Detection of Fighter Planes in Aerial Images using YOLO V8

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Detection of Fighter Planes in Aerial Images using YOLO V8

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Abstract

This research explores the efficacy of YOLO v8 in detecting fighter planes in aerial images, crucial for military defense. YOLO v8 strikes a balance between speed and accuracy, making it ideal for realtime applications. The study evaluates its performance against previous versions, addressing challenges in identifying small targets amidst clutter.Using a large dataset and YOLO v8, the mean Average Precision (mAP) achieved 70 percent, indicating the potential for improved accuracy. However, computational constraints hampered completion, implying unrealized potential with more data and training. The achievement of 54 percent mAP in a difficult situation with 35 lessons emphasizes the need of thorough training. The study predicts the significance of YOLO v8 in transforming military aerial surveillance, highlighting the critical balance of precision and speed in fighter aircraft identification. For realizing potential of YOLO v8, in depth research could entail amalgamation of added fighter planes intense data training.

1 Introduction

Recently, satellite remote sensing has significantly improved the amount of information obtained from aerial photos. This technological progress is particularly noteworthy for military purposes, as ability to accurately identify fighter jets is essential for safeguarding against potential dangers posed to these exceptionally advanced aircraft. Despite thorough investigation into many ways for identifying objects, including traditional techniques sophisticated deep learning algorithms like as SSD with YOLO, difficulties remain, notably in recognizing tiny target items within complicated backdrops and identifiable patterns.This study aims to improve the accuracy of identifying and classifying fighter aircraft by using capabilities of YOLOv8, the most recent version developed by ultralytics. The YOLOv8 model achieves a harmonious combination of fast processing and precise results, making it very well suited for military applications that need realtime performance. The main aim of this research is to evaluate extent of improvement in precision gained by YOLOv8 when identifying fighter aircraft in comparison to its previous versions, in addition to examining any possible limitations. mAP) is main assessment parameter used to assess success of YOLOv8 implementation. Primary objective is to completely transform aerial surveillance in military sector, acknowledging vital importance of immediate detection. Countries allocate significant money to their defense, with fighter planes playing a crucial role in their modern military capabilities. Identification of these aircraft during aerial surveillance is vital for evaluating potential risks, because precise identification allows for deployment of countermeasures to reduce such dangers. The sample images of dataset can be seen in Fig 1 and 2

Figure 1: Sample Images of planes from Dataset

Figure 2: Sample Images of planes from Dataset

This study has applications in military airport surveillance of data, effective management. Despite promising results from deep learning algorithms like YOLO, aerial combat aircraft identification remains difficult. Zhang et al.'s (2018) aircraft identification using YOLO with deep learning showed promise, but there's always potential for enhancement, particularly when recognizing small target objects in congested clusters identifiable shapes. Liu et al. (2021) suggested an SSD-based model for aircraft detection, introducing DAFFNet to improve accuracy. However, recognizing small objects remains a challenging area for development. Jindal et al.'s (2022) study highlighted the need for well organized datasets and accurate annotations to overcome difficulties in military aviation research. Recognizing tiny airplanes in remote sensing photos remains a challenge for current algorithms, particularly in the presence of complex backgrounds.In the realm of object detection, two primary types of algorithms exist: one-stage and two stage. In military contexts, where the detection of fighter aircraft is time critical, two-stage algorithms, such as RCNN versions, are unsuitable for realtime applications due to their sluggish processing speed, despite offering high accuracy. On the contrary, one-stage algorithms like SSD and YOLO provide quicker detection at the expense of some accuracy.Previous work using YOLO v5 showed encouraging outcomes, but there is room for improvement, especially in terms of detection speed and accuracy, particularly for remote sensing applications. Leveraging state-of- the-art YOLOv8, this research aims to contribute to the progress made in fighter aircraft identification in aerial images. Developed by ultralytics, YOLOv8 is wellsuited for the specific military domain due to its renowned balance of speed and accuracy.The one-shot approach of YOLOv8, processing the entire image at once, proves particularly advantageous for realtime object detection, especially for fastmoving and structurally complex objects like fighter jets in the air. The research anticipates that leveraging YOLOv8 will not only enhance detection accuracy but also redefine the landscape of aerial surveillance within the military context Sample images of fighter planes are provided in Figure 1 and Figure 2, showcasing the potential impact of this research on the field. samples images of fighter planes are shown in Figure **??**

1.1 Reasearch Question

"What level of accuracy does YOLO v8 achieve in the detection of fighter jets within aerial images, and what factors influence its performance in this specific context?"?

1.2 Structure of Report

- Section 1 - Introduction A general introduction of why waste segregation is important and how can computer vision help improve it.
- Section 2 - Related Work A procedural go through of research required that led to the research problem and its proposed solution
- Section 3 - Methodology A Methodological approach dividing the project into stages which are important and need to be completed in order.
- Section 4 - Results & Evaluation All the experimentation performed will be critically evaluated in this section
- Section 5 - Conclusion & Future Work Insights that have been gained by this research and possible recommendations that can help improve upon this research will go in this section.

2 Related Work

2.1 Yolo Related work

2.1 YOLO Related Work 2.1 YOLO Related Work YOLO Related Work Recent advancements in object detection methodologies, particularly those based on the YOLO architecture, showcase a significant leap forward in various domains. Researchers have been diligent in tailoring and optimizing YOLObased models to address specific challenges across diverse applications, demonstrating the versatility and adaptability of these models. Gong et al. (2022) introduced SPH YOLOv5, a modification of the YOLOv5 model tailored explicitly for satellite image analysis. This adaptation, named SPH YOLOv5, exhibits superior performance in detecting small objects and navigating complex scenes. Leveraging innovative features and attention modules, the model demonstrated its prowess on datasets like NWPU VHR10 and DOTA. Authors emphasize possibility of further investigation in incorporation of multispectral data, which presents an opportunity for further improvement in interpretation of satellite images Liang et al. (2022) introduced

