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DEEP LEARNING AND FUZZY LOGIC-BASED HYBRID FRAMEWORK FOR AERIAL OBJECT TRACKING

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Abstract: This study introduces an aerial target detection and tracking system using the YOLOv8 model combined with the ByteTrack algorithm. The proposed system is built on improving accuracy and efficiency in the detection and tracking of aerial objects in video frames. Detection is performed using a specially trained YOLOv8 model. ByteTrack further completes the tracking in a robust manner, even for dynamically changing environments. The presented scheme also embeds a new decision-making layer by using a Fuzzy Logic System. This system adopts Trapezoidal Membership Functions for confidence and distance evaluation of detected objects. It enables the framework to achieve priority levels in tracking. For prediction of future positions, a Kalman Filter is applied. This enhances the ability of the system to foresee various situations. Different scenarios effectively demonstrate how the system can dynamically prioritize and track multiple objects in accordance with their threat level and proximity. The findings of this study could contribute to existing methods by improving detection and tracking accuracy. They also incorporate a decision-making process like humans. Hence, its highly applicable domains are defense and surveillance, which require real-time and accurate threat assessment. This system can operate reliably under different operational conditions and may provide a valid tool for enhancing airspace security.

Keywords: Aerial target detection, Object tracking, Deep learning, ByteTrack, Fuzzy logic, Kalman filter

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1. Introduction

Nowadays, video processing and object detection are the fastest-growing technologies with huge applications in vital systems relating to security, autonomous vehicles, smart cities, and many others. The effectiveness of such systems depends not only on the ability to detect objects but also on the prioritization and tracking of the detected objects. For instance, the autonomous vehicle system needs to detect all the objects around it. However, it needs to give more importance to nearby obstacles or main targets to perform the optimizations required in its decision-making processes (Cai et al., 2021). In this context, the development of an integrated system in which object detection, prioritization and monitoring processes work together is of great importance.

Deep learning-based methods, especially models like YOLO (You Only Look Once), are widely used in the literature for object detection (Zhao et al., 2019). These models have evolved into a powerful tool for object detection in video streams. They ensure high accuracy with the possibility of real-time processing. However, only identifying the objects is not enough. The determination of priorities among the detected objects and acting based on these priorities enhances system performance by a big margin. This is especially true in noisy environments or critical scenarios. Traditional approaches to prioritization usually rely on strict rules. In contrast, fuzzy logic-based systems can develop their full capability in solving situations that include unsharpness and variability (Bukhsh et al., 2020). Besides, object-tracking algorithms are performed to keep continuous objects and also track the displacements of all objects. Approaches such as the Kalman filter are preferred in object tracking due to their accuracy and stability (Brookner, 1998). However, most current research regards object detection, prioritization, and tracking processes independently. Additionally, there is not enough academic research to integrate these processes into a real-time system.

This paper offers an integrated approach for object detection in video streams using fuzzy logic-based prioritization and Kalman Filter-based object tracking. In the suggested method, aerial vehicles are detected by the YOLOv8 model. Additionally, the priority values are computed using a fuzzy logic system based on the aircraft's security scores and distance from the frame center. The movement of these aircraft is tracked using the Kalman Filter (Welch, 2021). The proposed study aims to come out with a solution having high accuracy, quick processing time, and dynamic prioritization capability for applications based on video processing. This method will be useful in various applications, including air defense systems, traffic analysis, and autonomous vehicle technologies.

This study consists of several sections. In this section of the study, the aim and approach of the study are mentioned. In the Related Studies section, the studies conducted on the detection and tracking of aircraft are summarized. In the Object Recognition and Tracking System section, the models and algorithms used are explained. In the Results and Discussion section, the findings are presented and discussed briefly. Finally, in the Conclusion section, the contribution of the study is summarized, and future studies are emphasized.

1.2. Related Works

Recently, the deep learning model-based aerial recognition and tracking system has gained wide attention due to its growing demands in surveillance, environmental monitoring, and disaster responses. Among such models, the YOLO algorithm has attained wide recognition with its robust performance in real-time object detection and tracking, particularly in UAV-based aerial imagery (Jawaharlalnehru et al., 2022). The model was recommended for real-time aerial applications owing to its high balance between speed and accuracy. Based on improving performance in accuracy, efficiency, and scalability, several research works have been made that have reached a variety of challenges about YOLO-based models: small object detection, occlusion, and variable environmental conditions (Diwan et al., 2023).

Target detection based on YOLO is applied in UAV (Unmanned Aerial Vehicle) imagery. Xue and Wu have proposed an improved model of YOLOX, incorporating EfficientNet as the backbone to improve target detection in terms of accuracy and computational efficiency in UAV imagery (Xu and Wu, 2023). Their methodology has considerably improved mAP while improving computation cost, hence it will be suitable for real-time applications in UAVs. On the other side, Zhang et al. in 2022, proposed an improved YOLOX framework for an aerial orthophoto-based recognition and positioning system (Zhang et al., 2022). Their work outperformed all others by a high mAP and better localization, hence could solve real-time UAV surveillance. They perform real-time object recognition and tracking. Zong et al. (2023) give an overall review of YOLO models starting from YOLOv1 to YOLOv8. They outlined the evolution process of YOLO from architecture design to improved performance and concluded its use for UAV surveillance and reconnaissance (Zong et al., 2023). Shao et al. (2024) proposed a lightweight UAV-based detection method named Aero-YOLO, optimized for small object detection (Shao et al., 2024). This research showed its better performance both in accuracy and processing speed on aerial datasets.

