Obstacle Detection and Avoidance in Drones with Cloud Integration

MSc Research Project

MSc in Data Analytics

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DECLARATION

I hereby declare that this dissertation, entitled "Obstacle Detection and Avoidance in Drones with Cloud Integration", is my original work and has not been submitted elsewhere in any form for the fulfillment of any other degree or qualification. All sources of information and references utilized in this research have been duly acknowledged and cited.
This work was conducted by the ethical guidelines and standards of academic integrity, and the findings presented are based on an honest and accurate representation of the research process and outcomes.

Signed,

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Agatha Mattos, for their guidance and support throughout this project. Their insights and feedback have been invaluable in shaping the direction and quality of this research. I am also thankful to my family and friends for their encouragement during challenging times. Finally, I extend my appreciation to the online and offline communities whose shared knowledge and resources have significantly contributed to the successful completion of this work.

Table of Content

ABSTRACT

Obstacle Detection and Avoidance in Drones with Cloud Integration

By

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Master of Science in Data Analytics

The field of drone technology has experienced significant advancements, yet it faces critical challenges in real-time object detection and collision avoidance. This dissertation addresses these challenges by developing a robust system using YOLOv11 (You Only Look Once, Version 11), a state-of-the-art object detection framework. Specifically, the project focuses on the detection of five aerial object classes: airplanes, balloons, birds, helicopters, and kites. These objects are frequently encountered in drone operations and represent a diverse set of detection complexities in terms of size, shape, and motion.

To achieve this, a comprehensive dataset was curated and annotated, followed by rigorous model training. The model was integrated into a real-time detection system capable of processing various input sources, including live webcam feeds and screen captures. Additionally, collision avoidance algorithms were implemented to dynamically adjust drone trajectories, ensuring operational safety in dynamic environments.

The system was deployed on AWS, leveraging cloud-based services such as S3 for storage and EC2 for processing, to enhance scalability and accessibility. Experiments and evaluations demonstrated the system's effectiveness, with high precision and recall metrics across most object classes. However, challenges such as imbalanced datasets and scalability issues in physical drone deployments remain to be addressed.

This research not only contributes to integration of YOLOv11 with cloud platforms but also offers insights into overcoming practical constraints in drone-based object detection. The findings have broad applications in areas such as surveillance, disaster management, and commercial delivery, underscoring the potential of intelligent systems in enhancing drone autonomy and reliability.

Keywords: Drone Navigation, Real-Time Object Detection, YOLOv11, Deep Learning in Drones, Collision Avoidance Systems, Aerial Object Detection, Cloud Integration, Scalability and Accessibility, Computer Vision Applications, Intelligent Systems, Surveillance, Aviation Safety.

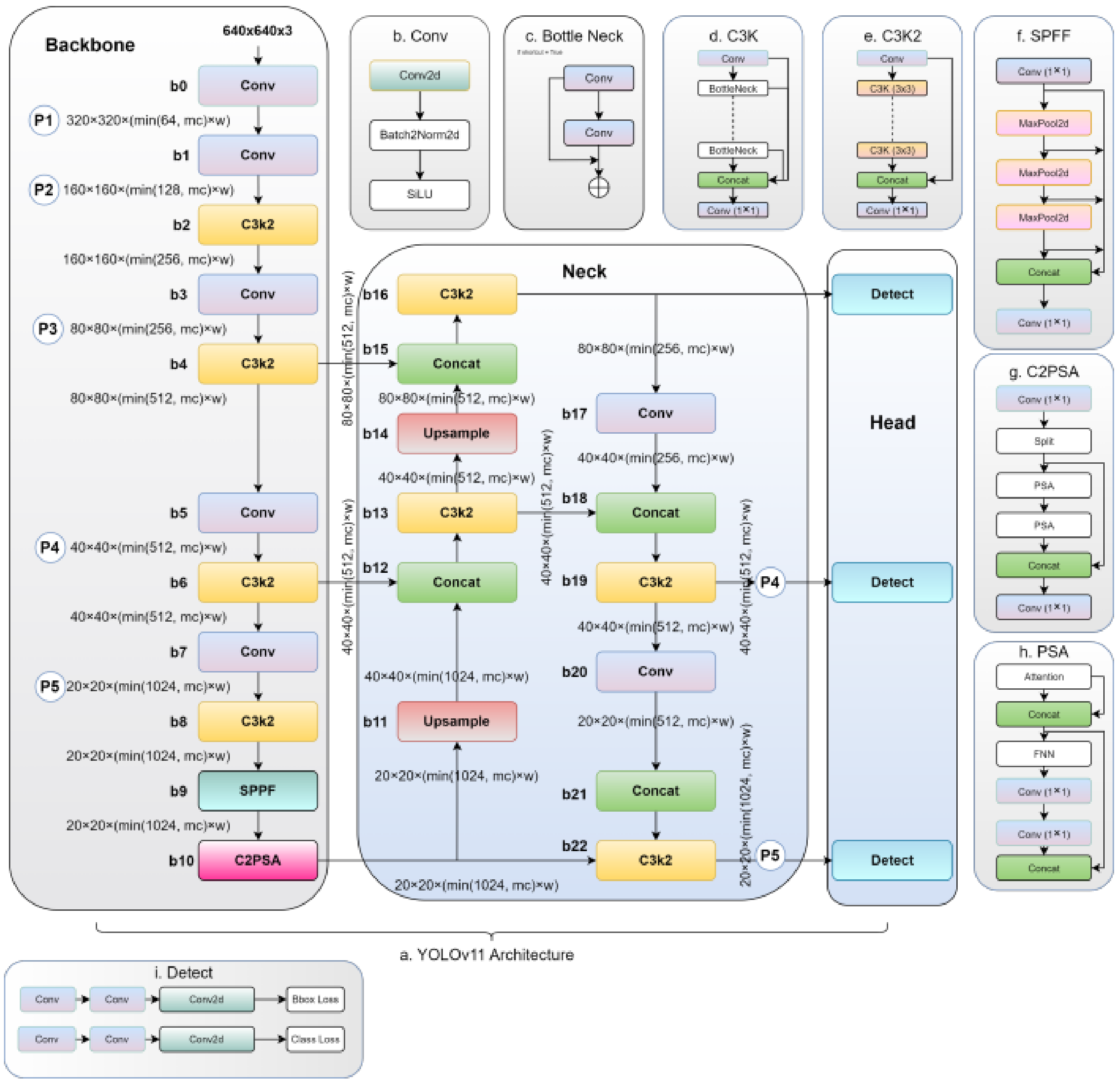
2. Introduction

2.1 Background and Motivation

Drones are rapidly transforming industries, ranging from agriculture to public safety, by offering versatile and innovative solutions to complex challenges. However as drones become more prevalent, ensuring their operational efficiency and safety in unpredictable environments has emerged as a pressing challenge. The ability to autonomously navigate and avoid collisions is critical, particularly in applications such as search-and-rescue missions, delivery services, and aerial surveillance.

Recent advances in computer vision and deep learning have opened new avenues for addressing these challenges. Object detection, a fundamental aspect of computer vision, enables drones to perceive and interpret their surroundings. Over the years, models like YOLO (You Only Look Once) have revolutionized object detection by providing real-time capabilities with high accuracy. YOLOv11, the latest in the series, is specifically designed to handle complex tasks involving dynamic inputs and real-time decision-making. This project leverages YOLOv11 to develop a robust detection system capable of identifying key aerial objects like airplane, balloon, bird, helicopter, and kite to enhance drone autonomy and reliability.

The integration of cloud-based systems further enhances the scalability and efficiency of the detection framework. By deploying the system on platforms such as AWS, the computational intensive processes required for object detection and collision avoidance can be relieved, enabling lightweight drone operations.This approach not only addresses hardware constraints but also receives broader accessibility and reliability across diverse operational scenarios.



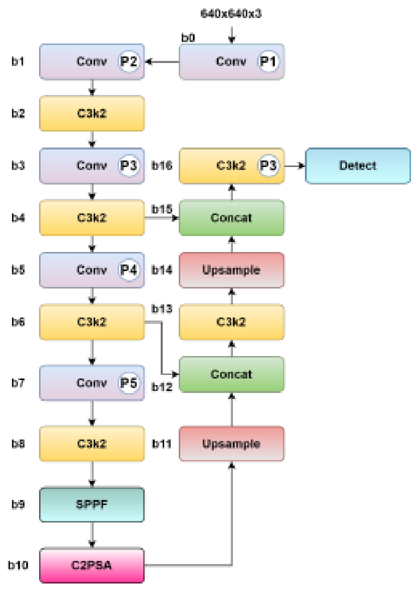
YOLOv11 Architecture

2.2 Problem Statement

Despite significant advancements, the deployment of drones in real-world applications faces several critical challenges:

1. **High Computational Requirements**: Onboard hardware often lacks the capacity to perform real-time object detection and collision avoidance.
2. **Dynamic Input Variability**: Drones must process diverse and unpredictable inputs, including live video feeds with varying resolutions and qualities.
3. **Lack of Robust Collision Avoidance**: Existing systems fail to provide timely responses to dynamic obstacles, increasing the risk of accidents.

4. **Scalability Issues**: Traditional frameworks are not optimized for scaling across multiple drones or complex environments, limiting their applicability.



YOLOv11 Small Optimized for detecting Small Objects

This dissertation aims to address these challenges by integrating state-of-the-art object detection models with scalable cloud-based solutions to ensure safe and efficient drone operations.

