Defence Science Journal, Vol. 75, No. 4, July 2025, pp. 418-425, DOI : 10.14429/dsj.20755

Automated Classification of Military Aircraft Using Deep Neural Networks

Debadrita Mukherjee, Sadaf Zahra, Soumya Sharma, Tummenye Amos and Ali Imam Abidi*

Sharda School of Engineering & Technology, Sharda University, Greater Noida - 201 310, India

**E-mail: ali.abidi@sharda.ac.in*

ABSTRACT

Military aircraft detection in aerial imagery is critical for defence operations, airspace management, and automated surveillance. This paper presents a dataset of 74 military aircraft types, including high-value models like the F-35, B-52, and Rafale, annotated with precise bounding boxes across diverse conditions. The proposed approach, leveraging YOLOv10, achieves a precision of 82 %, recall of 66.4 %, and an F1 score of 0.687. Model evaluation yields a Mean Average Precision (mAP) of 76.4 % at Intersection over Union (IoU) 0.5 and 68.7 % across IoU 0.5–0.95, demonstrating robust detection performance. Real-time feasibility is ensured with an inference speed of 3.8 ms per image. Confusion matrices, PR curves, and annotated results highlight model strengths and areas for improvement, particularly in distinguishing visually similar aircraft. This study positions YOLOv10 as a strong candidate for real-time military aircraft recognition, contributing to defence surveillance and threat monitoring advancements.

Keywords: Military aircraft detection; YOLOv10 framework; Real-time classification; Aerial imagery; Bounding boxes; Mean Average Precision (mAP); Defence surveillance; Object detection

1. INTRODUCTION

The classification of military aircraft is crucial for defence monitoring, airspace surveillance, and threat evaluation. Conventional methods like template matching and boundary-based detection are affected by low accuracy because of occlusion and high visual similarity of aircraft models[5,17]. The detection techniques SIFT and HOG and feature-based methods during the early stages tried to improve detection despite their inability to handle different aircraft size scales lighting conditions and orientation variances. Speed and resource requirements limited the suitability of the region-based method Faster R-CNN for real-time military deployment[14]. With the development of deep learning, CNN-based models like YOLO revolutionized object detection with real-time classification and increased precision[1,3,6]. Complete image processing occurs through one forward-pass operation in YOLO enabling both fast performance and superior accuracy levels. YOLO's capability to scan entire images at once through one operation provides excellent suitability for military use which requires immediate threat detection.

The progression of YOLO from its primitive forms to YOLOv10 has brought several improvements. YOLOv3 enhanced feature extraction using Darknet-53[7], while YOLOv5 brought mosaic augmentation for improved small-object detection[8]. YOLOv8 advanced architecture with better bounding box regression but had issues with class imbalance, occlusion, and detection in crowded scenes[9,14]. YOLOv10 achieves this with feature selection via automation, multi-scale object detection, and Complete IoU (CIoU) loss for improved bounding box optimization[10,12].

ViTs introduced as CNN-replacement detectors bring computational burdens that prevent real-time defence system deployment. The self-attention mechanisms in ViTs enhance classification precision however these models require 50 ms per image processing time which exceeds YOLOv10's 3.8 milliseconds thus YOLO-based methods show better practicality in UAV missions and satellite imaging and automated defence systems control[6]. Hybrid systems such as TransEffiDet try to enhance global feature extraction by uniting Transformers with EfficientDet architecture, but these methods struggle with deployment issues due to their excessive computational requirements according to reference[13].

Recent works have investigated deep learning-based aircraft detection techniques. Guo*, et al.* suggested CNN-based feature extraction methods for aerial surveillance processing[1]. Likewise, Xu*, et al.* presented a hybrid deep learning framework for better occlusion management in remote sensing images[2]. Wang,*, et al.* evaluated transformer-based designs against CNN models, emphasizing the effectiveness of YOLO-based designs for high-speed classification processing[3]. In addition, studies by Yang*, et al.* highlighted the need for dataset diversity in enhancing detection robustness[4].

