



## Real-Time Drone Type Detection for Smart Air Traffic Monitoring

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**ABSTRACT:** Numerous industries, including defense, logistics, surveillance, agriculture, and entertainment, have undergone radical change as a result of the quick development of Unmanned Aerial Vehicles (UAVs), also referred to as drones. However, the increasing deployment of drones has introduced significant challenges in ensuring airspace security, privacy, and safety, particularly due to their resemblance to birds and other aerial objects when viewed from a distance. Accurate and real-time detection and classification of drones have thus become critical to mitigating threats such as unauthorized surveillance, espionage, and potential attacks. Using cutting-edge deep learning techniques, this study suggests a reliable drone identification and classification system that makes use of the YOLOv8 (You Only Look Once version 8) object detection algorithm. YOLOv8 is notable for striking a compromise between accuracy and real-time performance, which makes it ideal for dynamic settings.

An extensive and varied collection of drone photos— including fixed-wing, single-rotor, and multi-rotor drones— was cited, and the PASCAL VOC format was used for annotation. To guarantee the best possible model performance, the dataset was preprocessed, enhanced, and divided into training, validation, and test sets. To enable users to upload photos or stream videos for real-time drone identification, the trained YOLOv8 model was implemented in a Flask-based web application.

**Keywords:** YOLOv8, Smart Air Traffic Monitoring, Security Enforcement, Deep Learning

### 1. Introduction

As time goes on, the quantity of drones manufactured for military, commercial, or recreational uses increases noticeably because of the quick developments in the field of unmanned vehicles and the innovation in their construction. When the drones have cameras or weapons attached to them, this situation poses serious security and protection risks. Consequently, it is now essential to detect the position and attributes of drones such as their speed and track before something unwanted occurs. Drones can move quickly, and they resemble birds in appearance from a distance. This makes it difficult to detect, identify, and locate them accurately because similar objects vary greatly in their appearance [1]

[7]. Moreover, object detection in the physical world is a laborious task, and variations in appearance, lighting, and viewpoint also lessen a detector's effectiveness. When there are changes in scale and distortion, the majority of detectors operate ineffectively. Categories can be separated into two groups: advanced and available. ANNs, support vector machines, decision trees, and object-oriented classifiers are more classification methods that can be discussed. Lastly, the accuracy of the intended classification is evaluated using test data [2].

Unmanned Aerial Vehicles (UAVs), also known as drones, have seen exponential growth in use in a variety of fields, from surveillance and

filmmaking to agriculture and infrastructure inspection.

## 2. Related Works

Ahmad Bilal Zaidi, Sadaf Zahera, has summarized in the paper “Modern drone systems must have real-time object identification and video monitoring in order to carry out a variety of duties, from monitoring and surveillance to search and rescue missions. Advanced computer vision algorithms and deep learning models that can process data in real-time and accurately detect objects are used to enable these capabilities. Although deep learning algorithms like SSD, YOLO, R-CNN, and Faster R-CNN are quite effective for detecting objects in high frame rate videos, there is a major problem simply because of the size of drones. Because these technologies are quite complex and require a lot of computation, it is difficult to provide such a high end system on a drone. Therefore, the cloud connecting drone is introduced, and all these complex computations are computed on dedicated server machines and then the result is sent back. Traditional computer vision algorithms are good for detecting objects in static images, but they become a little slower for 40fps to 60fps videos and it becomes quite difficult to detect objects in a live stream.

Muhammad Hanzla and Ahmad Jalal, has conveyed that “The article offers a technique for

detecting and tracking vehicles that utilizes the YOLO method with centroid tracking. Automated traffic monitoring relies heavily on vehicle tracking and identification, and advances in computer vision and image processing have increased the use of unmanned aerial vehicles (UAVs). Our recommended technique recognizes and tracks vehicles with good accuracy while utilizing minimum computing resources. We used result photographs from the VAID dataset to illustrate the effectiveness of our method. In the future, we hope to refine our approach by adding deep learning methods to enhance segmentation and classification methods. Additionally, we plan to incorporate calculations for different traffic characteristics.”

## 3. Proposed Work

The YOLOv8 model, a cutting-edge deep learning algorithm known for its outstanding accuracy and real-time performance, is used in the suggested drone object identification system. The system seeks to acquire superior detection skills across a variety of situations and conditions by improving the model's parameters and training it on annotated drone datasets. For smooth engagement, the system also integrates a Flask web application interface, which enables users to contribute pictures or videos for drone detection.