Edge YOLO, mobile object detection system designed for edge computing devices. It is as per YOLO architecture specifically tailored for this purpose. Despite its low computational capacity, this system has outstanding capability in supporting object identification as per deep learning into edge settings. With just 8 million parameters, Edge YOLO accomplishes the astounding feat of finding a balance between speed and accuracy at the perimeter. Authors recommend extending capability of Edge YOLO to a broader array of edge computing devices integrating it in other ITS platforms and scenarios.Wan et al. (2023) investigated issue of optical remote sensing image object identification models underutilizing feature pyramid output. They introduced the YOLO HR approach as a potential answer to this problem. By recycling output of feature pyramid, this technique improves efficacy of detection. It employs unique approach by combining multihead strategy and MAB. In comparison experiments, YOLO HR performed better since it provides faster results without sacrificing speed. The goal of the research is to find more feature reuse opportunities and to apply these changes to additional object identification systems. To address challenge of detecting small objects Ji et al. (2023) presented MCS YOLO v4, a modified version of YOLO v4 model. Model includes three new components: detection scale, an EFB module providing contextual data, module for attention in PANet. While achieving improved accuracy, the increased model parameters impact realtime detection speed. The study underscores the ongoing effort to strike a balance between accuracy and speed in future work Hu et al. (2023)shifted the focus to small object detection in aerial images with their modification of S-scale YOLOv5. The study introduces novel architectures, an ESPP feature extraction method, and an CIoU loss function, outperforming existing lightweight models on DIOR and VisDrone datasets. This study represents a significant advancement, particularly in the context of applications in agricultural settings. Future work involves further optimization for other plant species, exploration of hyperspectral images, and analysis of multiple growth stages of maize. Contributing to the field of intelligent agriculture Pu et al. (2023)(2023) introduced Tassel YOLO, an improved version of YOLOv7 specifically designed for maize tassel detection and counting. The model achieves high accuracy, realtime detection, and reduced model parameters, showcasing practical applications in agriculture. Future plans for optimization for other plant species, exploration of hyperspectral images, and analysis of multiple growth stages of maize indicate the potential for broader applicability.Huangfu and Li (2023) proposed LW YOLO v8 to address the challenge of poor small target detection in UAV scenarios. The model incorporates the SE module and GSConv module, outperforming mainstream counterparts with a 36.3 percent mAP@0.5 on the VisDrone2019 dataset. The study emphasizes the need for further optimization for practical applications, indicating the commitment to refining the model for realworld scenarios. 2 Wang et al. (2023) introduced UAV-YOLOv8, an optimized model for UAV aerial object detection based on YOLOv8. The model incorporates the WIoU v3 loss function, BiFormer attention mechanism, and FFNB block for five scale detection. The improved model achieves a 7.7 percent accuracy boost without increasing size or para meters, outperforming similar algorithms. Challenges include increased complexity and the need for further optimization in computational resource consumption and accuracy for very small objects. Liu et al. (2023) enhanced remote sensing image target detection, particularly for aircraft, by optimizing model structure, introducing dilated convolution, and improving loss function convergence speed. While demonstrating notable improvements, challenges include weather related image issues hindering the extraction of various aircraft features, a focus for future research. Zhai et al. (2023)contributed an enhanced

YOLOv8 model for accurate UAV target detection, considering size, background, and light variations. The model introduces a high resolution detection head, reduces parameters for efficiency, and incorporates a GAM attention mechanism. Experiments on the TIB Net dataset show improved precision, recall, and mAP, with reduced parameters. However, there's a tradeoff with decreased FPS and potential challenges in complex air space backgrounds, guiding future research for improved accuracy and inference speed. Tang et al. (2023) tackled challenges in detecting ultra low pixel objects, specifically tiny people, in the TinyPerson dataset. Improvements to YOLOv7 include recursive gated convolution, a tiny object detection module, and a coordinate attention mechanism. The proposed TOD YOLOv7 model outperforms mainstream detectors, achieving a 9.5 percent AP in the TinyPerson task, making it suitable for efficient detection of tiny people in remote scenes. The study contributes valuable insights to tiny object detection research. Wu et al. (2023) proposed the enhanced YOLOv7 model, featuring tailored anchor boxes, a new multiscale feature fusion module, and improved data preprocessing, excels in ship detection and recognition. Achieving a remarkable mAP of 90.15 percent, it outperforms existing methods, particularly excelling in identifying small fishing boats, showcasing its practical applicability in maritime scenarios.Kumar and Muhammad (2023) proposed an enhanced YOLOv8 based object detection approach by combining severe weather datasets through transfer learning. Utilizing diverse datasets, including fog, rain, snow, night, and sand, the merged dataset significantly improves detection accuracy compared to individual datasets. The findings suggest the potential for further improvements with additional datasets and environmental factors to individual datasets. The findings suggest the potential for further improvements with additional datasets and environmental factors.Al Mudawi et al. (2023)introduced an innovative approach for vehicle identification and classification in aerial images. It employs noise removal and FCM segmentation before utilizing YOLOv8 for detection. Extracted features undergo SIFT, KAZE, and ORB for training a DBN classifier, achieving promising accuracies of 95.6 percent and 94.6 percent on VEDAI and VAID datasets. Future improvements involve expanding vehicle classes and incorporating additional features for enhanced accuracy in diverse traffic environments. Afonso et al. (n.d.) assessed the performance of YOLOv5 and YOLOv8 regression based algorithms for vehicle and license plate detection in Intelligent Transportation Systems (ITS). YOLOv8 slightly outperformed YOLOv5 with lower training time. Future plans involve implementing a license plate character recognition model and conducting embedded tests on a Raspberry Pi for realtime applications in parking system monitoring and access control.

2.2 Other Related Work

In the rapidly evolving landscape of cutting edge object detection methodologies,Chen, Chen, Yang, Xuan, Song, Xie, Pu, Song and Zhuang (2022) presented a ground breaking solution, LabelMatch, designed to tackle the persistent challenge of label mismatch in semi supervised object detection. Skillfully addressing both distribution level and instancelevel mismatches, LabelMatch incorporates a redistribution mean teacher for adaptive label distribution and a proposal self assignment method for precise instance level handling. Meanwhile,Han et al. (2022)put forth FCT, an innovative few shot object detection model integrating fully cross transformers. The model showcases its efficacy through the use of asymmetric batched cross attention. In the domain of dense object detection.Li et al. (2022) innovatively introduced dual weighting (DW), an adaptive label assignment for accurate dense object detection. DW assigns individual weights dynamically, breaking from conventional methods, and incorporates a new box refinement operation. Experiments on MS COCO with ResNet50 demonstrated DW's effectiveness, setting a new state-of-the-art. However, societal concerns, particularly in military and privacy applications, necessitate cautious consideration before widespread deployment.Chen, Li, Chen, Wang, Zhang and Hua (2022) unveiled DSL, a model that surpasses existing methods through adaptive filtering and aggregated teacher strategies. Transitioning to vehicle detection and classification. Kaur and Singh (2023) provided a comprehensive overview of deep learning (DL) techniques, contributing valuable insights to the evolving landscape of neural networks in this domain. Their study serves as a cornerstone for understanding the intricacies of DL in the context of vehicle related applications. Each of these studies represents a significant stride in their respective fields, propelling the frontier of 3 object detection and deep learning applications. Wang et al. (2022) introduced TranEffidet, a fusion of EfficientDet and Transformer methods, showcasing superior accuracy and mean average precision (mAP) compared to individual approaches. However, article recognized constraints in feature extraction, particularly whilst handling complicated aspects of objects, like fighter planes.