Specialized applications of YOLO have also been developed regarding UAV systems. Other than generic tracking and recognition, YOLO finds applications in specialized tasks related to UAVs. For example, Shen et al. (2022) have proposed the YOLO-based drogue recognition method in autonomous aerial refueling (Shen et al., 2022). They optimize feature extraction and loss functions to improve real-time detection and tracking of aerial targets. Zhang et al. (2023) have proposed a YOLOv4 and OpenCV-integrated electro-optical tracking system for UAV-based anti-drone applications (Zhang et al., 2023). They showed very strong adaptiveness in dynamic tracking scenarios.

Advancements within YOLO have significantly upgraded UAV-based surveillance. Recently, there have been further developments regarding the computational efficiency of the models. Zhao et al. have proposed G-YOLO-an improved infrared aerial remote sensing detection model (Zhao et al., 2024). Their contribution led to greatly reduced computational overhead while maintaining the high accuracy of detection, and thus it became feasible for its deployment on resource-constrained UAVs. Kaymakcı et al. (2023) conducted a comparative analysis of various YOLO versions and stated that YOLOv8 is the best model in small-scale object detection in aerial surveillance tasks (Kaymakcı et al., 2023). Akyüz et al. (2025) showed that YOLOv11 combined with ByteTrack provided fast inference suitable for real-time multi-object detection and tracking applications, while Faster R-CNN achieved higher detection accuracy at a greater computational cost. Their evaluation indicated that model selection should depend on the specific requirements of the intended application (Akyüz et al., 2025).

These studies show how much the YOLO-based Aerial Recognition and Tracking Systems keep on improving continuously. These enhancements expand the potential field of application in UAV-based surveillance, object recognition, and autonomous navigation. Future research should therefore be focused on reinforcing the robustness of the YOLO model in complex scenarios, the fusion of multimodal data, and the improvement of computational efficiency for real-time tracking tasks in aerial environments.

3. Materials and Methods

This work presents a system that covers object detection, prioritization, and tracking processes specifically designed for real-time aerial surveillance of military aircraft. The system detects, prioritizes, and tracks objects by combining video processing techniques such as the YOLOv8 object detection model, the ByteTrack tracking system, fuzzy logic prioritization, and Kalman filter methods. Figure 1 shows the flowchart of the operational process for a target detection and tracking system using a YOLO model, Kalman Filter, and fuzzy logic. The process includes a stream of images where, in each frame, image processing is applied along with the

YOLO model for detecting potential targets. If the model recognizes a target, it determines whether it is an aircraft. If the object is an aircraft, it applies fuzzy logic to determine the priority regarding detection. Further, the state prediction and correction are done for the detected targets by using the Kalman Filter and appending them into a list of detections. The system iterates in cycles, continuously updating and refining target information across frames of the stream. This is a very orderly approach to going about object tracking within a surveillance area.

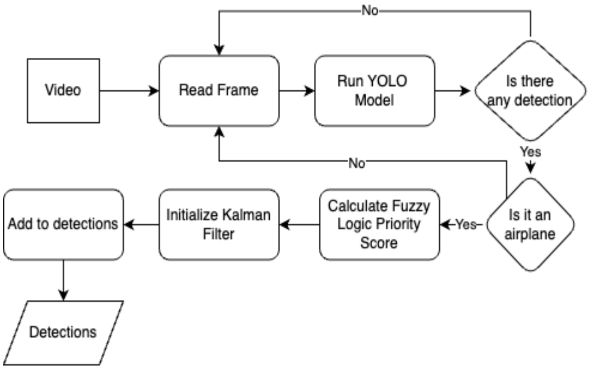


Figure 1. Flowchart of object classification and target detection.

Figure 2 is a flowchart of target-locking decisions in a tracking system that starts from the detected objects. In case of an already locked target, the model checks whether a target change event occurred; in case of a need for a change or in the absence of a locked target, it selects the most important target with the highest priority score. If the first target is not available, it will select the second-best priority target. The system also ensures that the chosen target has been in its view for more than three seconds before locking on to it. If this is satisfied, the Kalman Filter will be applied to refine the tracking of the target to make it accurate and stable to monitor the target. This structured approach facilitates effective prioritization and stable tracking of critical targets.