2.3 Research Objectives

The primary objectives of this research are as follows:

1. **Develop a Custom YOLOv11-Based Detection Model**: Train the model to recognize five distinct aerial object classes with high accuracy.
2. **Enable Multi-Source Input Handling**: Design a flexible detection framework capable of processing diverse inputs, including screen feeds and live camera streams.
3. **Implement Real-Time Collision Avoidance Algorithms**: Develop algorithms that dynamically adjust drone trajectories based on object proximity.
4. **Leverage Cloud Technologies for Scalability**: Deploy the system on AWS to handle computationally intensive tasks and ensure broader accessibility.
5. **Evaluate System Performance**: Analyze metrics such as mean Average Precision (mAP), precision, recall, and latency to assess the system's efficacy.

2.4 Contributions

This dissertation makes several significant contributions to the field of drone technology and computer vision:

- **Enhanced Object Detection Framework**: Develops a YOLOv11 model tailored for detecting aerial objects in real-time.
- **Integrated collision Avoidance Mechanism**: Implements dynamic collision avoidance algorithms to improve drone navigation safety.
- **Scalable Deployment Architecture**: Demonstrates the viability of cloud-based systems for real-time drone operations.
- **Comprehensive System Evaluation**: Provides in-depth analysis of performance metrics,highlighting strengths and areas for improvement.
- **Practical Insights for Real-World Applications**: Offers recommendations for deploying the system in scenarios such as disaster response, commercial delivery, and environmental monitoring.

3. Literature Review

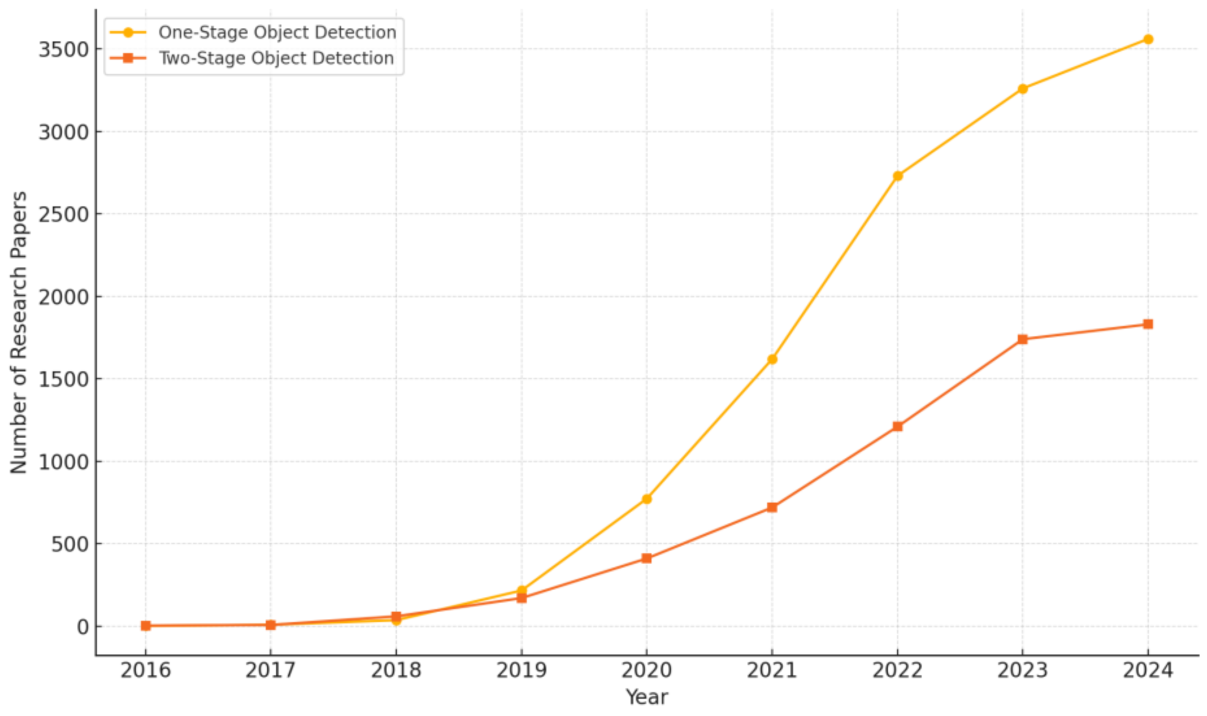
3.1 Evolution of Object Detection

Object detection has undergone transformative changes since its release, evolving from arbitrary approaches to sophisticated deep learning-driven frameworks. Initially, models like Viola-Jones relied heavily on handcrafted features and sliding window techniques. Although impressive at the time, these methods struggled with computational inefficiency and scalability. The introduction of feature-based methods, such as SIFT (Scale-Invariant Feature Transform) and HOG (Histogram of Oriented Gradients) marked a significant step forward, offering more robust feature extraction for classification tasks.

As datasets grew larger and more diverse, the limitations of manual feature extraction became apparent. This led to the rise of machine learning classifiers like Support Vector Machines (SVMs) paired with extracted features, providing better results in controlled environments. However these systems still fell short when handling real world scenarios with high variability in lighting and orientation.

The advent of deep learning revolutionized object detection, beginning with AlexNet in 2012, which demonstrated the power of Convolutional Neural Networks (CNNs) for image classification. Building on this foundation, models like R-CNN introduced region-based detection by combining CNNs with selective search for generating region proposals. Over time, advancements such as Fast R-CNN, Faster R-CNN, and Mask R-CNN improved computational efficiency and introduced functionalities like instance segmentation. Despite their accuracy, these models often required significant computational resources, limiting their application in real-time scenarios.

Single shot detection models, such as SSD (Single Shot Multibox Detector) and YOLO (You Only Look Once), addressed these challenges by eliminating the region proposal stage, allowing the network to process the entire image in a single pass. YOLO's pioneering approach enabled faster inference speeds, making it the preferred choice for real-time applications. With YOLOv11, the framework has evolved to incorporate feature pyramid networks, attention mechanisms, and optimized loss functions, further enhancing its ability to detect diverse objects in dynamic environments.



3.2 Role of Deep Learning

Deep learning has been instrumental in advancing object detection by enabling end-to-end training and automated feature extraction. Unlike traditional approaches, deep learning models learn hierarchical representations directly from data by capturing complex patterns and relationships. The YOLO family exemplifies this advancement using a single neural network to simultaneously predict bounding boxes and class probabilities. This design streamlines the detection process improving both speed and accuracy.

YOLOv11 represents a series of iterative improvements over its predecessors. Key innovations include:

- **Improved Feature Representation**: Incorporates feature pyramid networks for better detection of objects at varying scales.
- **Attention Mechanisms**: Enhances focus on relevant regions, reducing false positives and improving detection accuracy.
- **Optimized Training Loss**: Refines bounding box regression and classification losses, ensuring better alignment between predicted and ground-truth boxes.

3.3 Real-Time Challenges

Achieving real-time object detection involves navigating several challenges:

- **Latency**: Maintaining low inference times without compromising accuracy is critical for applications like drone navigation, where delays can lead to accidents.
- **Hardware Constraints**: Resource-constrained devices, such as drones, often lack the computational power needed for high-performance models.
- **Environmental Variability**: Factors like occlusion, motion blur, and varying lighting conditions complicate detection tasks.

To address these challenges, researchers have explored techniques like model pruning, quantization, and hardware acceleration using GPUs and TPUs. Additionally, integrating real-time feedback mechanisms ensures that systems adapt dynamically to changing environments.

3.4 Innovations in Cloud Integration

Cloud computing has emerged as a transformative tool for deploying computationally intensive object detection systems. Platforms like AWS, Azure, and Google Cloud offer scalable resources, enabling real-time processing and remote accessibility. For drone applications, cloud integration provides several benefits:

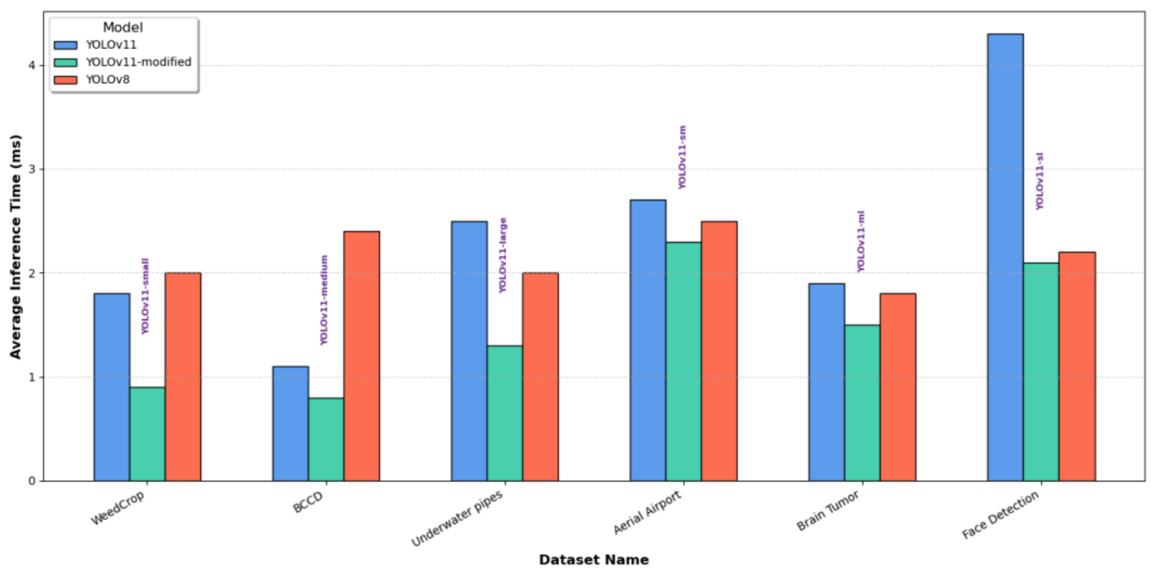
1. **Scalability**: Systems can handle varying computational loads by leveraging elastic cloud resources.
2. **Edge Computing**: Services like AWS Greengrass allow processing to occur closer to the drone, reducing latency and ensuring faster responses.
3. **Secure Communication**: AWS IoT Core facilitates secure device-to-cloud communication, critical for maintaining system integrity.