Overall, this compilation of academic papers constitutes comprehensive investigation in complexities of object identification approaches. These research contribute to continued improvement and development of object recognition approaches by resolving label mismatches, developing innovative fewshot detection models, and exploring social factors in label assignments. Environment is always changing, driven by need for precision, effectiveness, and flexibility in numerous uses of deep learning.

3 Methodology

Study progresses via five essential stages: beginning with Data Collection, advancing to Data Preprocessing, including Data Augmentation approaches. Intentional selection of CRISP-DM model is based on its best suitability for implementing YOLO v8. Systematic approach of this model facilitates research, enabling optimal processing of data at every phase. By leveraging the strengths of CRISP-DM, the research aims for a robust and effective implementation of YOLO v8, promising a comprehensive and methodical exploration of the chosen object detection model. Modelling and Model Evaluation. These stages are illustrated in Figure 3

Figure 3: Stages of Modelling

3.1 Data Collection

In this project, a diverse dataset of fighter aircraft images has been gathered from Kaggle, encompassing various resolutions. A uniform resolution of 640x640 pixels is developed for ensuring compatibility with YOLO. Dataset, which has total size of 12 gigabytes, consists of mixture of photographs corresponding Excel files. Files provide vital data regarding aircraft, including its classifications descriptions. Purpose of this carefully selected dataset is to enhance object identification capabilities of YOLO v8 for fighter jets. It seeks to provide a thorough uniform training environment for model

3.2 Data Preprocessing

During data preparation step, a specialized code file is used to classify photos in their corresponding categories. To enhance dataset quality, images not featuring fighter planes in the sky are systematically removed. The labeling process is facilitated by the use of the roboflow tool, effectively identifying and annotating fighter aircrafts within the images. The resulting annotations are stored in a YAML file, streamlining the integration of labeled data into the training pipeline. Data augmentation strategies are then applied, encompassing transformations like flipping, cropping, and rotation. This augmentation enriches the dataset by introducing diverse perspectives, contributing to the model's adaptability and robustness when confronted with previously unseen data, ultimately optimizing its performance in fighter aircraft detection. The dataset is around 12000 images in initial stages will be split in multiple ratios to determine which will provide better accuracy.It was split into 70:20:10, When splitting training and testing data.The final data set achieved after cleaning was around 5000 images of 35 different classes with 1750 total annotated images with 50 images of each class. we randomly choose samples while ensuring the ratio of images in each class remains consistent. This approach maintains a balanced representation of classes in both the training and testing datasets.

3.3 Data Augmentation

After partitioning the data into training, validation, and testing sets, the subsequent step involves the implementation of data augmentation. This approach aims to improve variety of training data, specifically to tackle anomalies in class distribution among pictures. Several augmentation techniques are utilized into this study to accomplish this goal, including rotation, horizontal flipping, scaling, brightness change, as well as contrast modulation. Rotation is action of shifting pictures over angle, usually 90 or 180 degrees. The purpose of both vertical and horizontal flipping is to create mirror images. Scale allows for the introduction of randomness by choosing lower picture dimension from an assortment of specified values. Altering brightness contrast within specified limits also makes the training sample more comprehensive diversified. As a result, model is able to generalize to different kinds of data more effectively.

3.4 Modelling

3.4.1 Yolo Architecture

Modifications to YOLO V8 model's structure have been substantial, and they represent leap forward for object recognition methods. This version primarily replaces the earlier, less contemporary CSP module with the more sophisticated CSPDarknet53 backbone. 2 C2f modules that have been included into this redesigned backbone are ConvModules Bottle Neck. Hence, it enhances procedure for feature extraction. Network layers are strengthened using batch normalization SiLU activation functions to enhance learning capacity stability.Yolo V8 Architecture is shown in Figure4