This research investigates YOLOv10 in aircraft detection for military use, displaying its performance with imbalanced datasets, partial occlusion, and similarly coloured aircraft without sacrificing real-time performance. A dataset of 74 aircraft classes is presented, marked with accurate bounding boxes to improve training robustness. The subsequent sections

Received : 21 November 2024, Revised : 25 March 2025
Accepted : 15 April 2025, Online published : 26 June 2025

present the dataset, methodology, and comparison to existing YOLO versions and competing detection models.

2. LITERATURE REVIEW

In the field of computer vision, object detection and aircraft classification have been thoroughly studied, progressing from conventional approaches to sophisticated deep learning techniques. Early approaches, such as template matching and boundary based methods, struggled with scale variations, occlusion, and background clutter prevalent in military imagery[5,17]. Conventional techniques that depended on manually created features, such as Template Matching, Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT), performed well in controlled environments but poorly in complex ones[4]. In their 2020 study, Liu[17], *et al.* illustrated this limitation by demonstrating that in order to address real-world remote sensing challenges, feature extraction for five different types of American military aircraft required more reliable solutions. Similarly, Aziz[5], *et al.* emphasized the need for adaptive architectures by pointing out that edge-based and region-based segmentation are ineffective for overlapping or visually similar aircraft.

Deep learning transformed object detection by providing notable advancements over manual methods. In their UAV based study, Gupta, *et al.*[1] demonstrated this change by showing that CNN-driven Tiny YOLO v3 achieved greater efficiency and accuracy on edge devices[1], outperforming Quantized SSD Mobilenet v2 on a dataset of 6,772 images, including military aircraft. By dividing an aircraft into four parts (head, wings, body, and tail) and improving focus on occluded regions, Zhou[2], *et al.* developed a local attention network for occlusion-insensitive aircraft detection in remote sensing images, outperforming state-of-the-art detectors[2]. Vision Transformers (ViTs) have also been investigated in the same context recently; Wang[18], *et al.* achieved a 75.74 % IoU for building extraction, indicating potential for aircraft detection with a mAP@0.5 of 80.3 %.[3] However, YOLOv10 provides a better trade-off by cutting inference time to 3.8 ms per image, while ViTs' computational cost of 50 ms/image makes them unsuitable for real-time military applications[16].

Real-time object detection has advanced thanks in large part to the YOLO family. By introducing YOLOv3 with Darknet-53, Redmon and Farhadi[7] improved feature extraction and achieved 28.2 mAP at 22 ms, which is three times faster than SSD[7]. This paved the way for military applications. With the addition of mosaic augmentation and the lightweight YOLOv5n (1.9M parameters), Jocher[8], *et al.* improved this with YOLOv5 v6.0, increasing mAP to 48.8 on COCO datasets[8], which is perfect for small aircraft detection. Nevertheless, Lei[11], *et al.* discovered that YOLOv8l had trouble with occlusion, class imbalance, and visually similar aircraft, [11] even though it achieved 84.2 % mAP@0.5 on the Military Aircraft Detection Dataset (MADD) using CSPDarkNet53 and CIoU loss. While real-time constraints remained until YOLOv10, which improves robustness and speed, Yang[15], *et al.* addressed some of these issues in YOLOv3 with GIoU loss, improving precision to 95.12 % and recall to 86.21 %.[15]

According to Saeed[12], *et al.*, real-world remote sensing datasets are frequently noisy and unbalanced. By using few-shot techniques and similarity learning to refine the MTARSI dataset, they were able to increase classification accuracy by 26 %. This is consistent with the current study's focus on preprocessing techniques like bounding box refinement and data augmentation. On the MAR20 dataset, Touati[10], *et al.* compared YOLOv5, YOLOv7, and YOLOv8. YOLOv7 had the best accuracy (90.3 % mAP@0.5, 0.895–0.901 precision, 0.995–0.993 recall), but its 6.4 ms inference time was slower than YOLOv10's 3.8 ms.[10] By combining Representative Batch Normalization, Mish activation, and VariFocal loss, Liu, *et al.*[6] proposed YOLO-Class, which increased mAP to 70.4 % for occluded and unbalanced satellite imagery[6]; however, YOLOv10 outperforms it in terms of both mAP and speed.