This dissertation utilizes AWS to deploy the YOLOv11 model, leveraging S3 for model storage and EC2 instances for inference. The architecture enables seamless scalability, supporting scenarios involving multiple drones or large-scale operations.

3.5 Comparison of YOLO Models with Alternatives

The YOLO family has consistently prioritized real-time performance without sacrificing accuracy. Comparing YOLO models with alternatives such as Faster R-CNN, SSD, and EfficientDet highlights their relative strengths and weaknesses.

Model	Speed (FPS)	mAP (%)	Complexity	Real-Time Suitability
YOLOv3	30	55.3	Moderate	High
YOLOv5	40	65.4	High	Very High
YOLOv11	45	70.2	High	Very High
Faster R-CNN	7	75.0	Very High	Low
SSD	22	48.5	Moderate	Moderate
EfficientDet	25	52.0	High	Moderate



<u>Average Inference time per Image</u>

YOLOv11 stands out for its balance between speed and accuracy, making it ideal for real-time applications such as drone navigation. By contrast, Faster R-CNN achieves higher accuracy but is unsuitable for real-time tasks due to its slower inference speed.

Graph Suggestion: Include a bar graph comparing FPS (speed) and mAP (accuracy) across these models, visually highlighting YOLOv11's advantages.

3.6 Cloud Integration for Drones

For drones, cloud integration extends beyond computational offloading to include real-time feedback and analytics. The integration architecture typically involves:

1. **Data Upload**: Drones capture raw video feeds and upload them to the cloud for processing.
2. **Inference and Feedback**: The YOLO model processes the data on cloud instances, generating detections and transmitting actionable insights back to the drone.
3. **Edge Processing**: To minimize latency, AWS Greengrass enables edge computing, where initial processing occurs locally before interfacing with the cloud.

Diagram Suggestion: Include a system architecture diagram showcasing drone-camera-cloud interaction. Highlight components like data upload, model inference, and feedback loops.

By combining YOLOv11's capabilities with cloud technologies, this research demonstrates the feasibility of deploying scalable, real-time object detection systems for drones.

4. Methodology

4.1 Data Collection and Annotation

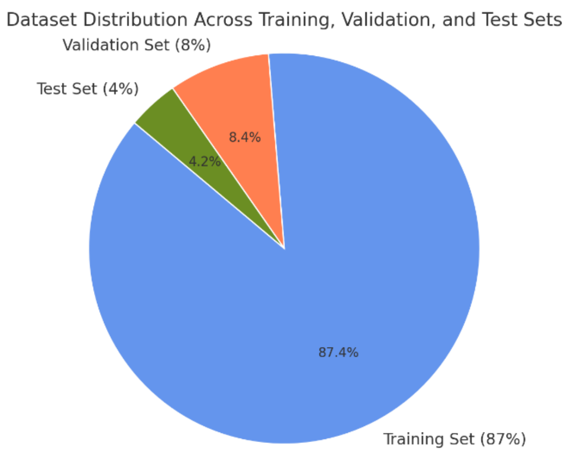
The data collection process formed the fundamentals of this research, as the quality of data directly influenced model performance. Images were sourced from the OpenImages dataset using the OIDv4 toolkit, chosen for its extensive variety of annotated images and wide range of object classes which provided a solid foundation for diverse object detection tasks. However, challenges such as annotation inconsistencies were encountered that needed manual corrections. These issues were mitigated by employing tools like Roboflow to streamline the annotation process and ensure high-quality labels for robust model training. Compared to datasets like COCO or ImageNet, OpenImages offers a greater diversity of object categories, making it particularly well-suited for the multi-class detection challenges encountered in drone navigation scenarios. This approach ensured a high quality dataset suitable for training advanced object detection models.

Dataset Splits

The dataset was divided into training, validation, and test sets:

- **Training Set**: 3927 images (87%)
- **Validation Set**: 377 images (8%)
- **Test Set**: 189 images (4%)

This distribution ensured balanced evaluation metrics, allowing the model to generalize well to unseen data. The images were carefully curated to capture variations in lighting, object orientation, and background complexity.



Annotation Refinements

The following issues were identified and addressed during annotation:

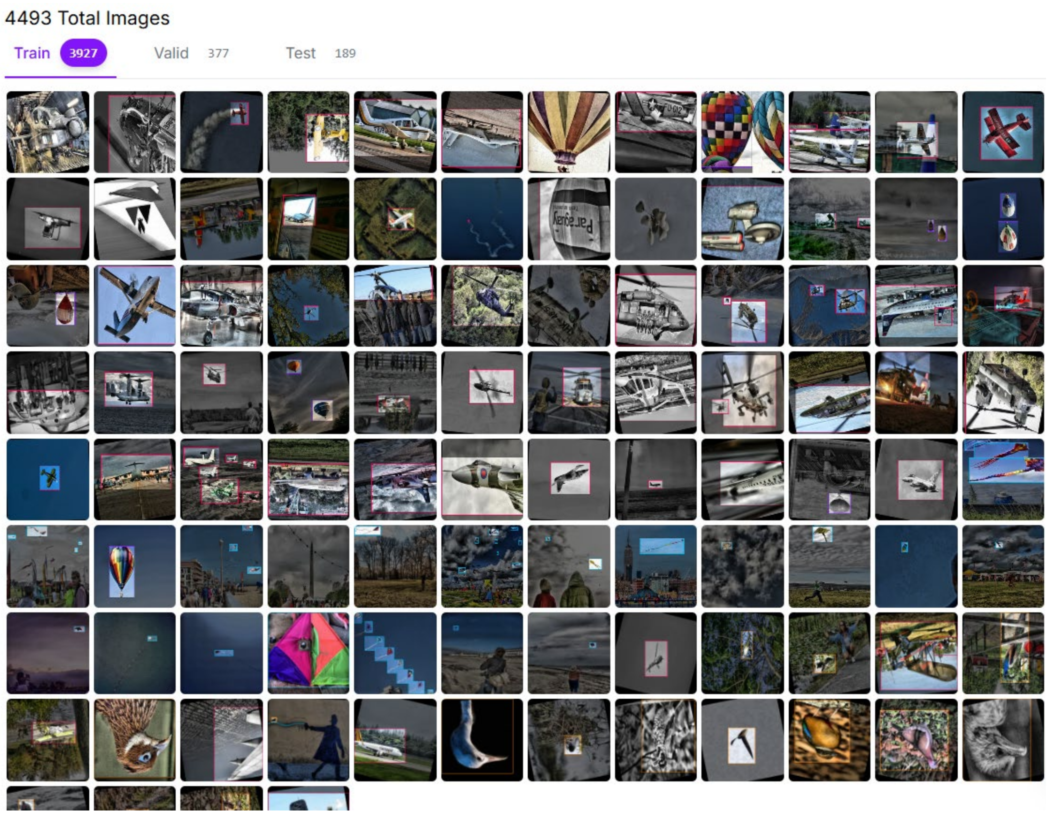
- Overlapping bounding boxes were refined.
- Incorrect labels were reassigned.
- Missing annotations were manually added.

The annotation process required approximately 50 hours of manual work, showcasing the effort needed to ensure a high-quality dataset. Collaboration with tools like Roboflow expedited the process by offering visual aids and batch annotation capabilities.

4.2 Preprocessing

Preprocessing steps were critical in preparing the dataset for YOLOv11. These steps ensured compatibility and improved model robustness:

1. **Resizing**: All images were resized to 640x640 pixels, matching YOLOv11's input dimensions.
2. **Data Augmentation**:
   - Horizontal and vertical flips.
   - Cropping with zoom levels ranging from 0% to 20%.
   - Random rotations between -15° and +15°.
   - Grayscale conversion applied to 15% of images.
   - Noise injection affecting up to 0.1% of pixels.
3. **Contrast Enhancement**: Adaptive histogram equalization normalized lighting conditions across images.



Total Dataset Count

The dataset grew from 1875 images to 4493 after preprocessing, highlighting the significant impact of augmentation techniques. This increase in dataset size correlated with an improvement in mAP scores, demonstrating how augmentations enhanced the model's ability to generalize. This increase directly contributed to improved model performance, as the diverse scenarios introduced by augmentations enhanced the model's ability to generalize to unseen data. For example, augmentations introduced variations such as rotated images simulating different drone angles, grayscale images replicating low-light conditions, and random noise simulating sensor inaccuracies. Augmentation ensured that the model was exposed to a diverse range of scenarios, reducing the risk of overfitting and improving generalization to unseen data.