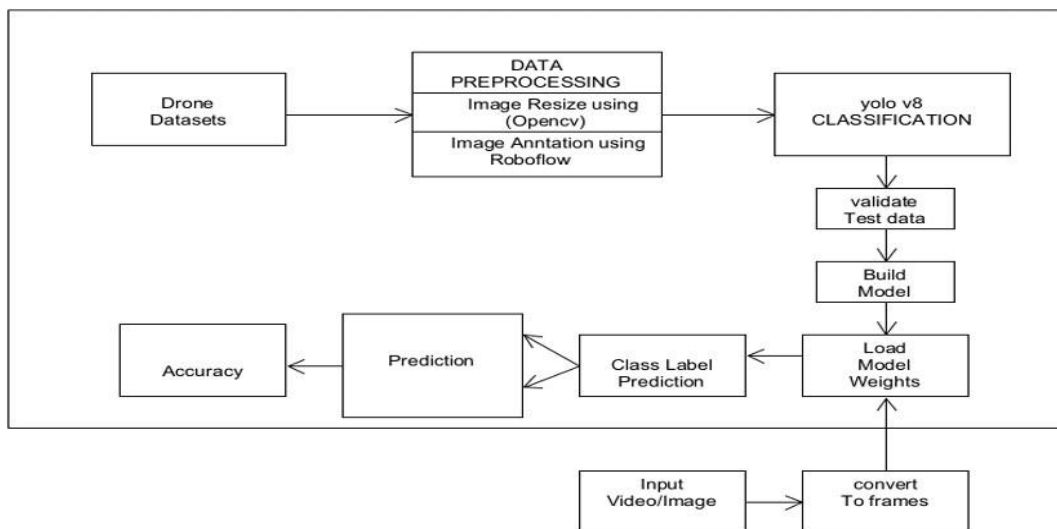


Figure 1: System Architecture

The System Architecture flow diagram is shown in Figure 1. Architectural design seeks to address and satisfy the needs for the construction of habitable environments by utilizing certain methodologies and, above all, creativity. Design focuses on looking at a framework as a combination of different pieces and how they interact to produce the desired result. The focus is on differentiating components or subsystems and their interfaces. As a result, paying attention to important details is necessary.

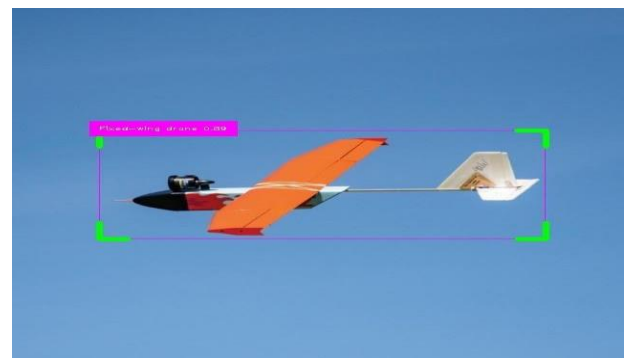
### 3.1 High Level Design

The modules that need to be worked on to support the framework and decisions of these modules are identified by a defined level plan. At the very conclusion of the framework configuration, all essential information structures, document designs, yield designs, and so forth are fixed. The modules' identification is the primary concern. Finally, the relevant modules are taken into account.

## 4. Results and Discussion

The dataset was created by gathering pictures from the internet and removing frames from various drone recordings. Over 10,000 photos featuring various drone categories are available. The number of rotors on a drone allows for classification of its type. Every drone in this case has many rotors. For instance, if it has three rotors, it is a tricopter. If it has four rotors, it is a quadcopter; if it has six, it is a hexacopter. Drones are used to capture photographs in the drone category in order to train the algorithm if they are unable to difference between different types owing to problems with light or viewpoint. The images show the drones in a range of sizes, positions, lighting, and