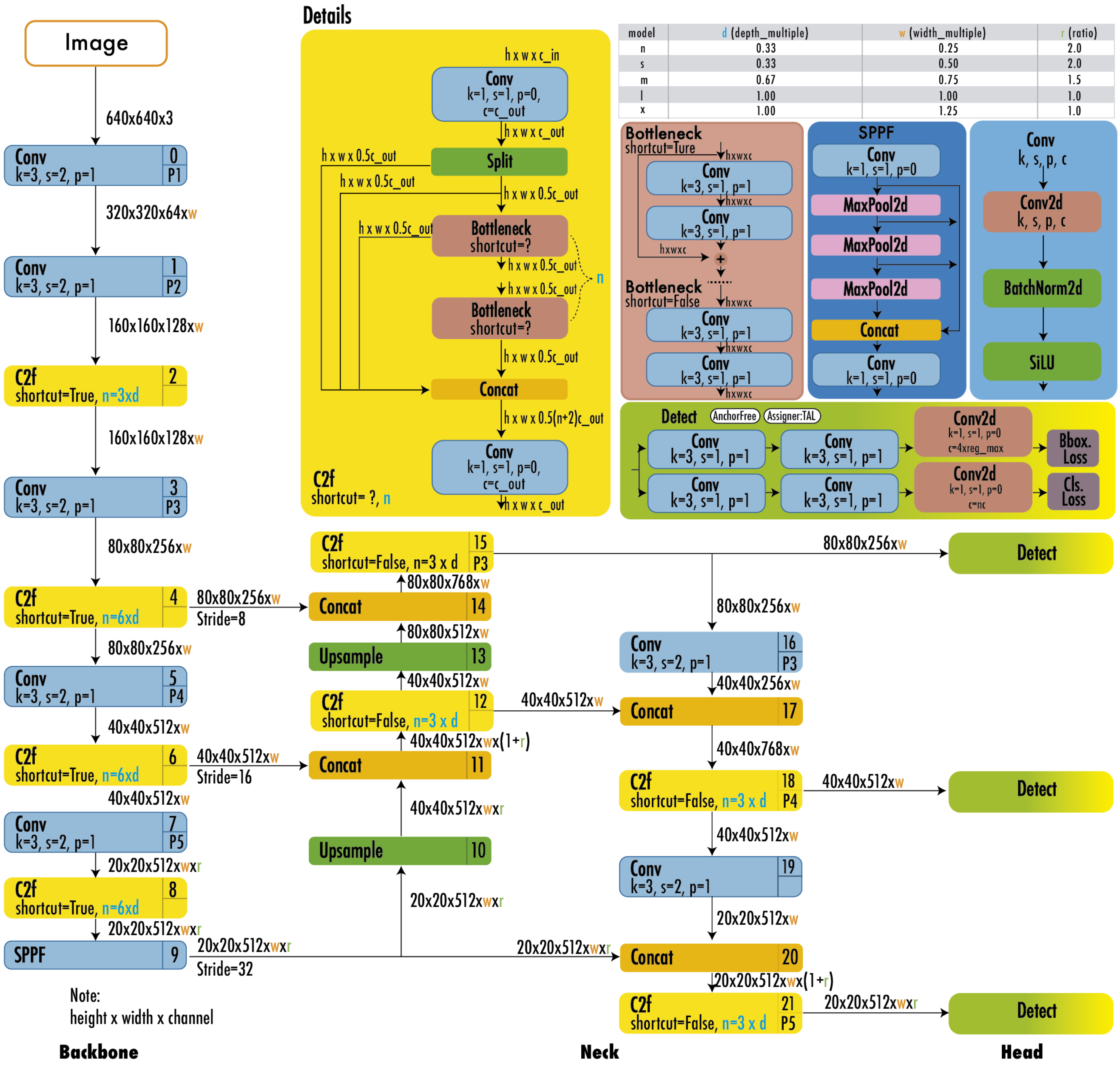


Figure 4: Yolo V8 Architecture from Terven and Cordova-Esparza (2023)

By connecting its core structure with the upper section, the architecture expands into three tiers that seamlessly integrate components from different network layers. This innovative approach enables the model to gather both contextual information and intricate features from hierarchical levels. Notably, the leader of the YOLO v8 network handles classification, identification, and regression separately. The primary element predicts item positions along with neighboring boxes, eliminating anchors in object identification pipelines—a noteworthy paradigm shift. YOLO v8 adopts soft NMS, a significant departure from the standard NMS, enhancing its ability to handle overlapping bounding boxes, a common challenge in item identification.This new and improved approach, incorporating a more forgiving suppression method, safeguards crucial bounding boxes, leading to an overall enhancement in performanceThe introduction of Tiny YOLO v8 meets the growing demand for efficient computing by providing a version designed for limited resources. Balancing productivity and essential features, Tiny YOLO v8 demonstrates its adaptability to different computing conditions, emphasizing its practicality. The YOLO v8 model reflects a commitment to enhancing and redefining object detection. The enhancements in architecture not only elevate effectiveness and precision but also demonstrate a nuanced understanding of the intricacies involved in object identification. YOLO v8 surpasses existing systems by revolutionizing feature extraction, connection, and post-processing techniques, thereby setting a new standard in the field of object identification. Serving as a catalyst, YOLO v8 inspires further exploration and advancements in the development of robust, adaptable, and effective techniques for object detection.

3.4.2 Model Building

Model was constructed utilizing Google Colab as coding environment, having Jupyter being used for task of categorizing photographs in their appropriate classes. The YOLO model m was used for precise effective speed detection, striking compromise between rapidity and precision. Classified photographs were then saved into Google Drive for simple retrieval. The dataset was split into three subsets: 70 percent for training, 20 percent for validation, and 10 percent for testing, following a standard model evaluation. Importing all YOLOv8 libraries ensured smooth implementation. Model improved its item recognition and categorization skills in 3 training sessions spanning 25, 50, and 100 epochs. We refined twice—without adding data and with. Consistency required 640x640 resolution throughout this procedure. This methodical approach to model building, including careful iterations and exact dataset partition, produced a robust and customized YOLOv8 model for quick object identification.

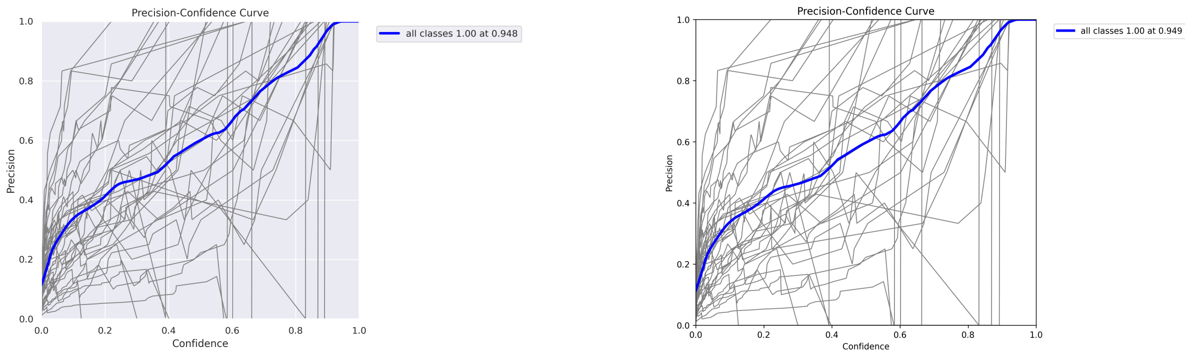
4 Results and Evaluation

This solution is evaluated using mAP, typical object identification model measure. It examines IOU, Precision, Recall, Precision-Recall Curve, and performance (Average Precision). For our experiments, we tested model for 25, 50, and 100 epochs. Our best mAP was 54 percent all through this excursion. Our best results were achieved utilizing default YOLO v8 architectural settings without data augmentation. After dataset augmentation, findings were less acceptable. Model performed well without augmentation, using YOLO v8 framework's default parameters.This shows dataset's inherent properties match model's parameters when unchanged. After adding augmentation strategies to dataset, model performed poorly. These results demonstrate model's sensitivity to dataset fluctuations and relevance of knowing how data alteration techniques like augmentation affect it. This information is essential for object detection success.