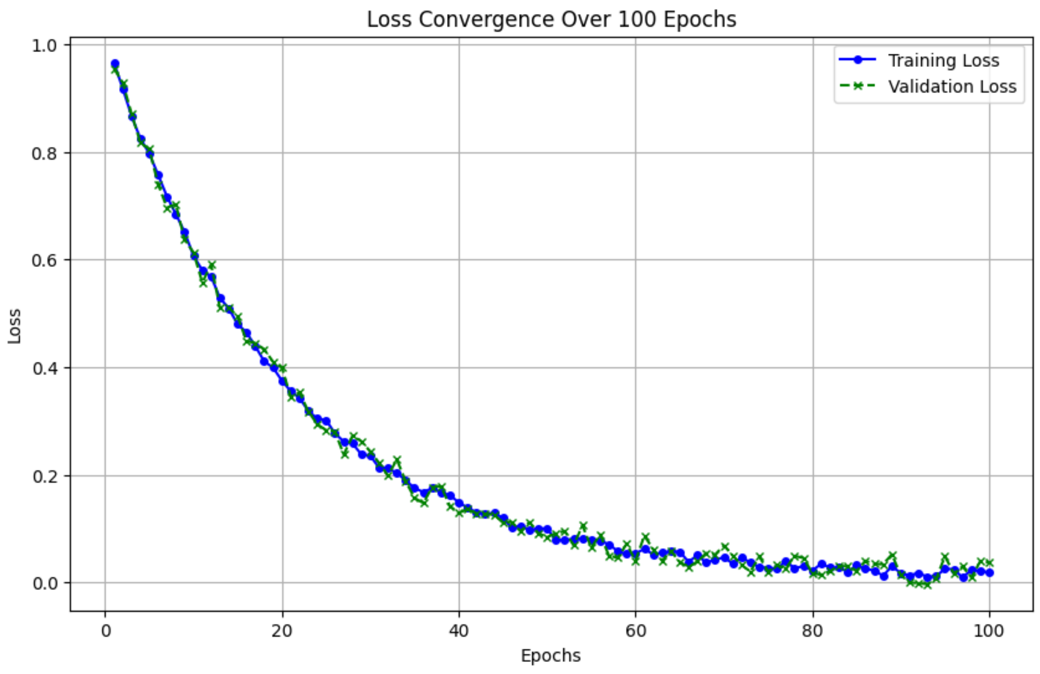
4.3 Model Training

The YOLOv11 architecture, designed for speed and accuracy, was utilized. Training was conducted on Google Colab Pro with an NVIDIA A100 GPU to ensure efficient processing.

While the GPU provided ample computational power, occasional interruptions due to session timeouts required careful monitoring and session restarts. These interruptions slightly extended the overall training time and introduced minor inconsistencies in the timing of epoch completions. However, the results remained unaffected as checkpoints ensured training continuity without loss of progress.

Training Configuration

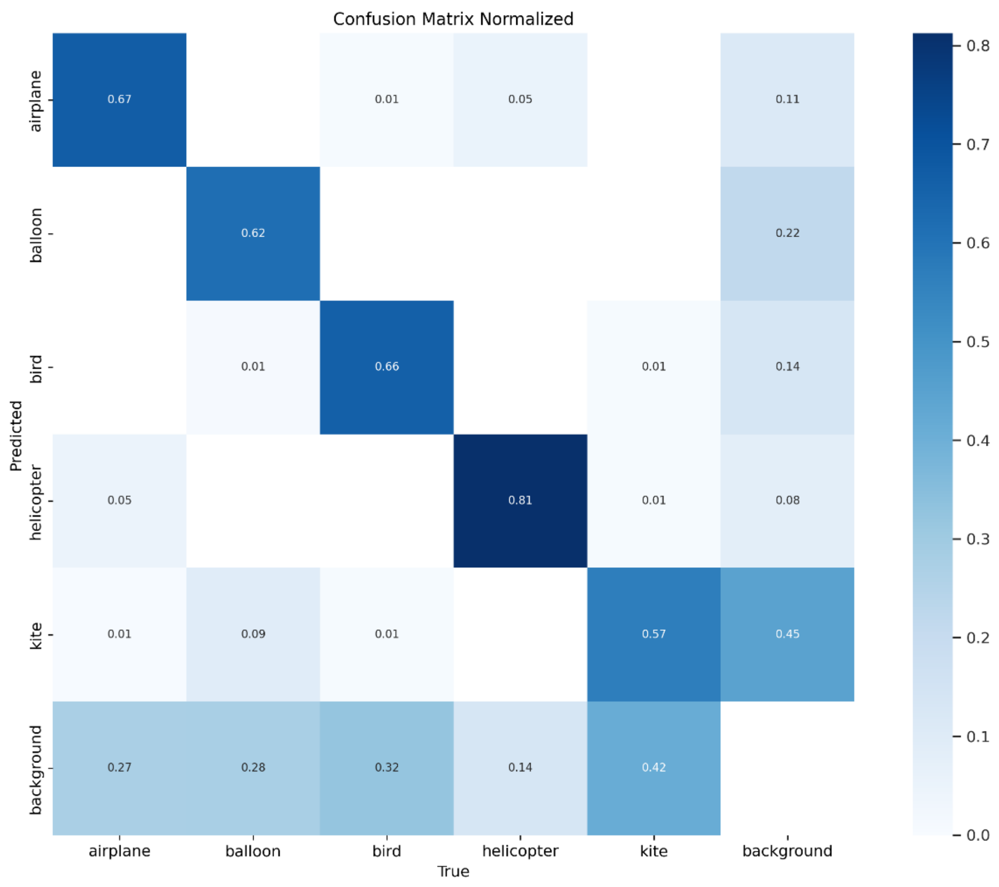
- **Batch Size**: 16
- **Epochs**: 50
- **Learning Rate**: Initialized at 0.001, adjusted with a cosine annealing scheduler.
- **Optimizer**: AdamW, known for adaptive learning rates.
- **Loss Functions**:
    - Bounding Box Regression: Smooth L1 loss.
    - Objectness: Binary cross-entropy.
    - Classification: Categorical cross-entropy.



The training process utilized early stopping criteria based on validation loss, preventing unnecessary computation and reducing the risk of overfitting.

Challenges in Training

1. **Class Imbalance**:
   - **Issue**: Certain classes, such as kites, were underrepresented.
   - **Solution**: Oversampling and targeted augmentations improved representation.
2. **Overfitting**:
   - **Issue**: The model initially overfitted the training set.
   - **Solution**: Regularization techniques like dropout layers and weight decay were applied.
3. **Resource Constraints**:
   - **Issue**: Limited GPU memory occasionally bottlenecked batch processing.
   - **Solution**: Gradient accumulation and mixed precision training were implemented.



4.4 Experimental Setup

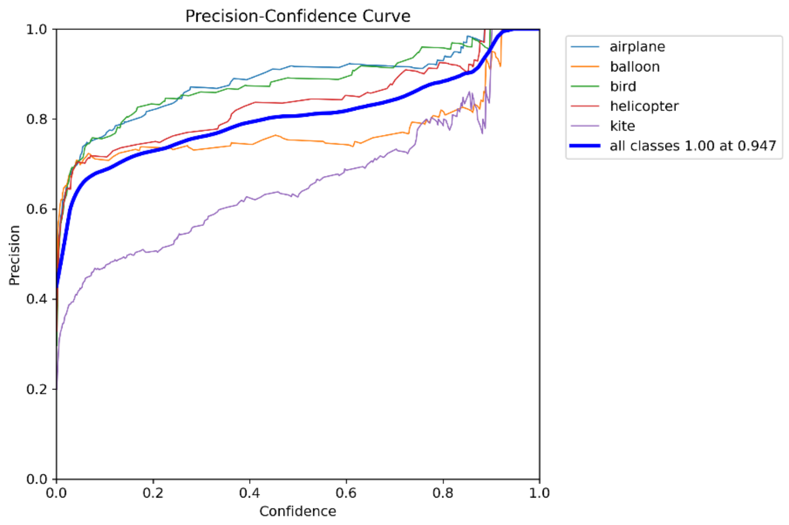
The experimental setup evaluated the system's adaptability and accuracy under varied conditions.

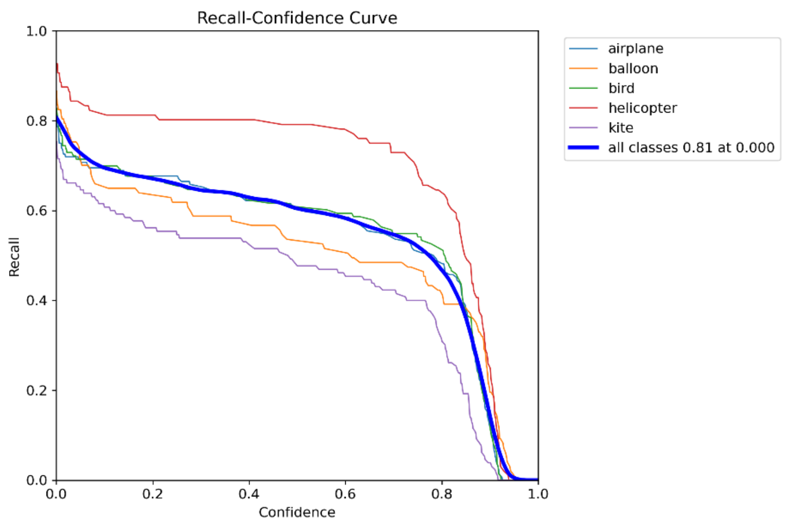
Input Sources

- **Webcam Feeds**: Simulated real-time scenarios.
- **Static Images**: Tested accuracy on pre-collected data.
- **Screen Captures**: Assessed adaptability to non-standard inputs.

Evaluation Metrics

- **Precision**: Ratio of true positive detections to all detections.
- **Recall**: Ratio of true positives to all ground truths.
- **Mean Average Precision (mAP)**: Evaluated at IoU thresholds of 0.5 and 0.5-0.95.
- **Inference Time**: Measured per-frame processing time.