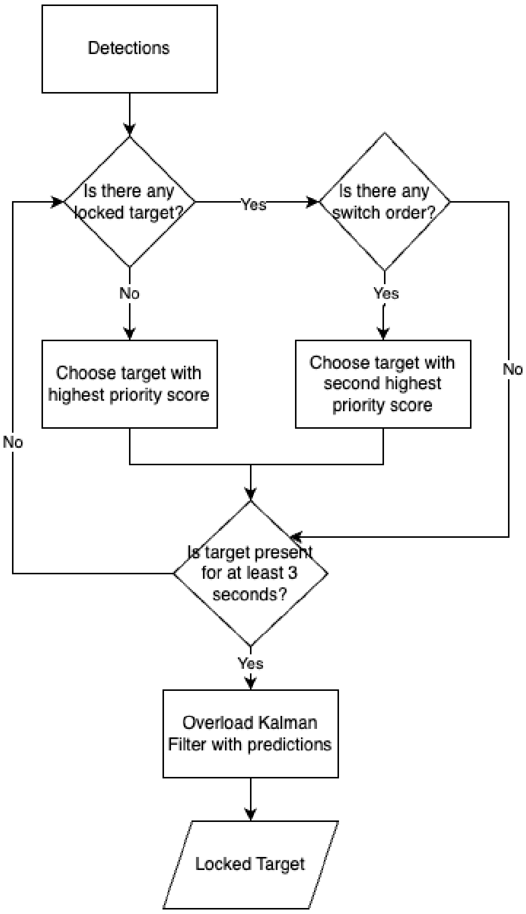


Figure 2. Decision process for target locking in a tracking system.

3.1. YOLOv8 Model and ByteTrack Algorithm

YOLOv8 is one of the latest versions of the YOLO family, which has been very dominant in object detection and other image processing-related tasks in recent years. YOLOv8 was selected as the detector in this study because it provides a strong accuracy–latency trade-off for real-time video analytics and has demonstrated competitive performance for small-object detection in aerial imagery compared with earlier YOLO variants (Sohan et al., 2024). This variant is more speedy, more accurate, and more efficient, especially in real-time applications. Beyond processing speed, YOLOv8's anchor-free decoupled head and Distribution Focal Loss provide specific advantages for aerial imagery, addressing the class imbalance between vast sky backgrounds and minute targets better than anchor-based predecessors. With a more modern architecture, YOLOv8 detects small, medium, and large-scale objects even better, with extensions to various computer vision tasks such as image classification (Rasheed and Zarkoosh, 2025). It is innovative in terms of performances with its anchor-free structure and advanced data augmentation technique compared to earlier models (Zhang et al., 2024).

The model mainly consists of three parts: the Backbone, Neck, and Head in Figure 3. This means that it involves the Backbone, optimized to extract features from an image at different scales, while the Neck strengthens multi-scale detection by combining these features, and the Head carries out classification and bounding box predictions (Vasanthi and Mohan, 2024). In addition, it contains an advanced loss function and dynamic learning rate strategies that make model training effective. The hyperparameters used during training play a significant role in increasing data diversity and improving the model's generalization performance. This will allow the YOLOv8 to be applied to a wide variety of fields, such as security, autonomous vehicles, healthcare, and industrial production (Ali and Zhang, 2024). Its performance in real-time object detection brings many advantages to tasks like traffic congestion analysis, medical image processing, and quality control. All these features make the YOLOv8 strong and flexible for modern computer vision applications.

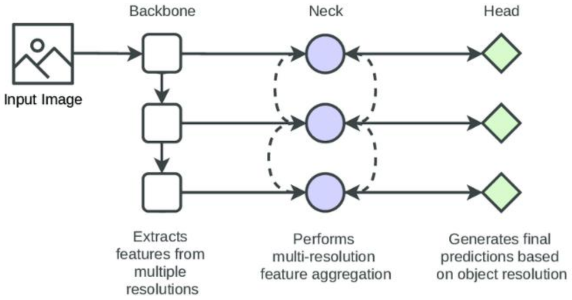


Figure 3. The detection model contains a backbone, neck, head module (Kateb et al., 2021).

The YOLOv8 model is applied for the detection of aerial vehicles in this work. The model identifies the class, identity, confidence score, and coordinates of the aircraft in each video frame. The detections constitute the primary input for the tracking and prioritization processes of aircraft. Confidence score refers to the model's accuracy in the detection of any particular object and is fed as an input parameter to the fuzzy logic system.

In addition, a ByteTrack tracking algorithm has been used to track the trajectories of the detected aircraft. We selected ByteTrack as our tracking algorithm due to its optimal balance between computational efficiency and tracking performance. A recent comparative analysis of Kalman Filter-based methods for fast-moving tiny objects (Singh et al., 2025) identifies ByteTrack as the fastest among state-of-the-art trackers. While complex trajectory modeling (such as in DeepOCSORT) can offer advantages for highly erratic motion, the study highlights ByteTrack's architectural simplicity and low latency as decisive factors for real-time applications. This efficiency allows our system to maintain robust tracking of small aerial targets without the computational overhead associated with more complex association mechanisms.

The ByteTrack operates on the "tracking-by-detection" paradigm. That is, the objects are first detected using a detection algorithm, such as YOLO, and then ByteTrack links these detections to track the movement of each object over time (Zhang et al., 2022). In our study, this algorithm will track the movement and position of each detected aircraft while maintaining the identity throughout the video. In this way, the aircraft movement is tracked according to Kalman Filters and prioritization criteria of fuzzy logic.