4.1 Precision

maP(mean average Precision) of YOLO v8 measures its object detection and pinpointing accuracy. At a precision rate of 54 percent, model accurately predicts 54 percent of bounding boxes, demonstrating its positive instance detection.maP graphs can be seen in Fig 5a and Fig 5b

$$Precision = \frac{TP}{TP + FP} \tag{1}$$



(a) P curve for Training data (b) P curve for Validation data

Figure 5: P curve

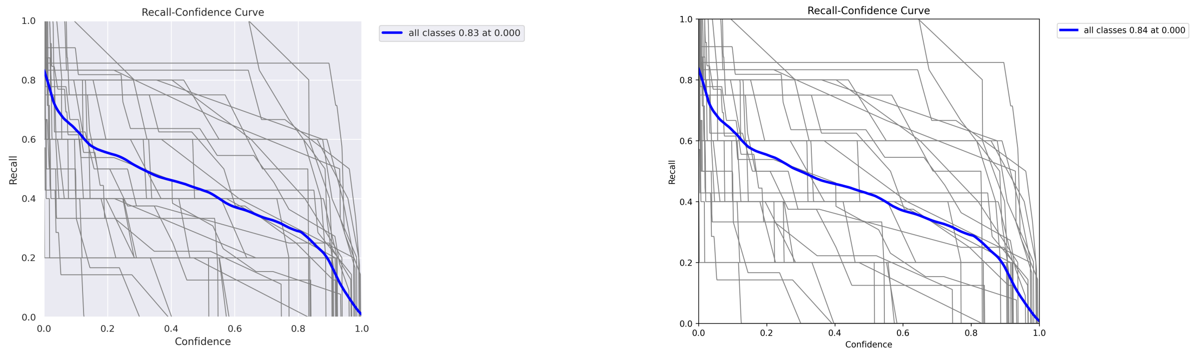
4.2 Recall

Recall measures a model's ability to discover all actual items in a dataset. Also known as sensitivity or true positive rate. It's calculated by comparing model's correct items to total number of true and missing things. In object detection, a higher recall means the model is good at catching most of the actual objects in the dataset. But, here's the catch: aiming for high recall might lead to more mistakes, like wrongly spotting things that aren't there.The R curve graphs can be seen in Fig 6a and Fig 6b

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

In the recall confidence curve analysis, when confidence (c) is 0, the recall (r) is 0.83, suggesting a high ability to correctly identify positive instances. However, when confidence is 1, the recall drops to 0, indicating that at maximum confidence, the model fails to identify any positive instances, signifying potential trade-offs between confidence levels and recall performance.

When precision is high at 0.87, there's a complete lack of recall, meaning the model correctly identifies instances but misses some. Conversely, when recall is 1 with a precision of 0.2, it catches all instances but also incorrectly identifies many. The maP achieved for during this period is 0.541 for all classes.PR graph can be seen in Fig 7



(a) R curve for Training data

(b) R curve for Validation data

Figure 6: R curve

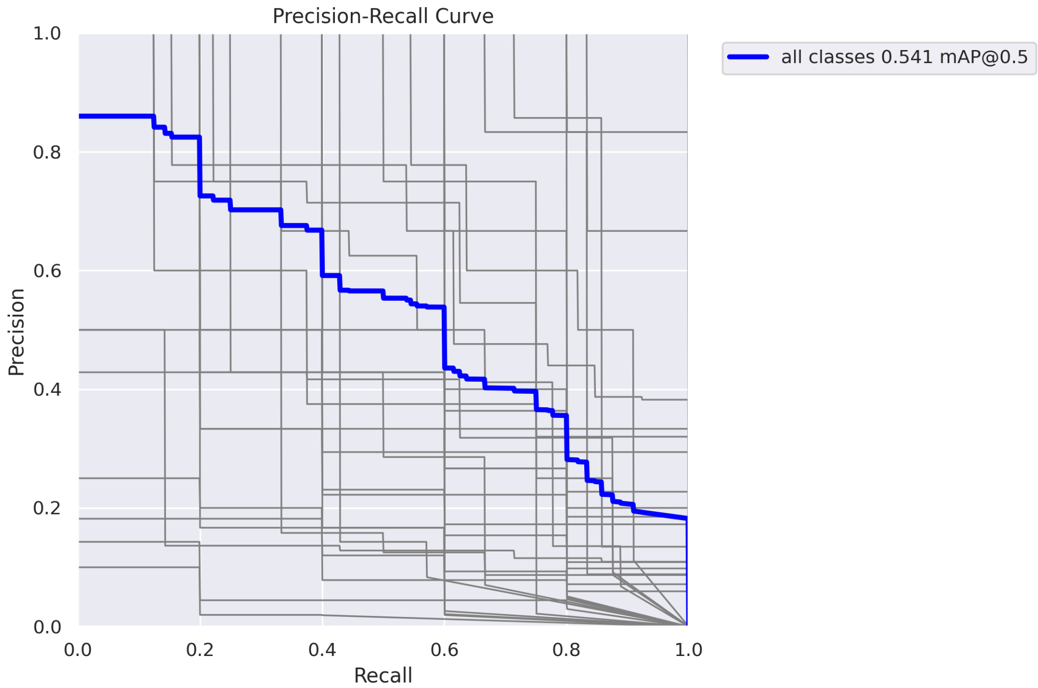
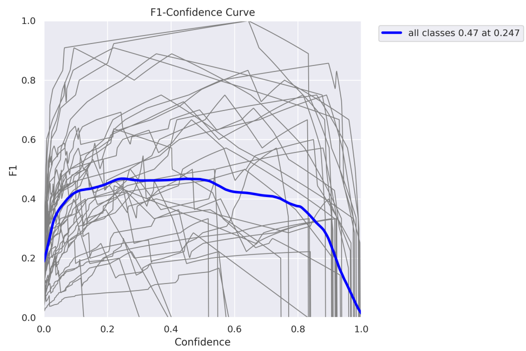