Other methods have also surfaced. By adding DenseNet and ConvNext-Transformer modules to YOLOv5, Zhou[3], *et al.* created CNTR-YOLO, which achieved mAPs of

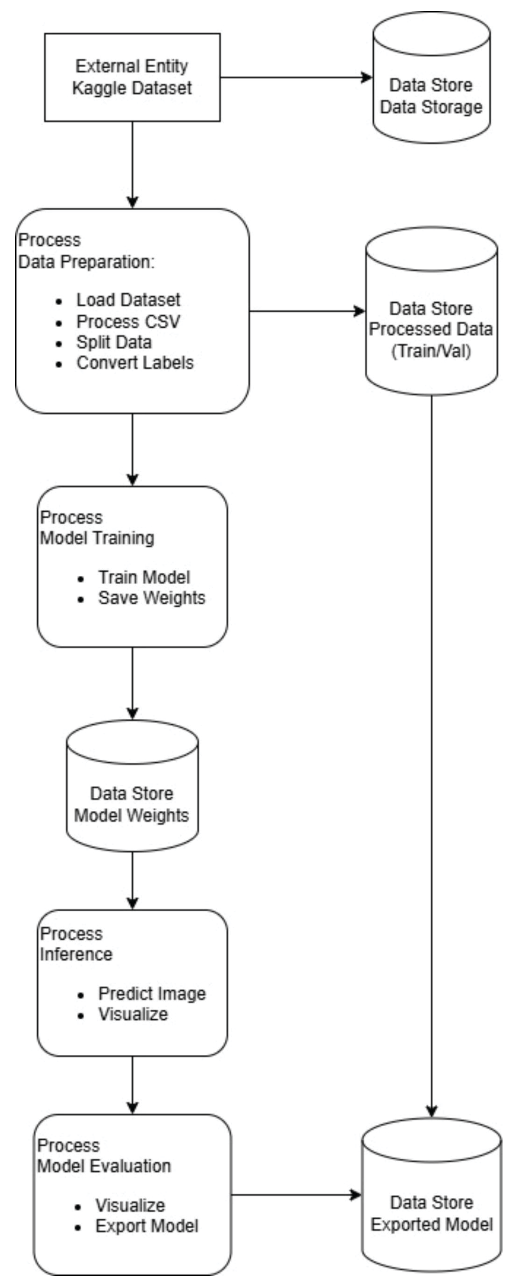


Figure 1. Flow diagram of the proposed model.

70.1 % (MAR20) and 63.7 % (DOTA)[3]. By using multiple class activation mapping to concentrate on discriminative parts, Fu[4], *et al.* introduced MultiCAM for fine-grained aircraft recognition, outperforming conventional CAM[4]. Although TransEffiDet, which Wang, *et al.*[13] created by combining EfficientDet and Transformers, has a mAP of 86.6 %[13], its complexity prevents real-time use in comparison to YOLOv10. For UAV surveillance, Ranjith[9], *et al.* combined YOLOv2 with ResNet-152, which performed exceptionally well in benchmark tests[9] but lacked YOLOv10's speed optimizations. This project builds upon these findings by integrating YOLOv10 with an improved dataset and enhanced preprocessing techniques to improve military aircraft detection accuracy.

3. METHODOLOGY

A number of crucial processes are involved in the methodology for creating and assessing the YOLOv10 model for military aircraft detection, including data preparation, model training, inference, and evaluation. An overview of the workflow is given in Fig. 1, which illustrates the steps involved in data collection, preprocessing, model training, and evaluation. Each step of this procedure is described in detail in the ensuing subsections.