3.2. Trapezoidal Membership Functions

Fuzzy logic is a mathematical approach that focuses on representing uncertainty and intermediate states rather than precision (Celikyilmaz and Turksen, 2009). Although traditional logic classifies each statement as either "true" or "false," fuzzy logic allows a situation to be "partially true" or "partially false." It is much more useful to analyze situations where it cannot be precisely expressed, and as far as the presentation goes, it presents a model of human thought and language that is closer. In fuzzy logic systems, using fuzzy sets to determine the situation's membership between 0 and 1, decisions would be made accordingly (Jain and Sharma, 2020).

The integration of Fuzzy Logic into tracking frameworks is well-supported in literature. For instance, (Hamid et al., 2018) demonstrated that fuzzy inference systems can effectively imitate human subjective decision-making to correct estimations in dynamic environments. By adopting a similar approach, our system leverages fuzzy reasoning to handle the uncertainty inherent in aerial detection confidence scores, translating vague inputs into precise tracking priorities.

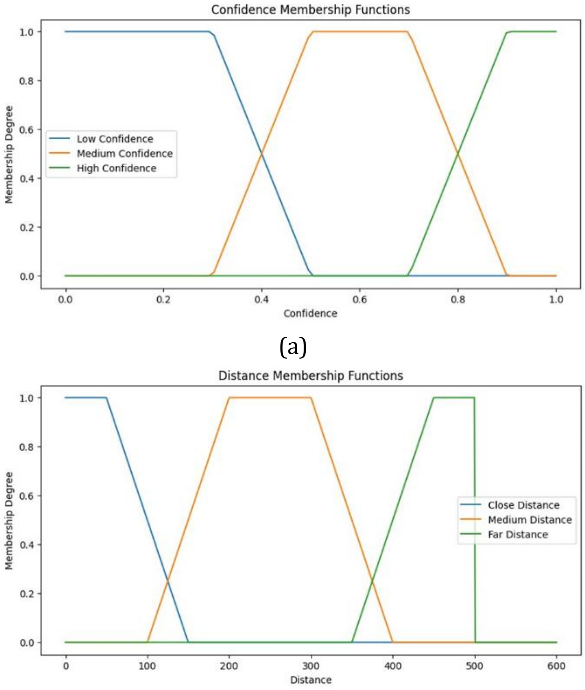
Some main applications of fuzzy logic have been so strong as to place it at the forefront while solving complex problems. Working on uncertain data provides flexibility and adaptation to decisions on fuzzy logic in systems like industrial control, climate control, or robotics (De Silva, 2018). Additionally, it is frequently used in fields such as artificial intelligence, agriculture, finance, and medicine. For example, in diagnosing a disease, the weights of different symptoms can be evaluated using fuzzy logic (Ahmadi et al., 2018). Due to its ability to handle uncertainty, fuzzy logic stands out as an effective analysis and decision support method in both engineering and social sciences.

The fuzzy logic system in this study is designed to determine the priority levels of aerial vehicles using trapezoidal membership function μ(x) in equation 1 where a, b, c, d are the parameters that define the trapezoidal shape.

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x < c \\ \frac{d-x}{d-c}, & c \leq x < d \\ 0, & x \geq d \end{cases} \tag{1}$$

This system uses two inputs: the confidence score of the detected object and its distance from the frame center. The confidence score is expressed with three terms: "low," "medium," and "high," while the distance is modeled with the terms "close," "medium," and "far" in

Figure 4. The 'Low Confidence' function (blue line) maintains high membership values between 0 and 0.3 and drops to zero at a confidence value of 0.5. The 'Medium Confidence' function (orange line) starts rising from 0.3, reaches a value of 1 between 0.5 and 0.7, and begins to decrease at 0.9. The 'High Confidence' function (green line) increases from 0.7 and remains at full membership values between 0.9 and 1.0. These functions are critical for evaluating decisions made by the system at different confidence levels and improving the decision-making process based on confidence scores. The 'Close Distance' function (blue line) is represented between 0 and approximately 150 units and decreases linearly to zero at 200 units. The 'Medium Distance' function (orange line) starts at zero at 100 units, reaches 1 at 200 units, and drops back to zero at 300 units. The 'Far Distance' function (green line) becomes active from 300 units and remains at full membership values up to 500 units. These functions are significant for determining how the system reacts to different distance ranges and provide precise control based on proximity.



(a)

(b)

Figure 4. a) Confidence membership function. b) Distance membership function for fuzzy logic.

The fuzzy logic rules determine the priority levels of objects based on these two inputs. For example, if an aircraft has a high confidence score and is close, it is considered high priority. Similarly, objects with a low confidence score or a large distance are classified as low priority. The output variable is expressed with two terms: "high priority" or "low priority." The pseudo-code presented below clearly outlines the decision-making procedure used to compute this priority score.

```
Algorithm 1: Priority score assignment
input: confidence, distance
output: priority score  // 1 = Low, 2 = High
if (confidence is high) and (distance is close) then
    priority ← 2
else if (confidence is medium) or (distance is far) then
    priority ← 1
else if (confidence is low) then
    priority ← 1
end if
```

3.3. Kalman Filter for Route Tracking

The Kalman filter is an iterative algorithm that predicts the state of a system while working on noisy measurements. Invented by Rudolf E. Kalman, this filter is particularly one of the strong tools for modeling past, present, and future states of a system, especially in time series data (Faragher, 2012). The Kalman filter updates system dynamics according to a mathematical model in Figure 5, incorporating error from measurement and system models. The parameters applied in this process are the measurement matrix, transition matrix, system noise, and measurement noise (Huang et al., 2017). For instance, a Kalman filter predicts the position and velocity of a moving object, taking the current measurements with respect to previous predictions for an optimum estimate devoid of measurement errors. This filter has wide applications in robotics, object tracking, navigation, and analysis of financial data due to the delivery of highly accurate and successful predictions in a noisy environment (Hun et al., 2016).

