition, mAP approached values greater to 0.96 the mAP values were almost 70th epoch and remained high for the duration of the remaining epochs. Interestingly, the mAP showed a faster slope than the AP, demonstrating the model's ability to reliably and properly identify military aircraft in a variety of classes as training went on.

1) Performance Analysis: The detailed performance anal- ysis results are summarized in Table 1. This table highlights the accuracy metrics for both YOLOv8 and Faster R-CNN . In table for understanding accuracy of 10 classes given apart form 42 classes .The overall accuracy of the YOLOv8 model is noted to be 96.7%, surpassing the performance .

TABLE I
ACCURACY FOR DIFFERENT CLASSES

Classes	mAP	IoU
Rafale	97.2	90.1
Tu160	90.4	82.5
Vulcan	89.6	88.6
XB70	91.1	89.5
AV8B	93.4	90.3
Be200	92.3	88.9
C17	95.8	86.4
EF2000	94.7	91.8
F14	97.9	95.4
F16	94.2	90.6
JAS39	88.1	98.9
Overall	96.7	92.3

R-CNN model, which achieved an overall accuracy of 92.3%. Figure 8 can be also observed for the results

Fig. 8. Output from yoloV8 [16]

V. CONCLUSION

In summary this study has delved into frameworks, for detecting objects Faster R CNN and YOLOv8 with the aim of improving the accuracy of identifying military aircraft. By adjusting the anchor ratios in Faster R CNN we have observed how it affects the models ability to detect objects with shapes.

These insights provide contributions to optimiz- ing detection accuracy and emphasizing the significance of customized anchor settings. Such advancements in computer vision play a role in strengthening security by enabling timely identification and response, to potential threats as defense technology continues to evolve.Moving forward, future research should focus on further optimizing anchor ratios in Faster R-CNN, exploring ad- ditional configurations, and fine-tuning settings to enhance the model's versatility across diverse scenarios. Additionally, investigating the potential of hybrid models that combine the strengths of Faster R-CNN and YOLOv8 could lead to superior performance in military aircraft detection.

Real-world deploy- ment scenarios should be considered to evaluate the models' performance in dynamic environments, and continuous dataset enhancement with a focus on scalability and efficiency is crucial for large-scale applications. Furthermore, exploring transfer learning for YOLOv8 and assessing the scalability and efficiency of the proposed models will contribute to the on- going advancement of military aircraft detection technologies, ensuring their effectiveness in diverse operational contexts.

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