3.1 Data Collection and Description

The dataset comprises several disparate classes of military aircraft, among them fighter aircraft (F-16, SU-35,

Figure 2. Sample dataset used from RarePlanes.

etc.) and bombers (B-52, Tu-95, etc.) comprising of a total of 74 different types. Each class encompasses images taken from different altitudes, points of view, and environments, aiming to cover all the possible appearances that an aircraft could be subject to under different conditions. Data was sourced publicly from datasets such as the Military Aircraft Detection Dataset on Kaggle[19], having synthetic images created by platforms like *RarePlanes*, a sample collection of which has been indicated in Fig. 2.

Combining all these sources diversifies and enhances the dataset. To maintain the dataset's diversity, aircraft images acquired from various perspectives and backgrounds and at different lighting conditions are considered to accurately mimic real scenarios. This diversity would allow for its generalization with recognition of aircraft from different angles and with environmental influences, among other attributes meant to be applied in real usage.

The dataset started out in CSV format, complete with bounding boxes defined by (x_{min}, y_{min}, x_{max}, y_{max}) coordinates. These were then transformed into a YOLO-compatible format, where the bounding boxes were normalized to fit the new structure. The bounding boxes coordinates are shown by Eqn. 1 to Eqn. 4.

$$x_{center} = \frac{x_{min}+x_{max}}{2\times width} \tag{1}$$

$$y_{center} = \frac{y_{min}+y_{max}}{2\times height} \tag{2}$$

$$w_{bbox} = \frac{x_{max}-x_{min}}{width} \tag{3}$$

$$h_{bbox} = \frac{y_{max}-y_{min}}{height} \tag{4}$$

Each image's annotations were saved in a '.txt' file, organized like this:

$< class\_id >< x\_center >< y\_center >< width >< height >$

3.1.1 Data Augmentation and Class Balancing

A number of data augmentation strategies were used to address class imbalance and enhance model generalization:

- 50 % flipping improves the robustness of detection for aircraft orientations
- Adjustments for brightness and contrast are used to replicate changes in lighting throughout the day
- By introducing size variations, scaling and cropping (50–150 %) aids in the detection of small objects
- HSV Transformations: Modifies color characteristics to increase weather adaptability
- GAN-Based Synthetic Data Generation: This technique ensures a balanced dataset by increasing the representation of uncommon aircraft types.

These preprocessing techniques aid YOLOv10 in managing environmental distortions, lighting fluctuations, and occlusion—all of which are crucial in practical defence applications.

3.2 Model Architecture

The three components of YOLOv10's architecture: the detecting head, neck, and backbone; are all tuned for precise object localization, multi-scale fusion, and effective feature extraction. These enhancements improve the ability to detect military aircraft in real time under a variety of circumstances, such as cluttered backdrops, different sizes, and occlusions.

3.2.1 YOLOv10's Architecture and Deep Neural Networks for Object Detection

Because of their capacity to recognize spatial patterns, Convolutional Neural Networks (CNNs) are the industry standard for object detection. YOLO's single-stage method predicts bounding boxes and class labels simultaneously, which makes it perfect for real-time military surveillance in contrast to slow, region-based techniques like R-CNN. This foundation is strengthened by YOLOv10's significant architectural enhancements:

By dividing feature maps, CSPNet (Backbone) improves feature extraction, computational efficiency, and the detection of small aircraft, such as stealth planes. In crowded areas like runways, PANet (Neck) improves detection across aircraft sizes and orientations by fusing multi-scale features. By taking aspect ratio and center distance into account, CIoU Loss (Detection Head) improves bounding box accuracy, minimizes misalignment, and efficiently manages occlusions.

3.2.2 YOLOv10's Improvements Over YOLOv8 and Previous Versions

By considering occlusion, class imbalance, lighting variations, and real-time requirements, YOLOv10 performs better than YOLOv8 in military aircraft detection:

- Feature Extraction: CSPNet enhances small aircraft detection in cluttered backgrounds by improving gradient flow over YOLOv8's CSPDarkNet
- Handling Occlusion: Improved detection in occlusions and unfavourable environments (such as fog or night vision) is made possible by enhanced spatial attention and anchor-free design
- Unbalanced Class: Weighted Task Aligned Loss (W-TAL) and Dynamic Soft Label Assignment (DSLA) balance rare aircraft types, like stealth fighters
- Robustness of Lighting: In low-light, infrared, or thermal imagery, detection is guaranteed by contrast-adaptive preprocessing
- Performance in Real Time: Optimized for edge deployment (e.g., UAVs, satellites), the inference time decreases to 3.8ms/image (compared to 6.2ms for YOLOv8)
- Precision: SIoU and Adaptive GIoU losses enhance localization for irregular shapes and lower false positives.
- Efficiency: Low-power military devices, like the Jetson Nano, are better suited for lighter architecture.