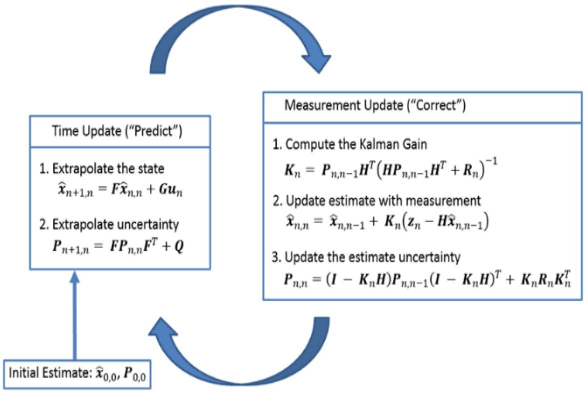


Figure 5. The cyclical process of the Kalman Filter used for state estimation in dynamic systems (KalmanFilter.net, 2024).

The information obtained from the processes of detection and prioritization is integrated with the Kalman filter for aircraft route tracking. It is used on each individually detected aircraft and thus provides the possible movement of such objects (Gunjal et al., 2018). This filter takes the center coordinates of every aircraft as its measurement data and thus tracks the aircraft's motions smoothly. Hence, aerial vehicles will be tracked effortlessly across frames.

The system is also designed to be interactive. A user can select an aircraft of interest through the "lock" option. The system highlights locked aircraft and boosts their priority values. By doing so, the user focuses on some objects, while the system's attention concentrates on those very objects. As a result, this method has integrated object detection, prioritization, and tracking processes to create a real-time monitoring and analysis system. The various components of the system work together to allow the user to focus attention on specific objects and track them with precision.

4. Results and Discussion

4.1. Aerial Object Detection

This section discusses the target detection findings using the YOLOv8 model, including model training and performance analysis. The implementation and training of models were performed using the Google Colab hosted Jupyter Notebook service (Carneiro et al., 2018). All experiments were conducted in a Google Colab environment. Training and evaluation were performed on a setup equipped with an NVIDIA L4 GPU (24 GB VRAM), 16 vCPU cores, and 62.8 GB of system RAM. The implementation was based on Ultralytics YOLOv8 (v8.0.196) with Python 3.10.12 and PyTorch 2.2.1+cu121. We fine-tuned the pretrained YOLOv8n model (yolov8n.pt) using an image size of 640×640, batch size of 16, and training schedules of 25, 50, and 100 epochs. The optimizer was set to auto, and the training logs indicate that AdamW was selected with an initial learning rate of 0.002 and momentum of 0.9.

The Military Aircraft Detection Dataset available on Kaggle was used for training. This dataset is for object detection on military aircraft and encompasses 77 different military aircraft types. The dataset's annotations were not in YOLOv8 compatible format. Data pre-processing was done to align the formats between the annotations and the model. After the pre-processing, this dataset contains only two classes: aircraft and background.

Figure 6. Image samples of aircraft from the dataset (Kaggle, 2024).

A total of 33.544 images are used for training purposes with the detection model, including 25.180 for training, 6.144 for validation, and 2.220 for testing. The YOLOv8 model was trained for 25, 50, and 100 epochs during training while monitoring the losses and accuracy rate of the model throughout the training. For assessing the performance of the model in detection, precision, recall, and mean average precision scores (mAP) were used as evaluation metrics (Vujović, 2021).

The model speed breakdown given by the Ultralytics YOLOv8 validation routine is reported in Table 1. The measured runtime was ~0.2 ms for preprocessing and ~1.0 ms for inference per image. Post-processing was 6.5 ms for the 25-epoch and 50-epoch checkpoints and 6.6 ms for the 100-epoch checkpoint. Overall, the detector latency was ~7.7–7.8 ms per image.

Table 1. Model processing time for different epoch sizes

Epochs	25	50	100
Preprocess (ms)	0.2	0.2	0.2
Inference (ms)	1.0	1.0	1.0
Postprocess (ms)	6.5	6.5	6.6
Total (ms)	7.7	7.7	7.8

Performance analysis of the obtained results is presented in Table 2. Precision values show a consistent increase per epoch, indicating that the model becomes more selective and produces fewer false positives as training progresses. Recall also improves notably from 0.917 to 0.962 between 25 and 50 epochs, showing that the model gains a stronger ability to detect a higher proportion of true objects. At 100 epochs, recall slightly decreases to 0.950, suggesting a minor trade-off between precision and recall at deeper training. The mAP@0.5 and mAP@0.5:0.95 values also increase steadily as the number of epochs grows. The largest improvement occurs between 25 and 50 epochs, where mAP@0.5 rises from 0.962 to 0.981. The highest overall performance is observed at 100 epochs, with mAP@0.5:0.95 reaching 0.881. This shows that extended training improves the model's capacity to generalize effectively.