Figure 7: Precision-Recall Curve

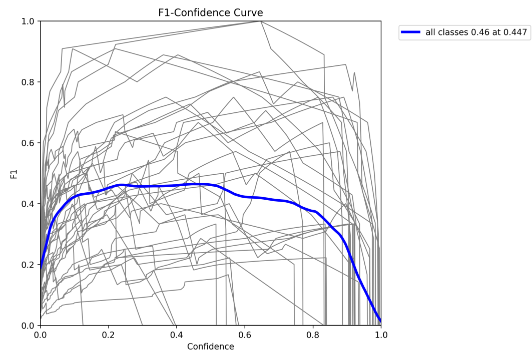
4.3 F1 Score

The F1 score is like finding a sweet spot between being careful and thorough. It's handy when making mistakes in spotting things (false positives) and missing things (false negatives) are both important. In tasks like finding objects, where getting it right and not missing anything are crucial, F1 score helps strike that balance.The images of F1 curve are shown in Fig 8a and Fig 8b

$$F1Score = 2 * (Precision * Recall)/(Precision + Recall) \tag{3}$$



(a) F1 curve for Training data



(b) F1 curve for Validation data

Figure 8: F1 curve

4.4 Confusion Matrix

In object detection, a confusion matrix acts like a report card for how well a model spots things in images. It sums up the model's predictions, showing when it gets it right (True Positive and True Negative) or messes up (False Positive and False Negative). From these, we can calculate important measures like precision, recall, and F1 score, helping us see where the model shines and where it could do better. It's like breaking down the model's performance into different aspects to understand how well it's working in spotting objects in images.

Here's a breakdown of the terms in the context of object detection:

- True Positive (TP):The model correctly predicted the presence of an object in an image.
- True Negative (TN):The model correctly predicted the absence of an object in an image.
- False Positive (FP):The model incorrectly predicted the presence of an object when it is not actually present. This is also known as a "false alarm" or "Type I error."
- False Negative (FN): The model incorrectly predicted the absence of an object when it is actually present. This is also known as a "miss" or "Type II error."

The Confusion matrix is shown in Fig 9

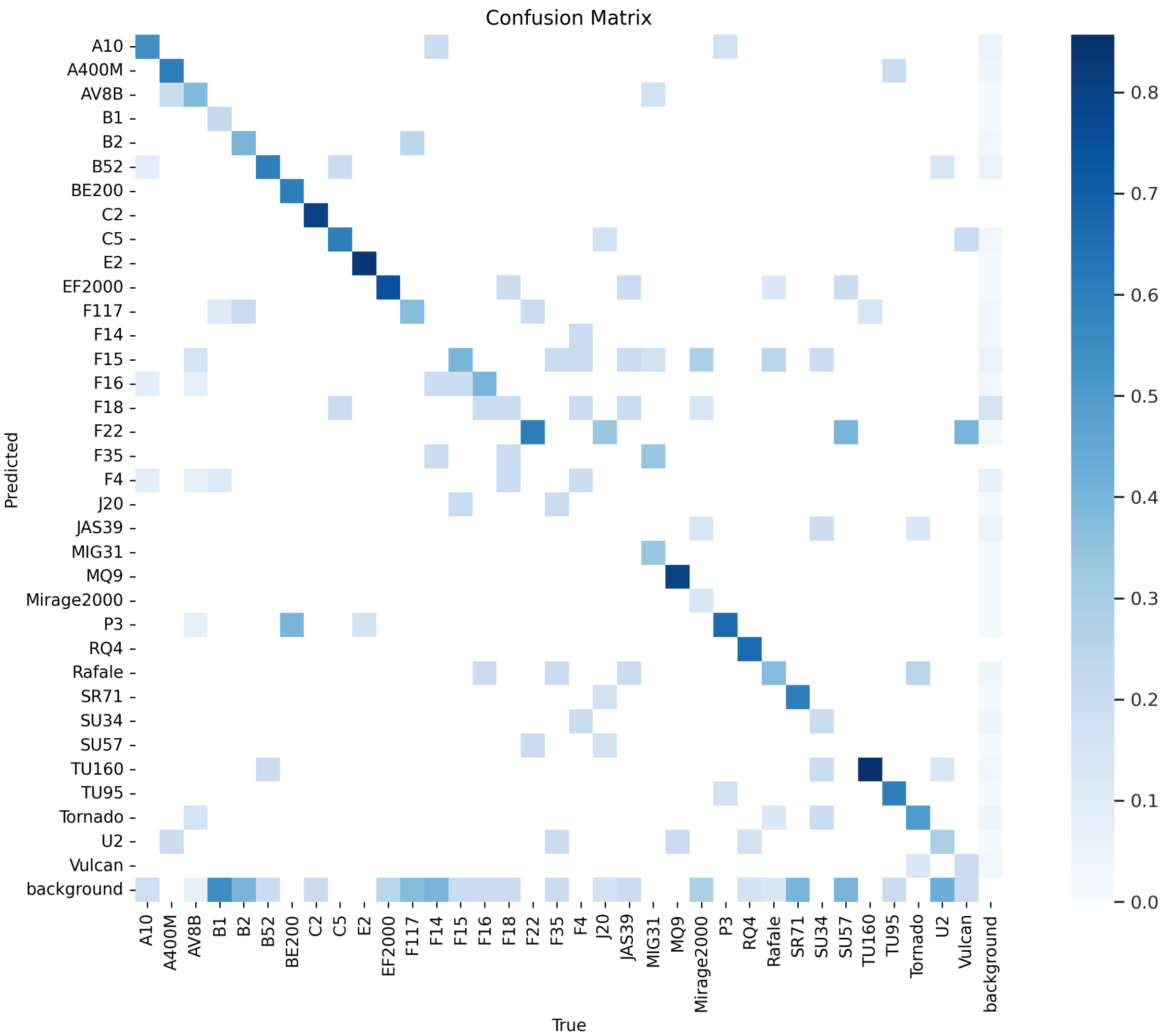


Figure 9: Confusion Matrix

4.5 Discussion

The assessment involved 50 diverse images representing various classes, but discrepancies arose as some were accurately classified while others weren't, possibly due to an insufficient number of training images. Achieving a higher mean Average Precision (mAP) and accurate classification demands a more robust training regimen with a larger dataset. This enhancement in performance and precision can be realized through extensive training and an increased number of diverse images. However, such improvements come with a computational cost, requiring substantial computing power for the model to effectively learn and generalize from a more extensive dataset. This underscores the crucial relationship between training data, computational resources, and the overall success of the model in accurately identifying and classifying objects, emphasizing the need for a comprehensive and well-resourced training approach in object detection tasks.Validation prediction results are shown in Fig 10 and overall results graph are shown in Fig 11. Some of the prediction images are shown Fig 12,Fig 13 and Fig 14