3.3 Training Procedures

3.3.1 Selection of Hyperparameters

- Batch Size = 16: This size strikes a balance between training stability and GPU memory; larger sizes run the risk of memory overload, while smaller sizes result in unstable gradients
- Image Size = 800: Reduces computational cost and improves detection accuracy for small objects

- Learning Rate: To prevent abrupt updates and enhance generalization, cosine annealing is applied at 0.05
- Dropout: For robust feature learning, it randomly disables neurons to prevent overfitting.

To handle different lighting, views, and object sizes, data augmentation techniques include color jittering, horizontal flip (50 %), vertical flip (50 %), and scaling/cropping.

3.3.2 Applying Fine-Tuning Technique & Pretrained Weights

Pretrained Weights: Strong feature extraction and quicker convergence are made possible by COCO-trained YOLOv10s. pt weights.

Fine-tuning involves first freezing the backbone layers, then updating the classification and detection heads before gradually unfreezing the inner layers to make aircraft-specific modifications.

3.3.3 Model Evaluation Metrics

YOLOv10's performance was evaluated using standard object detection metrics:

- Precision and Recall: Indicates how accurate predictions are in comparison to false positives or negatives.
- F1-Score: Offers a fair evaluation of recall and precision.
- Mean Average Precision (mAP@0.5 & mAP@0.5-0.95): Assesses the overall performance of the model at different IoU thresholds.
- Bounding box accuracy in relation to ground truth is measured by Intersection over Union (IoU).
- For real-time applications, inference speed (ms/image) is a measure of processing efficiency.

Confusion matrices and PR curves were used to illustrate the model's performance and show how well each architectural improvement worked. According to these tests, YOLOv10 performs better than YOLOv8 in terms of speed and accuracy, which makes it a good choice for military aircraft detection in real time.

4. RESULTS AND DISCUSSION

A detailed study of the YOLOv10 model's detection speed, classification accuracy, and comparison with earlier models is presented in this section for military aircraft classification. The outcomes emphasize the advantages, challenges, and areas for improvement of the model.

4.1 General Performance Indicators

The general performance indicators measured were precision, recall, F1-score, mean average precision (mAP),