Table 2. YOLOv8 model classification performance.

Epochs	Precision	Recall	mAP@0.5	mAP@0.5:0.95
25	0.966	0.917	0.962	0.828
50	0.967	0.962	0.981	0.866
100	0.984	0.950	0.982	0.881

Figure 7 illustrates the performance evolution of a machine learning model over various training times in epochs and evaluated on mean average precision score (mAP@0.5). Lines are drawn connecting models that were trained for different numbers of epochs. The initially rapid growth in performance stabilizes with increasing numbers of epochs. By 100 epochs, the green line shows that the model reaches a high mAP and stays there, meaning longer training increases the model's accuracy and stability of its predictions. It measures the proportion of correctly identified targets among all detected targets, while recall indicates the proportion of correctly identified targets out of all actual targets (Hao et al., 2024). The ratio of these metrics in Figure 8 can be considered as an important indicator that reflects the general performance of the model (Boyd et al., 2013).

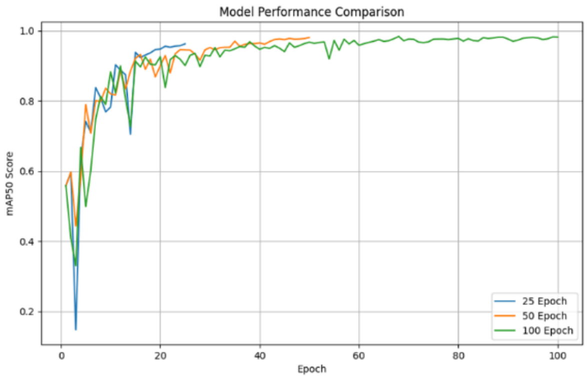


Figure 7. Performance progression of a machine learning model over different training durations, measured in epochs, and evaluated by mAP@0.5 mean average precision score.

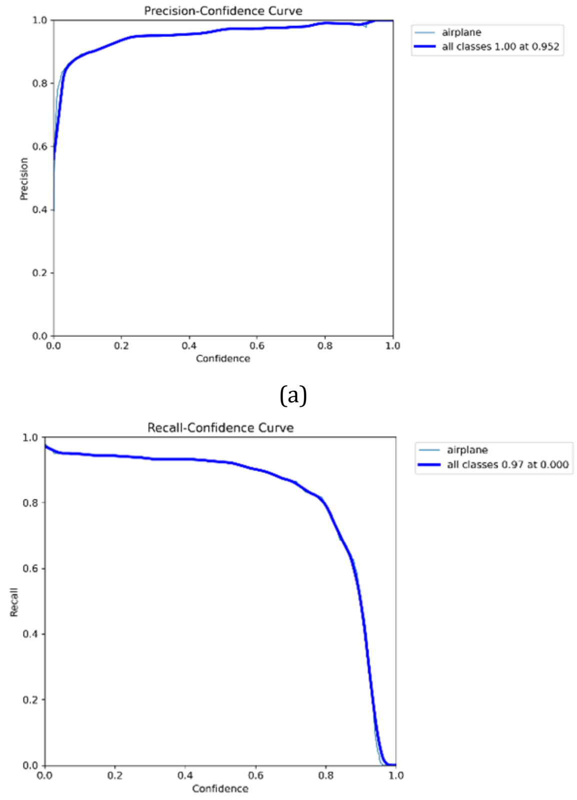


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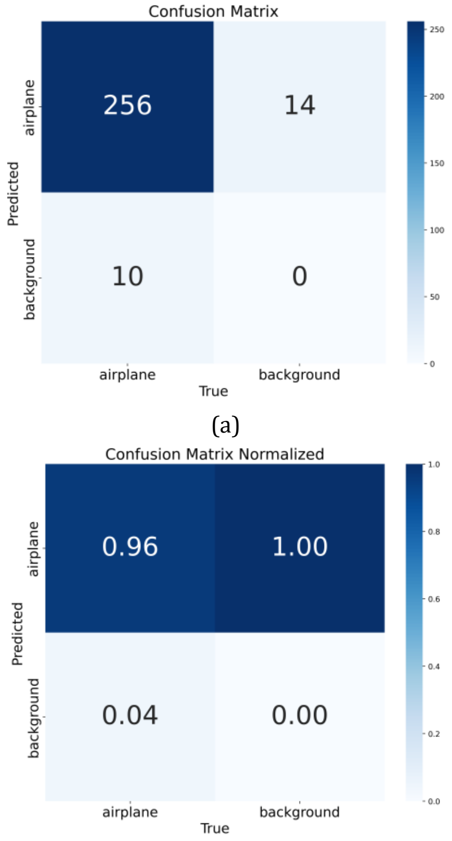
Figure 8. a) Precision-Confidence curve, tracking the precision of airplane detection across different confidence thresholds. b) Recall-Confidence curve, depicting how the recall of airplane detection declines as the confidence threshold increases.