[h]

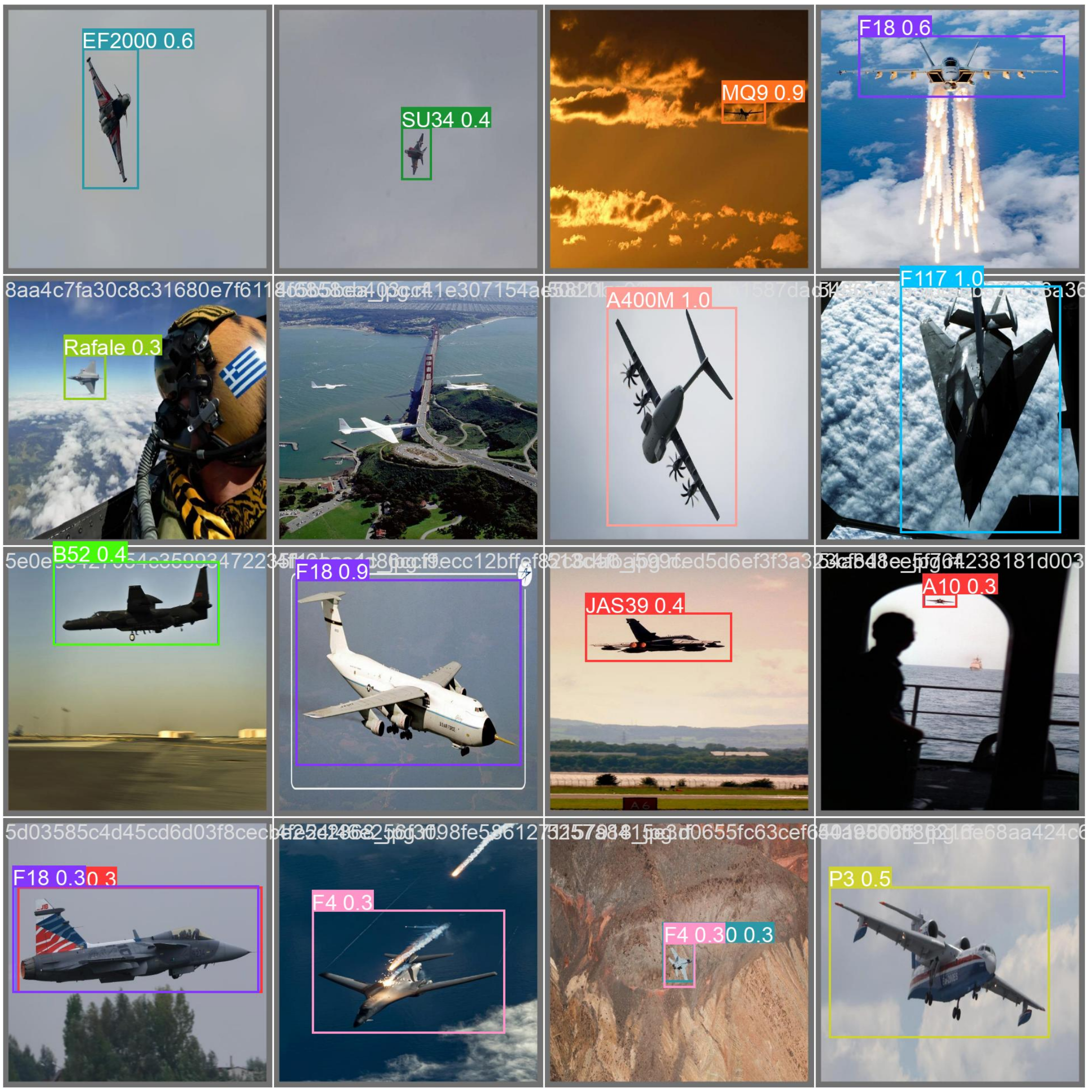


Figure 10: Valdiation Prediction

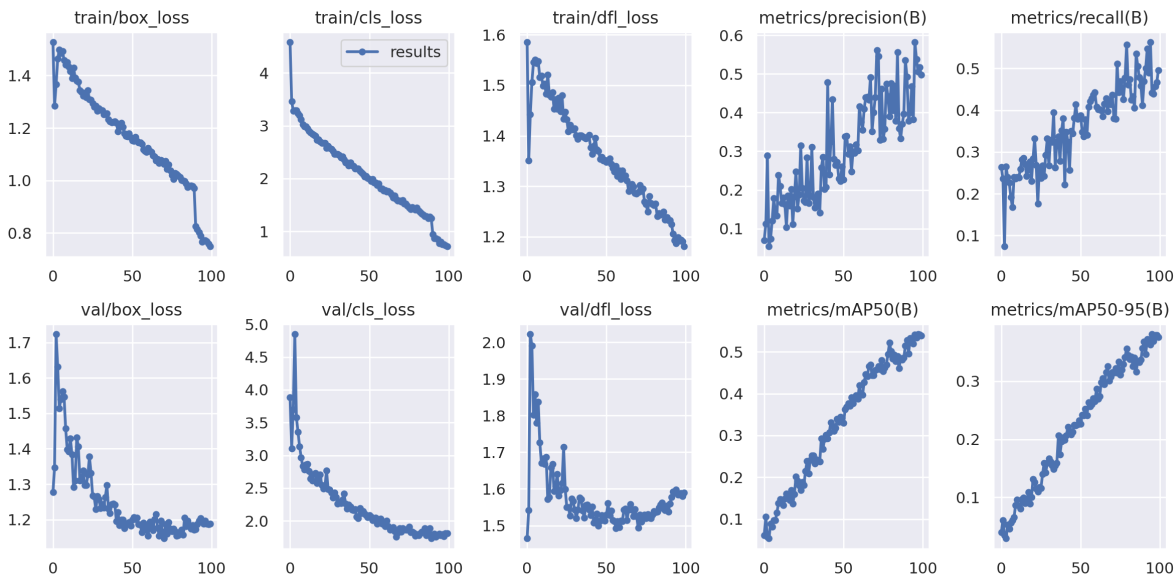
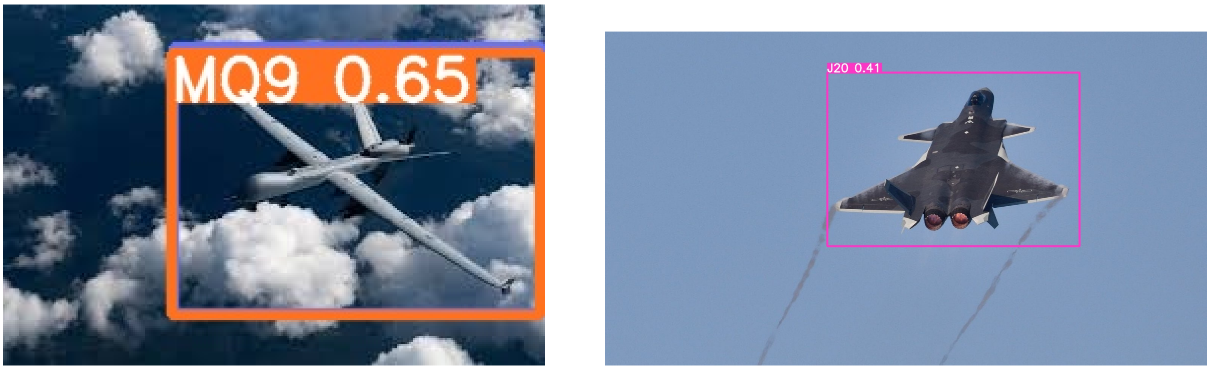
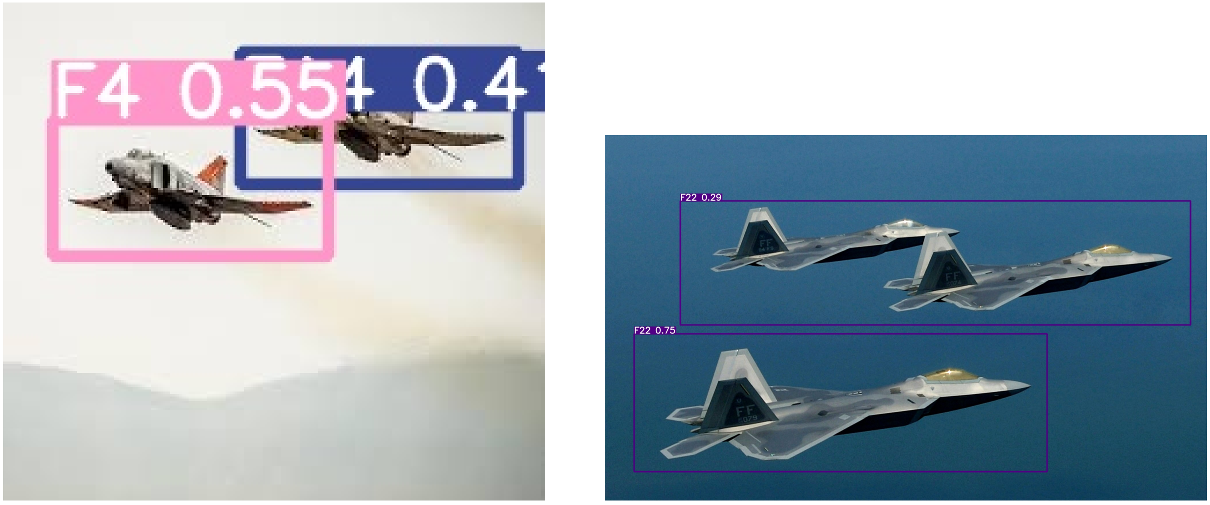


Figure 11: Overall Results of Training



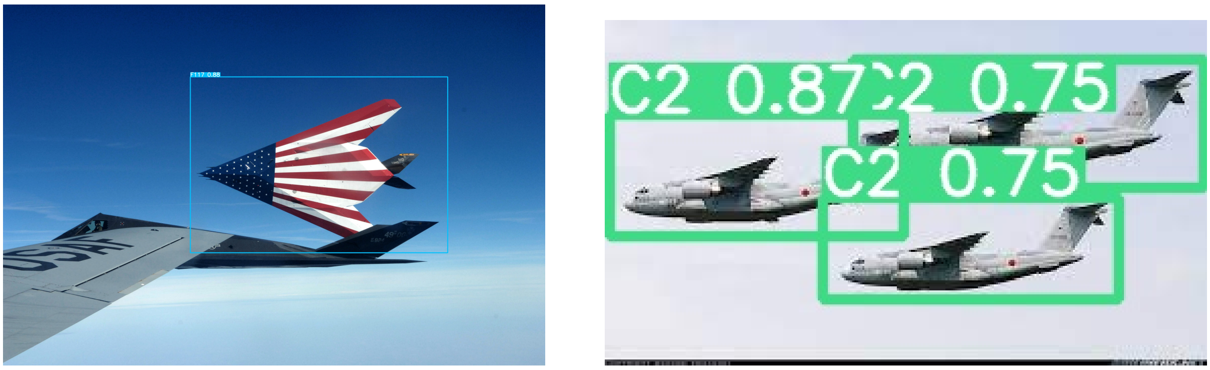
(a) MQ9 (b) J20 Plane

Figure 12: Predicted Planes



(a) F4 Plane (b) F22 Plane

Figure 13: Predicted Planes



(a) F117 Plane (b) C2 Plane

Figure 14: Predicted Planes

5 Conclusion and Future Work

In conclusion, this thesis underscores YOLO v8's effectiveness in detecting fighter planes within aerial images, positioning it as a strong choice for such tasks. Nevertheless, a critical trade-off surfaces between the precision and speed of detection. To address this, the YOLO m model was introduced to strike a balance, leveraging its nuanced capabilities.

The experimentation involved training with an extensive dataset, surpassing 3000 images, employing diverse augmentation techniques. During training, the mean Average Precision (mAP) reached an impressive 70 percent, indicating the model's potential. Unfortunately, computational constraints curtailed the completion of this exhaustive training regimen. It is our conviction that given the opportunity to continue training with an even larger dataset and heightened data augmentation, YOLO v8 can realize its maximum potential.

The obtained result showcased a mAP of 54 percent, considering the complexity of the task involving 35 distinct classes. Achieving optimal performance in object detection, especially in scenarios like identifying fighter planes, demands intensive training. The multifaceted nature of aerial images, compounded by the diversity among the 35 classes, necessitates a sophisticated learning process.Future works includes inclusion of upcoming fighter planes and feature extraction and traing with intesive data to reach the maximum potential of YOLO v8.

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