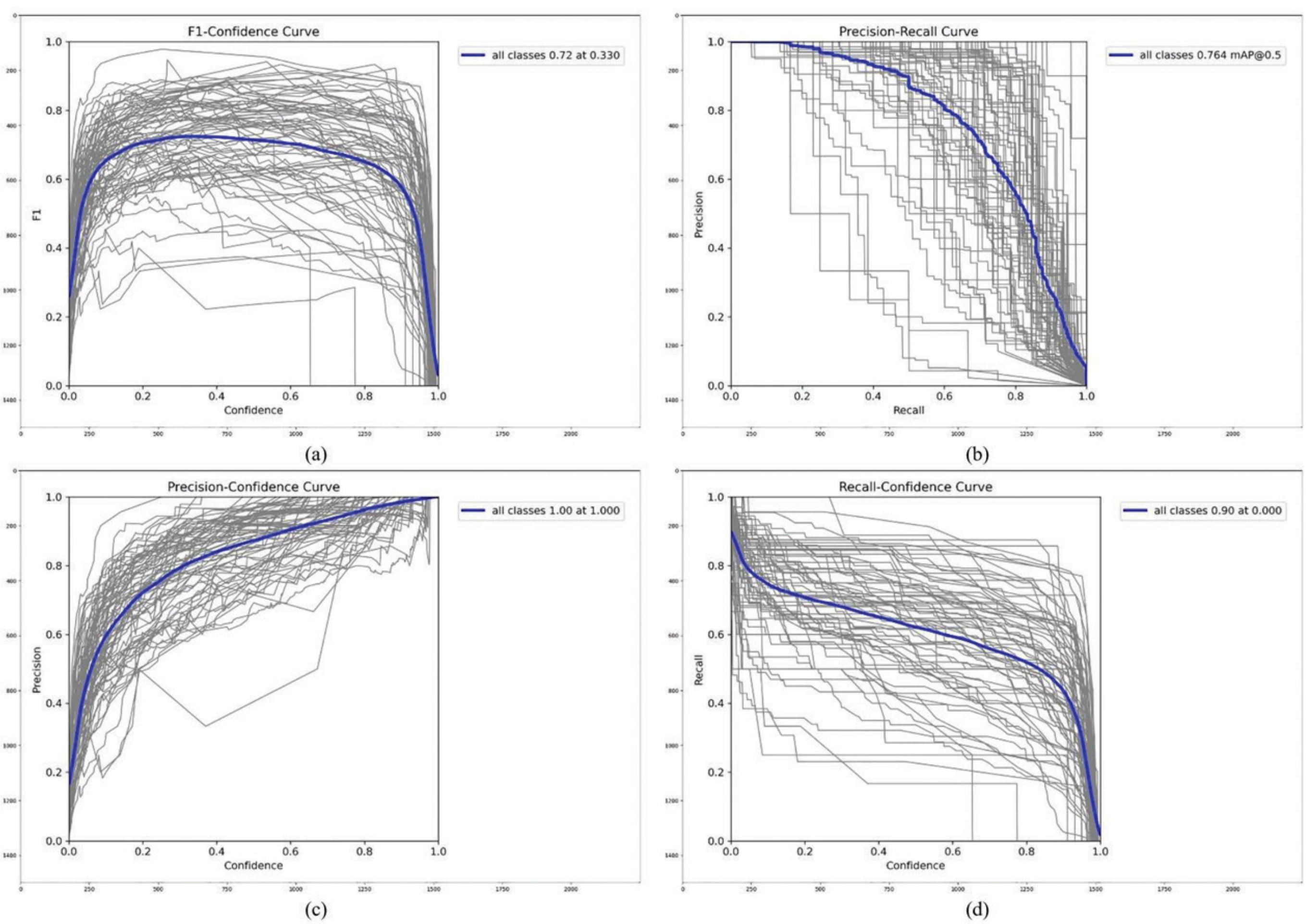


Figure 3. Performance of the proposed model on widely used indicators, (a) F1-confidence, (b) Precision-recall, (c) Precision-confidence, and (d) Recall-confidence.

intersection over union (IoU), and inference speed on the YOLOv10 model Numerous metrics were used to assess YOLOv10's performance. The (a) Precision-Confidence, (b) Recall-Confidence, (c) Precision-Recall, and (d) F1-Confidence curves, which are displayed in Fig. 3(a–d), respectively, demonstrate the success of YOLOv10 in achieving a precision of 82 %, recall of 66.4 %, and a mAP@0.5 of 76.4 %. Main performance indicators were:

- Precision: 82 %, which implies a ratio of appropriately predicted positive instances
- Recall: 66.4 %, expressing proportion of true positive instances
- F1-Score: 0.687, between precision and recall
- Intersection over Union (IoU): Average IoU of 0.764, for proper localization of objects
- Mean Average Precision (mAP):
    - mAP@0.5: 76.4 %, performing well with lower IoU thresholds.
    - mAP@0.5–0.95: 68.7 %, showing resilience for different IoU values.

With 3.8 ms per image, the model performed better than YOLOv8 (6.2 ms) and YOLOv7 (5.1 ms) in terms of inference time. Due to its fast-processing speed, YOLOv10 is ideal for real-time surveillance.