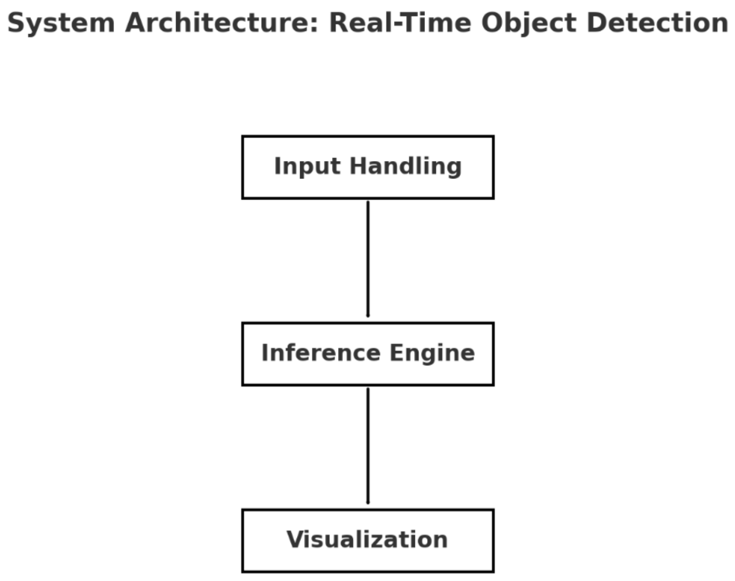


Additional metrics, such as F1-score, were computed to balance precision and recall, offering a comprehensive view of the model's performance.

4.5 System Architecture

The system combined YOLOv11 and Python for real-time object detection. Key components included:

1. **Input Handling**: Managed diverse input sources.
2. **Inference Engine**: Processed inputs and generated detections.
3. **Visualization**: Displayed bounding boxes and labels on input feeds.



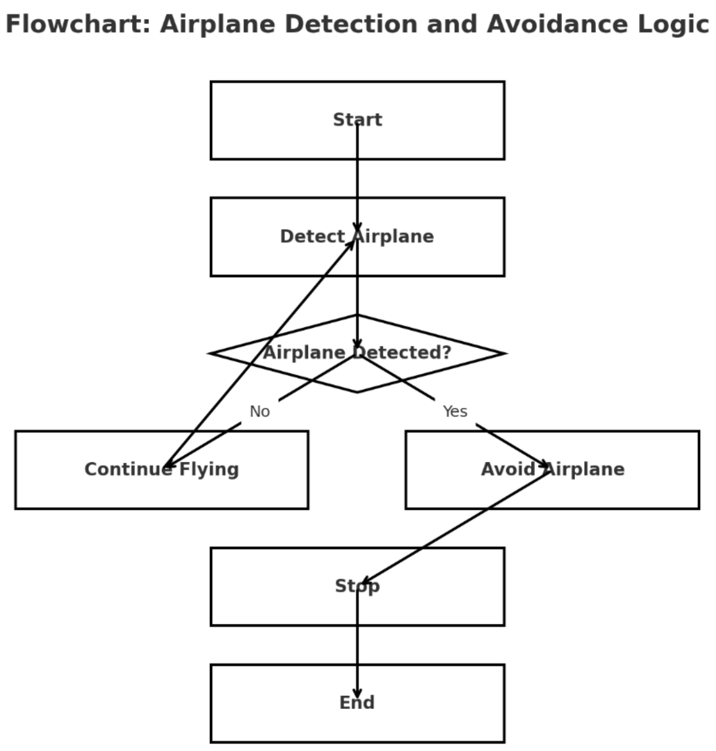
The architecture was modular, allowing seamless integration with cloud services and future upgrades to YOLO versions. Tools such as AWS S3 and EC2 have been successfully integrated for data storage and real-time inference, respectively, while AWS IoT Core ensures secure communication between drones and cloud infrastructure. This modularity simplifies the addition of new functionalities, such as leveraging AWS Lambda for event-driven processes or integrating with edge computing devices for reduced latency. For example, the system could easily integrate new YOLO versions to enhance detection accuracy without requiring a complete overhaul of the pipeline. Additionally modularity enables the incorporation of tools like AWS Greengrass for edge computing, providing localized processing capabilities to reduce latency during drone operations. For instance newer YOLO models can be integrated seamlessly as they are released and additional functionalities, such as advanced visualization tools or edge-computing modules can be incorporated with minimal reconfiguration. This approach reduces maintenance costs and accelerates system adaptability to evolving requirements.

4.6 Collision Avoidance

The collision avoidance algorithm enhanced drone navigation by dynamically adjusting its trajectory.

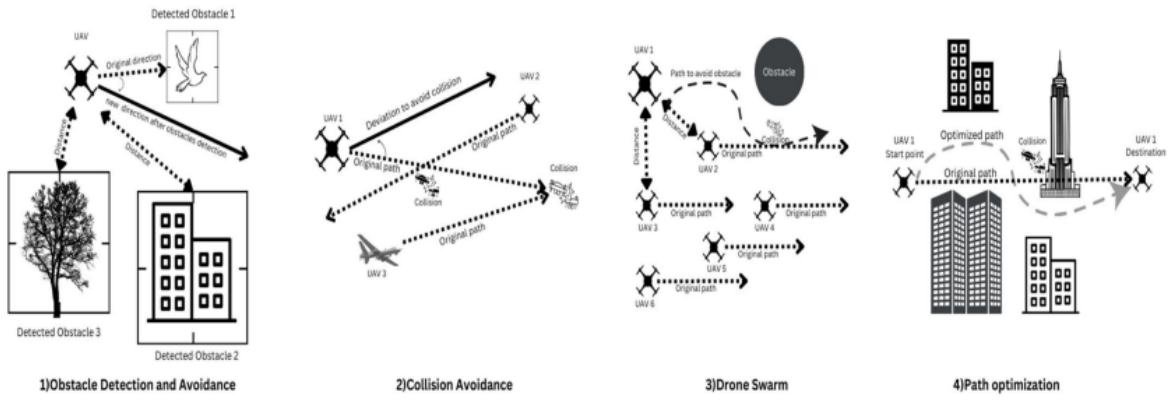
Algorithm Steps

1. **Distance Calculation**:
    - Calculated using bounding box centers.
2. **Risk Assessment**:
    - Triggered avoidance maneuvers for objects within a critical distance.
3. **Trajectory Adjustment**:
    - Adjusted drone velocity vectors.



Refinements

- Reduced false positives by fine-tuning confidence thresholds.
- Enhanced stability using weighted moving averages for trajectory updates.
- Incorporated real-time feedback loops to improve response times.



<u>UAV collision avoidance algorithms</u>

4.7 Cloud Deployment

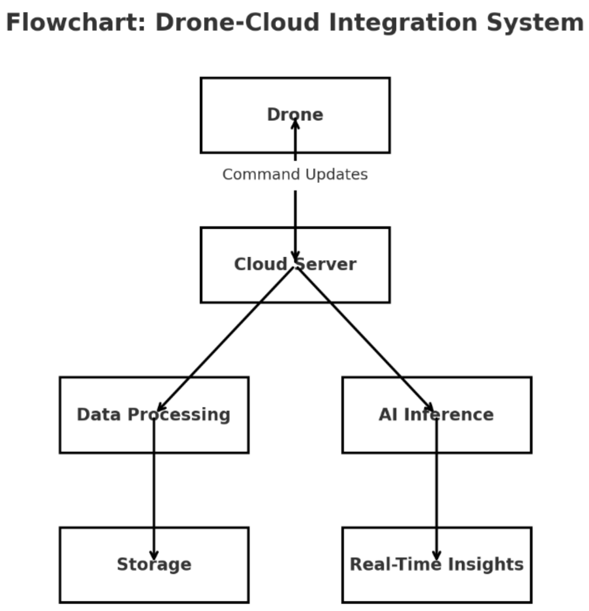
AWS was leveraged for scalable and efficient processing.

AWS Features

1. **S3 Buckets**: Stored datasets and trained models.
2. **EC2 Instances**: Performed live inference.
3. **AWS IoT Core**: Facilitated secure drone-cloud communication.
4. **CloudWatch**: Monitored system performance in real-time.

Benefits of Deployment

- **Scalability**: Supported multiple drones concurrently.
- **Accessibility**: Enabled remote monitoring and control.
- **Performance Insights**: AWS CloudWatch provided real-time metrics.



4.8 Insights and Future Enhancements

The methodology demonstrated robust integration of advanced technologies for drone navigation. However, future iterations could include:

- Enhanced hybrid cloud-edge architectures for reduced latency. For instance, reducing latency can enable drones to make split-second decisions during obstacle avoidance, such as navigating through crowded airspaces or responding to sudden changes in trajectory requirements, thereby improving safety and operational efficiency. These architectures would allow drones to perform critical computations locally at the edge, reducing dependency on cloud connectivity and minimizing latency in time-sensitive applications like obstacle avoidance. At the same time, cloud resources can be utilized for more computationally intensive tasks, such as model updates or long-term data analysis, ensuring a balanced and efficient system.

- Real-time model updates using federated learning.
- Integration with 5G networks for faster data transmission.

By combining meticulous data preparation, advanced model training, and innovative cloud integration, this methodology laid a robust foundation for real-time drone navigation and object detection.