One of the common techniques used to evaluate a model is the confusion matrix. It provides a visual summary of a classification algorithm's performance (Susmaga, 2004). Figure 9 shows the YOLOv8 model's detection performance in the confusion matrices. These matrices should be analyzed for model performance in regard to the difference between the 'airplane' and the 'background' classes. The first matrix is the actual number of predictions: 256 true positives for airplanes, 10 being false negatives, 14 as false positives, and rejection of background instances in all but 10. The second one of the two matrices is normalized, presenting how the correct and incorrect classifications break down. 96% of the airplane predictions are true positives, and 4% are false negatives, and background classification is correctly identified 100% of the time.



(a)

(b)

Figure 9. a) Confusion matrix for an object detection model. b) Normalized matrix, showing the proportion of correct and incorrect classifications.

4.2. Hybrid Tracking and Prioritization

Aircraft detection, tracking, and prioritization processes are also visually presented in the developed interface (Figure 10). Detected objects in the video frames are marked with frames and identity information (Kang et al., 2017). The priority status of the objects is color-coded based on the confidence score and distance. A distance indicator is drawn as a circle based on the center of the frame, and high-priority objects are dynamically highlighted (e.g., with blinking colors). The video frames are processed using the OpenCV library, and the results are presented to the user in real time (Pulli et al., 2012). Additionally, processed frames can be optionally saved to a video file.

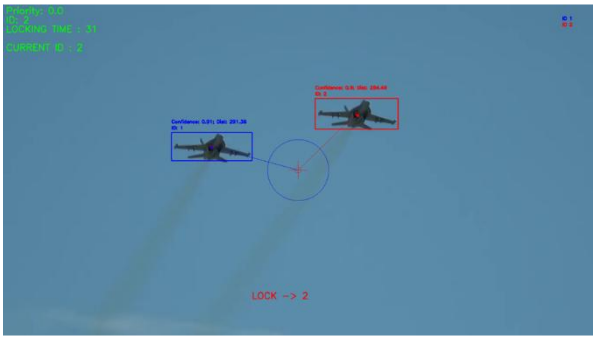


Figure 10. The interface of an aerial target tracking system during an airshow. It shows two identified aircraft with their IDs, confidence levels, and distances in bounding boxes.

To systematically evaluate the contribution of the proposed decision-making layer, we designed a comparative study involving three distinct prioritization strategies. These scenarios were tested across identical video sequences to measure tracking stability and target selection accuracy:

Scenario 1. Highest Confidence (Baseline 1): In this scenario, the system prioritizes the target with the highest YOLOv8 detection confidence score.

Scenario 2. Closest Distance (Baseline 2): This scenario prioritizes the target geometrically closest to the center of the frame.

Scenario 3. Hybrid Fuzzy-Kalman Framework (Proposed): This represents the complete proposed system. It utilizes the Fuzzy Inference System to calculate a weighted priority score based on both confidence and distance inputs, while employing the Kalman Filter to maintain state estimation during detection gaps.

To empirically evaluate robustness, we analyzed test video (www.youtube.com/watch?v=RNxCeOD4kMA), which features two simultaneous targets (ID 1 and ID 2) to test the system's ability to distinguish between a high-confidence distraction and a priority threat. As shown in Figure 9, the interface tracks these competing targets in real-time.

The results in Table 3 reveal the shortcomings of single-metric prioritization. Scenario 1 fixated on the distracting target (ID 2) for 132 frames simply because it had a higher detection score, tracking the true priority (ID 1) for only 96 frames. Scenario 2 improved performance by prioritizing proximity, holding the true target for 181 frames, but it still failed to fully suppress the distraction (locking onto ID 2 for 47 frames). The proposed Scenario 3 achieved the highest stability. By weighing both metrics, it maintained a lock on the true target for 199 frames and suppressed the distraction to just 29 frames. This confirms that the hybrid approach effectively filters out high-confidence clutter that confuses simpler baselines.

Table 3. Tracking performance measurements for different scenarios

Target ID	Role	Scenario 1 (FPS)	Scenario 2 (FPS)	Scenario 3 (FPS)
1	True Priority	96	181	199
2	Distraction	132	47	29

The Kalman Filter provides an effective method for predicting the future positions of airborne targets based on their current and past positions. The algorithm reduces noise in measurement data, resulting in more accurate position predictions (Le´sniak et al., 2009). With this approach, the future positions of airborne targets are predicted in advance, playing an important role in decision support systems and expert systems. The error rates in the Kalman Filter tests can be seen in Figure 11. As can be seen in this graph, it is observed that the error rate is gradually decreasing.

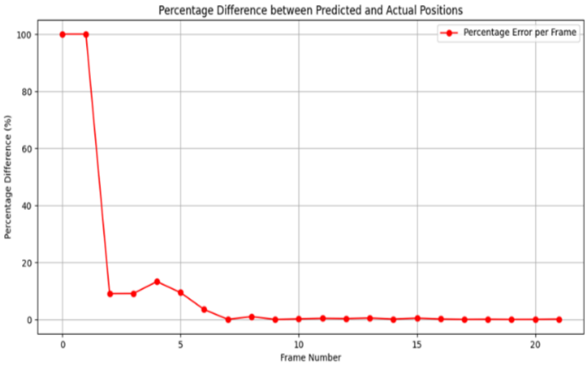


Figure 11. The percentage error per frame between predicted and actual positions.