4.2 Class-Wise Performance Analysis

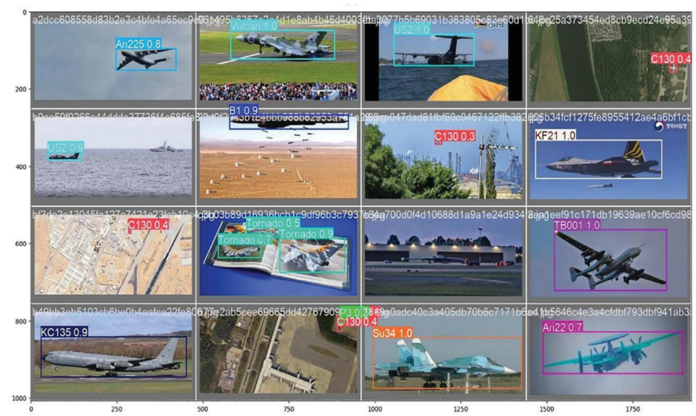
A summarization of YOLOv10 classification performance of across few aircraft types has been indicated in Table 1. The sample detection results of YOLOv10 on the military aircraft dataset are shown in Fig. 4(a-c), where certain types, including the F18, J20, and B52, are accurately identified with high confidence scores. These results are consistent with the class-wise performance metrics outlined below. The main performance indicators for selected aircraft types are as per Table 1. The Tu95 and B52 classes, with their distinct features that allow easier classification, were the best performers.

Table 1. Performance indicators for selected aircraft types

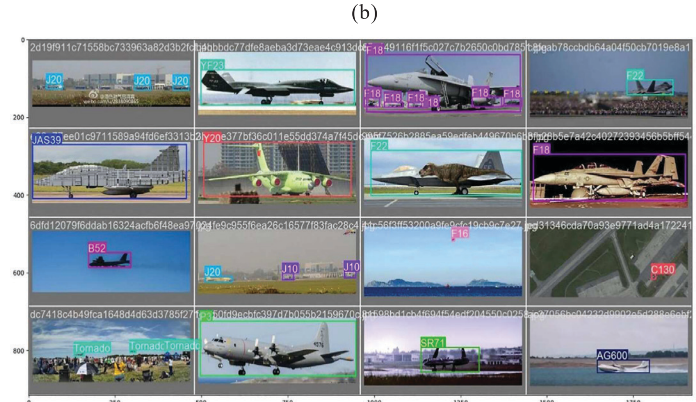
Aircraft type	Precision (%)	Recall (%)	F1-Score (%)	mAP@0.5 (%)
EF2000	64.9	62.0	63.4	71.6
Tu95	92.6	83.3	87.7	88.9
F15	83.3	70.6	76.5	80.3
F16	68.5	58.0	62.9	68.1
B52	89.9	68.1	79.1	79.1

Nevertheless, due to their physical and structural similarity, types like the EF2000 and F16 recorded lower recall, resulting in misclassifications.

(a)



(b)



(c)

Figure 4. Accurate identification of F18, J20, and B5 models by the classification model in 3 collections of instances i.e. (a), (b) and (c).

Table 2. Aircraft detection using YOLOv10 versus other YOLO variants

Model	Precision (%)	Recall (%)	mAP@0.5 (%)	Inference time	Occlusion handling
YOLOv5	74.3	60.2	71.1	7.4	Moderate
YOLOv7	78.1	64.5	74.6	5.1	Moderate
YOLOv8	80.4	65.9	75.2	6.2	Good
CNTR-YOLO	81.6	67.3	76.1	5.8	Strong
YOLOv10	82.0	66.4	76.4	3.8	Excellent

4.3 Comparative Analysis

An analysis of comparison amongst YOLOv10 YOLOv5, YOLOv7, YOLOv8, and CNTR-YOLO on several important metrics in order to evaluate its efficacy has been presented to evaluate the efficacy of YOLO v10 in comparison to its contemporaries and predecessors, same has been indicated in Table 2.