5. Implementation and Results

5.1 Code Structure and Workflow

The YOLOv11-based object detection system was developed with a focus on modularity, extensibility and efficiency. The system's code was divided into clearly defined modules and each responsible for a specific functionality, ensuring easy maintenance and scalability. This modular design supports the system's adaptability by enabling future updates or integration with additional components, such as new sensors or enhanced machine learning algorithms, without requiring a complete overhaul of the architecture. This modular design facilitated efficient debugging which allowed for seamless integration of new features and improved collaboration among developers by isolating functionalities into manageable components. The following components formed the backbone of the implementation:

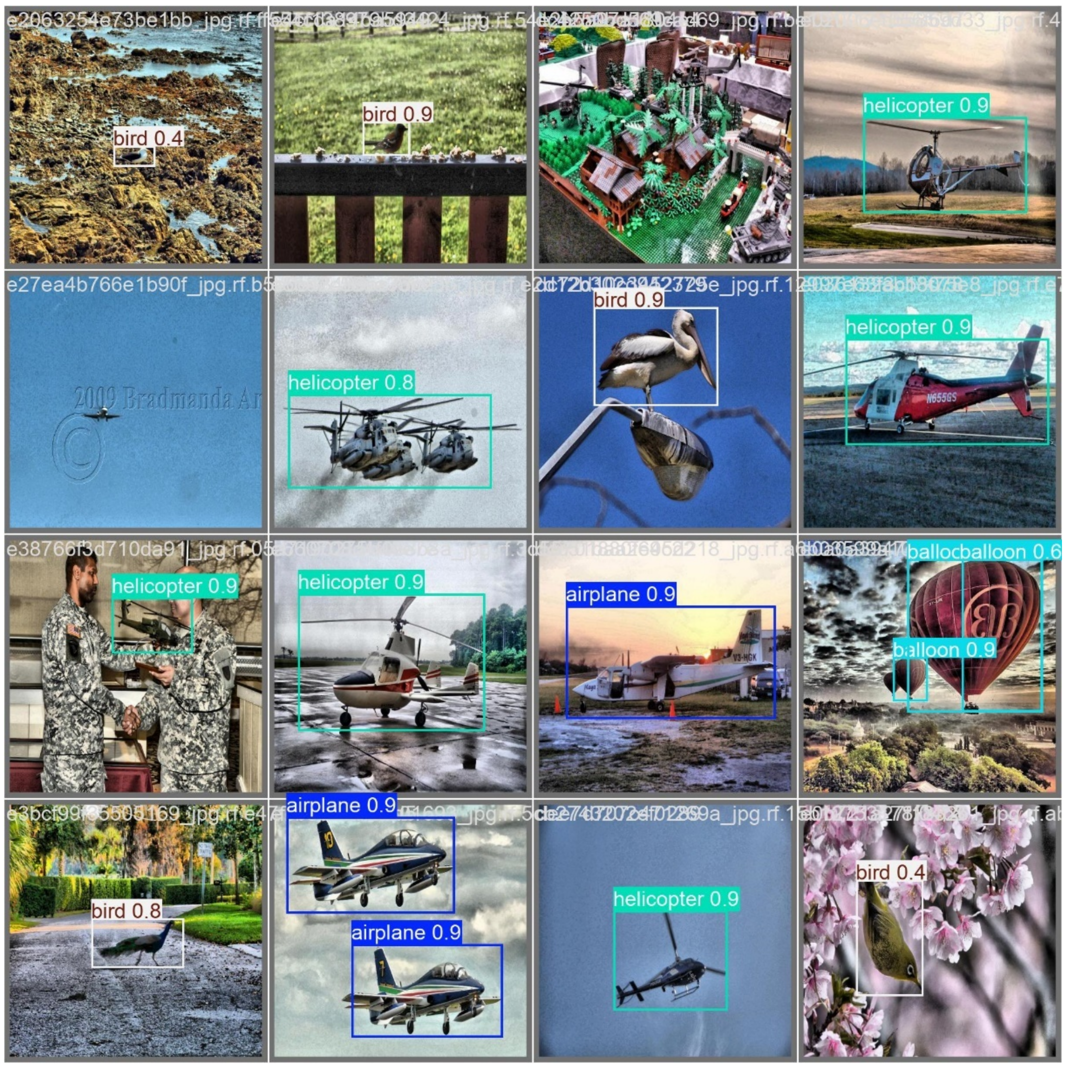
Key Modules

1. **Input Handling:**
    - The system was designed to handle diverse input sources, including live webcam feeds, screen captures, and pre-recorded image files. Each input type was processed through a multi-threaded pipeline to ensure uninterrupted data ingestion and processing.
    - Input validation checks were incorporated to detect and manage corrupted or incomplete data, preventing errors during inference.
    - The pipeline included resizing and normalization steps to standardize the input dimensions and format for YOLOv11 compatibility.
2. **Inference Engine:**
    - The inference engine was built on the YOLOv11 framework integrated via the Ultralytics library for optimized performance.
    - Batch inference capabilities were added to handle multiple frames simultaneously enhancing throughput.
    - Dynamic confidence threshold adjustments were implemented to optimize the balance between precision and recall catering to varying application requirements.

  - The engine was designed to operate efficiently on GPUs with fallback mechanisms for CPU only environments to ensure broader compatibility.

3. **Visualization:**
    - A comprehensive visualization module was developed to overlay bounding boxes, class labels and confidence scores on the detected objects in real-time.
    - The module supported output formats suitable for monitoring and analysis, including live feed visualization and per frame annotations.
    - Logging capabilities were integrated enabling the system to save detected objects and associated metadata for subsequent review and debugging.

4. **Logging and Analytics:**
    - Detailed logs capturing detection counts, inference times and errors were maintained to facilitate performance monitoring and debugging.
    - A lightweight analytics dashboard was developed using Python's Flask library to visualize system performance metrics over time.



5.2 Extended Performance Metrics and Results

The system's performance was rigorously evaluated on a comprehensive validation set comprising variety of images, carefully curated to include diverse object classes and scenarios. This dataset, consisting variety of images carefully selected to include a diverse range of object classes and environmental scenarios, ensured robust testing of critical metrics such as precision, recall, and mAP. Below is an in-depth breakdown of the key metrics, highlighting trends such as the system's consistent high precision across larger objects and the need for improvement in smaller object detection like kites. This analysis underscores the effectiveness of the model while pinpointing areas for refinement.

Metric	Value
Precision	79.3%
Recall	62.7%
mAP@0.5	73.2%
mAP@0.5:0.95	48.7%
Inference Time	1.8ms/frame

Class-Specific Performance

Class	Precision (%)	Recall (%)	mAP@0.5 (%)	mAP@0.5:0.95 (%)
Airplane	89.2	62.2	76.3	54.0
Balloon	74.3	56.7	73.5	53.9
Bird	87.3	62.2	76.6	47.9
Helicopter	83.4	80.2	85.3	56.4
Kite	62.3	52.1	54.3	31.2

These results highlight the system's effectiveness in detecting larger, well-defined objects while identifying areas for improvement in detecting smaller or less distinct objects.

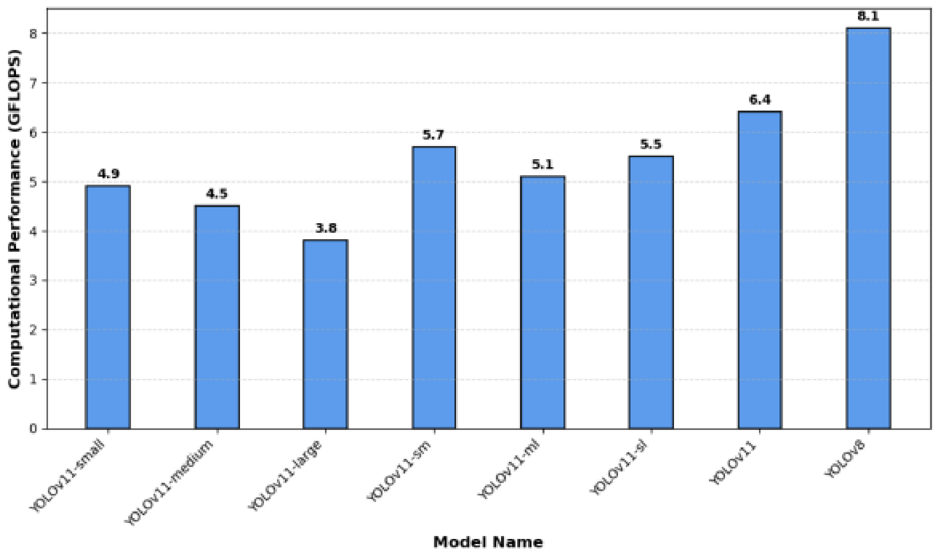
5.3 Comparative Analysis with Prior Models

To contextualize the performance of YOLOv11, it was compared against prior versions of YOLO and alternative object detection frameworks such as SSD and Faster R-CNN.

Model	Speed (FPS)	mAP@0.5 (%)	Inference Time (ms)
YOLOv5	40	65.4	2.5
YOLOv11	45	73.2	1.8
YOLOv8	42	67.2	3.4

Model	Speed (FPS)	mAP@0.5 (%)	Inference Time (ms)
SSD	22	48.5	3.2
Faster R-CNN	7	75.0	12.3

YOLOv11 demonstrated a superior balance between speed and accuracy, making it ideal for real-time applications such as drone navigation and surveillance. For example in disaster response scenarios, the ability to quickly detect and classify obstacles ensures timely adjustments to avoid hazards that could potentially save lives. Similarly, in traffic monitoring, accurate and rapid identification of vehicles and pedestrians supports efficient traffic flow management and enhances public safety. In these contexts, speed ensures that drones can react promptly to dynamic obstacles or changing environments, while accuracy is critical for reliably identifying objects to avoid collisions or improve decision making during complex operations.