Figure 12 presents a correlogram that checks the distribution and correlation of the attributes of objects detected by a tracking system (Granqvist and Hammarberg, 2003). The main diagonal contains histograms for the x and y coordinates, width, and height of the detected objects. Off-diagonal panels contain scatter plots and 2D histograms that indicate the relationships among these attributes (Kulesz et al., 2016). There is a high concentration of detections around the mid-range of x and y coordinates, while having a large spread in width but a smaller spread in height of the objects. This visualization can help to better understand the nature of the spatial distribution of detected objects and the dimensionality in this space.

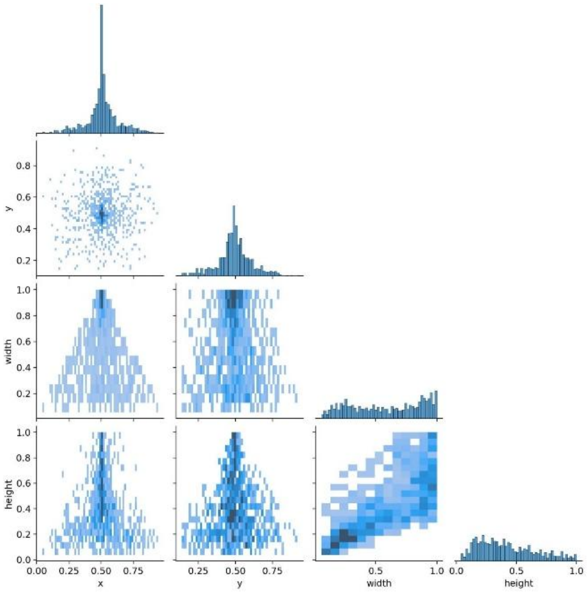


Figure 12. Correlogram of detected object coordinates and sizes.

5. Conclusion

This study aimed to develop an efficient system capable of detecting and tracking airborne targets by combining the YOLOv8 model with the ByteTrack algorithm. The proposed framework integrated Fuzzy Trapezoidal Membership Functions for target prioritization and a Kalman Filter for future position prediction, thereby strengthening the overall decision-making ability of the system. Experimental results demonstrated that the system achieved high performance in both detection and tracking tasks. The YOLOv8 model, for instance, reached 0.984 precision, 0.950 recall, 0.982 mAP@0.5, and 0.881 mAP@0.5:0.95 at 100 epochs, showing strong detection capability suitable for real-time aerial applications. ByteTrack ensured continuous identity maintenance and stable tracking performance by significantly reducing ID-switches, even in dynamic and crowded environments. The combination of fuzzy prioritization and Kalman-based prediction further contributed to robust tracking under varying operational conditions.

Overall, the findings demonstrate the potential of AI-based decision support systems to enhance the reliability, accuracy, and responsiveness of airborne target monitoring while reducing human intervention. From a practical standpoint, the proposed framework can be deployed as a real-time video analytics module in airspace monitoring and defense/surveillance systems. A video stream is processed frame-by-frame to output aircraft tracks, confidence scores, fuzzy priority values, and short-horizon position predictions. The priority output can cue a human operator (e.g., highlighting the most critical track) or drive downstream decision-support modules by selecting a "locked" target for closer monitoring while maintaining continuous tracking of other aircraft. Because the pipeline relies on standard video interfaces (OpenCV) and produces structured tracking outputs, it can be integrated with existing command-and-control, alerting, or logging systems.

Despite these promising results, several technical limitations were observed. Environmental factors such as bad weather, low visibility, and sudden target maneuvers occasionally caused fluctuations in detection and tracking performance. Practical deployment would additionally require sensor and mission specific calibration of fuzzy membership functions and validation under adverse weather, low visibility, and different operating altitudes. Real-time processing requirements increased the computational load, limiting operational speed under certain scenarios. Tracking accuracy also decreased when targets moved in close proximity or overlapped, which affected the stability of identity assignment.

Future research should address several directions based on these observations. The system can be improved by training the model with larger and more diverse datasets to enhance generalization and robustness across different environments. Expanding the dataset to cover various weather conditions and different types of airborne targets will also contribute to developing a more adaptable and operationally reliable system suitable for air defense and airspace security applications. Algorithmic adjustments may be introduced to better handle rapid target maneuvers, while parameter optimization of both the Fuzzy system and the Kalman Filter can further strengthen decision-making reliability. Additionally, integrating more efficient data processing techniques can help reduce computational cost, thereby improving real-time performance.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	T.C.	A.E.Ö.	A.H.E.	G.K.
C	30	30	20	20
D	30	30	25	15
S	20	20	40	20
DCP	35	35	20	10
DAI	30	30	30	10
L	30	30	30	10
W	25	25	40	10
CR	25	25	25	25
SR	25	25	25	25
PM	25	25	20	30
FA	30	30	20	20

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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