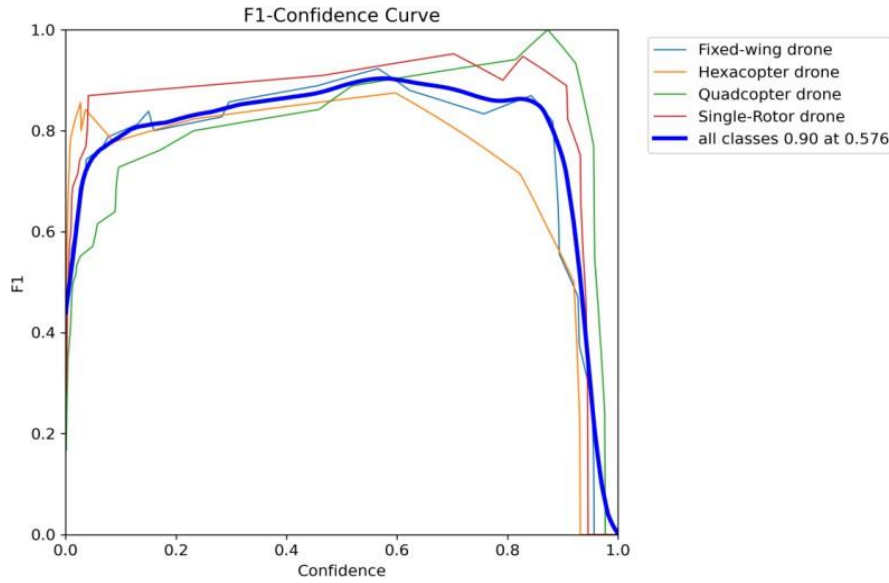
perspectives. The annotations give the drone type, height, width, and top left (x,y) coordinate for the ground truth bounding box. This experiment's annotations follow the YOLO format. This large dataset is used to train our model, which has a learning rate of 0.0001 and a batch size of 64. The performance of the model is analyzed in multiple iterations. The training phase lasts for 150 epochs, with the model's loss rate, precision, recall, and other parameters being saved for each of the ten training epochs. To understand the training phase and the training's efficacy, the loss, accuracy, and recall values are calculated. The detection performance is examined by calculating the mean average precision (MAP) value. The model's best performance, according to the results, was 0.74 at the 150th epoch.



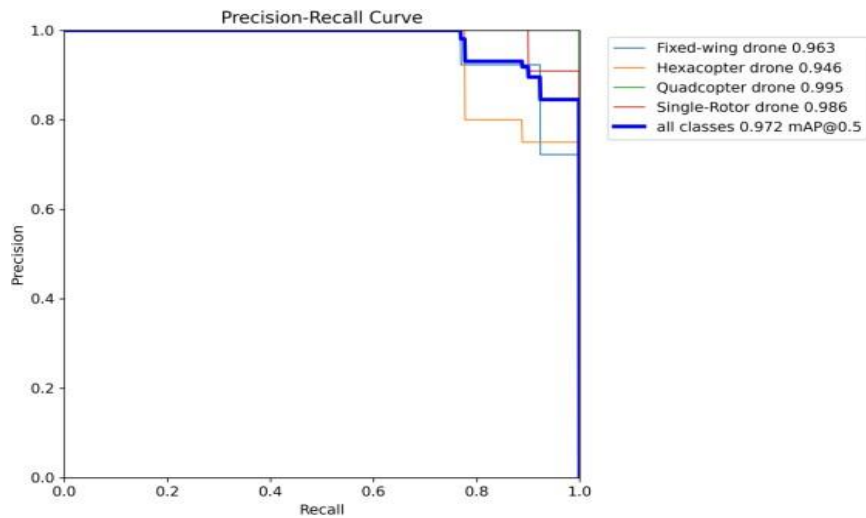
**Figure 2:** *Fixed-Wing drone detection and classification*



**Figure 3:** *Single-Rotor drone detection and classification*



**Figure 4:** *F1-Confidence curve*



**Figure 5:** *Precision-Recall Curve*

## 5. Conclusions

An important development in automated surveillance and security systems is the creation of a web application for drone object identification that uses YOLOv8 for real-time detection. In addition to achieving its goals, the project has demonstrated encouraging accuracy rates and usefulness in a range of applications, including environmental monitoring, disaster relief, and perimeter security. The project's high object detection accuracy rates, which were attained through meticulous model training and optimization procedures, serve as a testament to its effectiveness. The YOLOv8 model has strong performance in precisely recognizing and categorizing objects of interest in real-world

situations by utilizing cutting-edge machine learning algorithms and datasets gathered from drone-captured photos and videos. The model's accuracy has been measured using evaluation metrics like precision, recall, and mean Average Precision (MAP), which minimize false positives and false negatives and guarantee dependable detection findings. In addition to improving situational awareness, this real-time alerting system makes proactive security and incident mitigation techniques easier.