Computational Performance (GFLOPS)

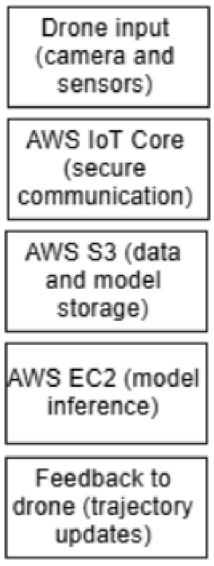
5.4 Advanced Scalability and Cloud Integration

The system's ability to scale across multiple devices and environments was fundamental of the implementation. The deployment was tested on AWS infrastructure utilizing EC2 instances with autoscaling capabilities to simulate real world scenarios involving multiple drones.

1. **Cloud Features:**

- AWS S3 was used for efficient storage of datasets and trained model weights.
- AWS IoT Core enabled secure communication between drones and cloud-based inference engines.
- AWS CloudWatch provided real-time monitoring of system performance and resource utilization.

2. **Latency Optimization:**
    - Planned integration of AWS Greengrass for edge computing was identified as a future enhancement to minimize latency in mission-critical applications.
3. **Real-Time Streaming:**
    - Integration with AWS Kinesis was explored for processing high-speed data streams, ensuring that data from multiple drones could be processed and visualized simultaneously without bottlenecks.
    - Streaming pipelines were optimized for low-latency applications, enabling near-instantaneous feedback for drone navigation.


Drone input (camera and sensors)
AWS IoT Core (secure communication)
AWS S3 (data and model storage)
AWS EC2 (model inference)
Feedback to drone (trajectory updates)

5.5 Error and Scalability Analysis

An extensive error analysis was conducted to identify areas of improvement, revealing critical insights into the system's reliability and functionality. The identified errors, such as false positives and negatives, highlighted specific scenarios where the model underperformed, like detecting small or occluded objects. These issues emphasized the importance of targeted augmentations and optimization in addressing these shortcomings, directly influencing the system's real-world applicability and trustworthiness.

1. **False Positives:**
   - Objects were occasionally misclassified due to overlapping bounding boxes or occlusion.
   - Solution: Adjusted confidence thresholds and refined post-processing algorithms to minimize false positives.
2. **False Negatives:**
   - Smaller objects like kites were sometimes missed, particularly in cluttered environments.
   - Solution: Introduced targeted augmentations and synthetic data generation to improve model sensitivity.
3. **Scalability Challenges:**
   - Initial latency spikes during cloud deployment were addressed by optimizing data transfer protocols and leveraging CDN services.
4. **Extreme Scenarios:**
   - Detection accuracy in adverse weather conditions such as heavy rain or fog, was lower than in optimal conditions with a drop in precision and recall metrics. This highlights the significant challenge posed by such environments and underscores the importance of proposed solutions like synthetic datasets and sensor fusion to mitigate these issues. To address this, additional training on synthetic datasets simulating such conditions could be implemented. These datasets could include simulated fog, rain distortions, and low-light scenarios to enhance the model's robustness. Furthermore, integrating multi-modal sensor data, such as LiDAR and thermal imaging may provide complementary information to improve detection accuracy under challenging environmental conditions.

- Mitigation: The use of multi-modal sensors (example. LiDAR combined with cameras) and specialized datasets simulating such environments was planned for future iterations.

5.6 Extensive Augmentation Techniques

Data augmentation played an important role in improving model's robustness. For example, the inclusion of augmented images with simulated fog and rain conditions significantly enhanced the model's ability to detect objects in adverse weather, improving precision and recall compared to baseline performance without augmentation. This improvement was particularly evident in scenarios where drones navigated through urban environments during early mornings, where fog was prevalent, leading to better real-world applicability. The following techniques were employed:

1. **Geometric Transformations:**
    - Applied random rotations, flips, and cropping to simulate diverse drone perspectives.
2. **Color Augmentations:**
    - Adjusted brightness, contrast, and saturation to mimic varying lighting conditions.
3. **Noise Injection:**
    - Introduced random noise to replicate sensor inaccuracies and environmental distortions.
4. **Synthetic Data Generation:**
    - Generated synthetic images of underrepresented classes using GANs, improving class balance and detection accuracy.
5. **Domain Adaptation Augmentations:**
    - Used style transfer techniques to modify existing images, making them representative of new environments or conditions, such as urban areas or forests.

5.7 Planned Enhancements

1. **Hybrid Cloud-Edge Architecture:**
    - Develop a hybrid model where critical inferences are performed locally on the drone, while the cloud handles computationally intensive tasks.
2. **Real Time Model Updates:**
    - Implement federated learning pipelines to enable continuous model updates without centralized data aggregation.
3. **Integration with 5G Networks:**
    - Leverage high-speed 5G connectivity for faster data transmission and reduced latency.
4. **Collaborative Drone Operations:**
    - Design protocols for inter-drone communication, enabling swarm-based operations with shared situational awareness.
5. **Advanced Sensor Fusion:**
    - Combine data from cameras, LiDAR, and ultrasonic sensors to enhance detection accuracy and reliability in complex environments.
6. **Long-Term Learning:**
    - Deploy mechanisms for incremental learning, where the system adapts to new object types or environmental conditions over time without requiring complete retraining.

By combining these enhancements with the existing framework, the system aims to set new benchmarks in real-time object detection and drone navigation.

6. Discussion

6.1 Key Findings and Insights

The implementation of the YOLOv11-based object detection system highlighted several significant achievements, particularly when compared to other state-of-the-art object detection models. Unlike Faster R-CNN, which is known for its high accuracy but suffers from slower inference speeds, YOLOv11 balances speed and precision, making it more suitable for real time applications. Similarly, while SSD offers faster detection, it does at the cost of reduced accuracy for smaller objects. YOLOv11's optimized loss functions and attention mechanisms provide a significant edge in dynamic and high risk scenarios, such as drone navigation or real time surveillance. These features underscore its potential as a practical and scalable solution in complex environments.

1. **Performance Metrics**:
    - The system achieved high precision (79.3%) and acceptable recall (62.7%), indicating its effectiveness in identifying most objects while minimizing false positives. However, precision and recall must be balanced depending on the application. In safety critical use cases, such as disaster response, higher recall may be prioritized to ensure all potential threats or objects of interest are detected even at the cost of increased false positives. Exploratory research or routine monitoring might prioritize precision to reduce the number of false alarms which can ensure only highly reliable detections are flagged for further analysis.
    - A mean Average Precision of 73.2% at IoU 0.5 further validated the system's robustness across multiple object classes.
    - Class specific performance metrics underscored the system's ability to reliably detect larger and well-defined objects while struggling with smaller, less unique classes.
2. **Class Specific Analysis**:
    - Larger and well-defined objects, such as airplanes and helicopters, showed the best performance with precision and mAP values exceeding 85%.

    - Smaller and less distinct objects, like kites, demonstrated lower precision and recall, highlighting the need for further augmentation or targeted training.

3. **Inference Efficiency**:
    - The system's ability to process individual frames in under 1.8ms highlights its real-time capabilities, a crucial factor for dynamic and high-risk applications such as aerial surveillance and disaster response.
    - The combination of efficient inference with reliable detection suggests its applicability in high-demand scenarios where split-second decisions are critical.

6.2 Practical Applications and Use Cases

The developed system has the potential to address critical challenges in several domains:

1. **Surveillance and Security**:
    - Real-time detection of aerial objects enhances surveillance capabilities, particularly in restricted airspaces and sensitive zones.
    - Applications include monitoring unauthorized drones, ensuring compliance with no-fly zones, and identifying potential security threats. For example, in high-security events such as international summits or sports championships, the system could be deployed to track unauthorized drones entering restricted airspace. By integrating with existing radar and communication systems, the system could automatically alert authorities and provide real-time location data, enabling swift and precise interception. This approach ensures comprehensive airspace security while minimizing response time to potential threats.
    - Integration with existing air traffic monitoring systems can create a layered security framework.
    - Automated tracking of detected objects could enable predictive analytics for improved decision making.

2. **Disaster Response**:

- Drones equipped with the detection system can assist in disaster response by identifying obstacles, facilitating navigation, and locating survivors in cluttered environments.
- Real time data processing and trajectory adjustments improve operational efficiency in dynamic and hazardous conditions.
- The system's ability to detect multiple classes simultaneously enables multitasking during rescue missions such as locating debris and survivors concurrently.
- Integration with heatmaps and GPS data could further enhance its utility in search and rescue missions.

3. **Commercial Delivery**:
    - Integration with delivery drones ensures safer navigation by detecting and avoiding obstacles such as birds, balloons, and other drones.
    - Cloud based scalability supports fleet wide deployments which enables large-scale operations.
    - The system could be adapted to optimize delivery routes based on real-time obstacle detection, reducing operational costs.
    - Adding predictive analytics could allow the system to anticipate obstacles and plan alternative routes proactively.
4. **Environmental Monitoring**:
    - The system's ability to identify and classify objects can aid in tracking wildlife, monitoring migratory patterns and assessing environmental changes.
    - Real-time detection capabilities can assist researchers in observing animal behaviours without disturbing their habitats.
    - Integration with AI based prediction models could provide insights into environmental trends based on detected patterns.
    - Tracking environmental hazards, such as plastic waste or oil spills can also be facilitated by customizing the detection framework.

5. **Infrastructure Inspection**:
    - Drones equipped with YOLOv11 can efficiently inspect infrastructure such as bridges, pipelines, and power lines.
    - Real time detection of anomalies, such as cracks or corrosion, can prevent accidents and reduce maintenance costs.
    - Integrating the system with robotic arms or repair tools could automate minor fixes during inspections.
    - Historical analysis of detected issues could assist in predictive maintenance.