4.4 Model Limitations and Error Analysis

YOLOv10 has many drawbacks despite its excellent performance:

- Visual similarity misclassification of planes: The model struggles to distinguish between planes with structural similarities such as the F16 and Rafale
- Reduced recall for small or obscured airplanes: Detection accuracy is diminished by partially obscured aircraft, particularly those in congested scenarios
- Class inequality problems: Since there are fewer training samples, less represented aircraft types do not perform as well.

4.5 Possible Improvements

Several enhancements would make YOLOv10 even more functional:

- Data Augmentation: Class imbalance can be reduced by incorporating synthetic data for underrepresented aircraft classes
- Attention Mechanisms**:** Incorporating transformer-based attention modules may enhance feature extraction and reduce misclassification
- Multi-Scale Detection Strategies: The ability of a model to detect smaller planes can be increased by introducing additional scale-aware modules.

5. CONCLUSIONS

This research successfully establishes the performance of YOLOv10 in military aircraft detection and classification. YOLOv10 achieves a robust balance of accuracy and real-time performance with an mAP@0.5 of 76.4 % and an inference rate of 3.8 ms per image. The combination of advanced feature extraction, data augmentation practices, and pre-trained models greatly improved detection resilience and training speed. The model was experimented on different setups, and outcomes verify its suitability in diverse working conditions. Nonetheless, confusion matrices and performance analysis point out areas that need improvement, especially in:

- Dealing with visually similar airplane models like F16 and Rafale, where misclassification is experienced
- Object detection for small or occluded objects, which still poses a challenge
- Maintaining class distribution since minority aircraft types have lower recall scores.

5.1 Key Insights

This study demonstrates YOLOv10's potential for military aircraft classification:

- **Model Performance:** YOLOv10 achieves 3.8 ms inference speed and 76.4 % mAP (IoU 0.5), ensuring suitability for real-time defence applications
- **Dataset and Preprocessing:** A large, varied dataset of 74 aircraft types, along with extensive preprocessing, increases model generalization and strength
- **Challenges:** Further refinements are needed for handling occlusion, small objects, and similar aircraft types
- **Comparison:** YOLOv10 is faster in inference speed compared to YOLOv8 and hence more appropriate for real-time military surveillance
- **Future Scope:** Multi-sensor data fusion and edge-device optimization integration will enhance deployment efficiency
- **Impact:** This research contributes to AI applications in defence surveillance and operational readiness.

5.2 Future Work

To further improve YOLOv10's performance, future research would need to emphasize:

- Use of attention mechanisms to enhance occluded object feature extraction
- Utilization of multi-sensor fusion (e.g., radar and infrared integration) for classification accuracy improvement
- Use of the model on edge devices for real-time military use
- Experimentation with semi-supervised learning strategies to deal with dataset imbalance and enhance training on minority aircraft classes.

Through these improvements, YOLOv10 will be ready to be an integral part of next-generation defence surveillance systems, providing precise, effective, and real-time military aircraft detection for national security use.

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CONTRIBUTORS

Ms Debadrita Mukherjee is a BTech CSE (Data Science) student at Sharda University, India. Her research interests include: Deep learning, object detection, and image processing. In the current study she led data preprocessing, performance evaluation, and contributed to the literature review.

Ms Sadaf Zahra is pursuing BTech in CSE (Data Science) at Sharda University. Her work focuses on machine learning, deep learning, and computer vision.
In the current study she worked on model architecture, training, and wrote the methodology section.

Ms Soumya Sharma is a BTech CSE (Data Science & Analytics) student at Sharda University. Her interests include: AI, business intelligence, and data-driven solutions.
In the current study she contributed to the experimental setup, model evaluation, and wrote the results.

Ms Tummenye Amos is a BTech CSE (Data Science) student at Sharda University. Her focus areas are image processing and deep learning.
In the current study she assisted in data collection, model comparison, and writing key sections.

Dr Ali Imam Abidi obtained his PhD from IIT (BHU) Varanasi and working as an Associate Professor at Sharda University. His expertise includes computer vision and AI.
In the current study he supervised the research and reviewed the final manuscript.