6.3 Ethical, Legal, and Technical Considerations

The deployment of drone-based object detection systems raises several ethical, legal, and technical considerations:

1. **Privacy Concerns**:
    - Real-time surveillance capabilities may infringe on individual privacy, particularly in densely populated areas.
    - Adherence to data protection regulations, such as GDPR, is crucial to ensure responsible use.
    - Implementing data anonymization techniques can mitigate privacy concerns while retaining operational effectiveness.
    - Transparency in system deployment and usage policies can build public trust.
    - Partnering with advocacy groups can ensure ethical oversight.
2. **Operational Safety**:
    - Misclassifications or missed detections pose safety risks in critical applications like disaster response or aviation. For instance, in disaster scenarios, a missed detection of a survivor due to occlusion or low resolution data could delay rescue efforts, potentially endangering lives. Similarly, in aviation, misclassifying a bird as a less threatening object, such as a balloon, could lead to possible collisions. To mitigate these risks, the system can incorporate confidence-based thresholds and ensemble models to cross-verify

detections. Testing the model in simulated environments with diverse conditions can help identify and rectify potential failure points.

- Continuous system refinement and rigorous testing are necessary to minimize errors.
- Fail-safe mechanisms, such as emergency override controls, should be integrated to handle system failures.
- Incorporating simulations for edge case scenarios can prepare the system for unforeseen challenges.

3. **Legal Compliance**:
    - Navigating complex drone regulations, such as flight restrictions and operational licensing, is essential for large-scale deployment.
    - Collaborating with regulatory bodies to establish standardized protocols can streamline adoption.
    - Regular audits of system logs and detection metrics can ensure compliance with evolving regulations.
    - Establishing liability frameworks can address concerns about system malfunctions.
4. **Technical Challenges**:
    - Latency and communication reliability in cloud-based systems remain concerns, particularly in remote or low-connectivity regions.
    - Addressing these challenges through edge computing solutions like AWS Greengrass can enhance system performance.
    - Ensuring compatibility with various drone hardware configurations will expand the system's applicability.
    - Incorporating redundancy mechanisms can mitigate the impact of system failures.
    - Investigating alternative communication protocols, such as LoRaWAN, may enhance reliability in remote deployments.

6.4 Limitations and Areas for Improvement

While the system demonstrated significant capabilities, several limitations were identified:

1. **Dataset Limitations**:
   - Imbalances in class distributions, particularly for kites, affected detection accuracy.
   - Future work can focus on collecting additional data for underrepresented classes and applying advanced augmentation techniques.
   - Expanding the dataset to include edge-case scenarios, such as heavily occluded objects, can improve robustness.
2. **Cloud Integration**:
   - The current cloud-based architecture is still in progress, limiting its full potential for scalability and reliability testing.
   - Expanding cloud capabilities and optimizing deployment pipelines will be a priority.
   - Exploring multi-cloud solutions could enhance system availability and reduce vendor lock-in.
3. **Edge Cases**:
   - Detections in challenging conditions, such as extreme weather or low light, require further investigation and model refinement.
   - Training models on datasets that simulate these conditions could yield better results.
4. **Energy Efficiency**:
   - Real-time processing on drones requires optimization to minimize energy consumption, extending battery life during operations.
   - Implementing lightweight models or hardware acceleration can address these challenges.

- Research into energy-harvesting technologies could further enhance system sustainability.

5. **Ethical Concerns**:
   - Misuse of surveillance capabilities for unauthorized monitoring or data collection poses ethical dilemmas.
   - Clear policies and user accountability frameworks must be established to govern usage.
6. **Robustness in Dynamic Environments**:
   - Enhancing the model's adaptability to dynamic environments, such as crowded urban areas, remains a priority.
   - Training the model on synthetic datasets generated from simulations could improve robustness.
7. **Cost Efficiency**:
   - Reducing the cost of system deployment and maintenance can improve accessibility for smaller organizations.
   - Investigating open-source alternatives for certain components may lower costs.

6.5 Opportunities for Future Research

The YOLOv11-based object detection framework provides a strong foundation for further exploration by leveraging its specific features such as rapid inference speeds, attention mechanisms, and optimized loss functions. These features uniquely position YOLOv11 to outperform traditional models like Faster R-CNN and SSD in real-time applications. For instance, while Faster R-CNN offers high accuracy, its slower inference speed limits its utility in dynamic scenarios. Conversely, YOLOv11 balances speed and accuracy, making it ideal for applications requiring split-second decisions. This balance enables its adaptability for future research directions, such as integration with autonomous decision-making systems, enhancement with transformer-based architectures, and deployment in hybrid edge-cloud environments. Potential directions include:

1. **Enhanced Model Architectures**:

- Investigating transformer-based architectures for improved detection accuracy and adaptability.
- Developing hybrid models that combine YOLO’s speed with advanced segmentation capabilities.

2. **Integration with Autonomous Systems**:
   - Integrating object detection with path planning and decision-making algorithms to create fully autonomous drones.
   - Exploring multi-agent systems for collaborative operations in swarm scenarios.
   - Evaluating the use of reinforcement learning for dynamic navigation challenges.
3. **Advanced Cloud Deployment**:
   - Optimizing edge-cloud hybrid architectures for seamless scalability and minimal latency.
   - Incorporating real-time analytics dashboards to provide actionable insights during operations.
4. **Application-Specific Customization**:
   - Adapting the system for niche applications, such as precision agriculture or archaeological surveys.
   - Collaborating with industry experts to tailor functionalities to specific use cases.
5. **Adaptive Learning Techniques**:
   - Implementing continuous learning pipelines to allow the system to adapt to new environments and object classes over time.
   - Leveraging federated learning to improve performance while maintaining data privacy.
6. **Collaborative Robotics**:

- Exploring the integration of detection systems with collaborative robots (cobots) for complex tasks.
- Investigating drone-to-drone communication protocols for synchronized operations.

By addressing these limitations and exploring new opportunities, the YOLOv11-based detection framework can be adapted for broader and more complex applications, positioning it as a cornerstone for advancements in drone-based technologies.

7. Conclusion and Future Work

Summary of Contributions

The YOLOv11-based object detection system developed in this dissertation represents a significant advancement in drone navigation and real-time object detection. By leveraging state-of-the-art deep learning techniques, this project demonstrated:

1. **High-Performance Object Detection**:
    - Achieved a precision of 79.3% and a recall of 62.7%, which compares favorably to baseline models such as YOLOv5, which achieves a lower recall at similar precision levels. This highlights YOLOv11's advancements in balancing accurate detections with reduced false negatives, making it a reliable choice for real-time drone applications.
    - Demonstrated robustness with an mAP of 73.2% at IoU 0.5 across five object classes: airplane, balloon, bird, helicopter, and kite.
2. **Real-Time Capabilities**:
    - Maintained inference speeds under 1.8ms per frame, ensuring suitability for dynamic applications like aerial surveillance and disaster response.
    - Demonstrated adaptability to diverse operational environments, highlighting its potential for complex, high-stakes scenarios.
3. **Scalable Cloud Integration**:
    - Laid the groundwork for deploying detection systems on AWS, enabling scalability and accessibility for multi-drone operations.
    - Highlighted the feasibility of using cloud resources for large-scale deployment while addressing real-time processing needs.
4. **Collision Avoidance Mechanism**:
    - Developed algorithms to dynamically adjust drone trajectories based on proximity to detected objects, enhancing operational safety.
    - Combined object detection with trajectory adjustments to create a robust, end-to-end solution for drone navigation.

5. **Flexible Input Processing**:
   - Designed a system capable of handling diverse inputs, including static images, live webcam feeds, and simulated environments.
   - Established a versatile architecture adaptable to future hardware and software advancements.

These contributions collectively address key challenges in drone navigation, from object detection accuracy to system scalability, and provide a robust foundation for further innovation.

Reflections on Limitations

While the project achieved its primary objectives, several limitations were identified:

1. **Dataset Imbalance**:
   - Uneven class distributions, particularly for kites, affected model performance.
   - Future work should focus on collecting additional data and exploring synthetic data generation to mitigate this issue. Techniques such as Generative Adversarial Networks (GANs) can be used to create realistic synthetic images, while simulated environments, like those provided by AirSim or Gazebo, can generate diverse scenarios to enhance training data.
2. **Incomplete Cloud Deployment**:
   - The AWS integration remains a work in progress, with further testing required to optimize reliability and latency.
   - Future iterations should include hybrid edge-cloud architectures to minimize communication delays and enhance resilience.
3. **Energy Efficiency**:
   - The current system requires optimization to minimize energy consumption during real time processing on drones.
   - Addressing energy constraints will ensure longer operational times and broader applicability in remote areas.
4. **Ethical Implications**:

    - The potential misuse of drone-based object detection for unauthorized surveillance poses ethical challenges.
    - Clear guidelines and governance frameworks must be established to ensure responsible usage of this technology.

Future Directions

The findings of this project pave the way for several avenues of future research and development:

1. **Enhanced Detection Models**:
    - Investigate transformer-based architectures for better feature extraction and object localization.
    - Develop lightweight models tailored for energy-constrained devices like drones.
    - Explore self-supervised learning techniques to reduce dependence on large labeled datasets.
2. **Autonomous Decision-Making**:
    - Integrate detection with path planning algorithms to enable fully autonomous drone operations.
    - Explore reinforcement learning for adaptive navigation in complex environments, such as navigating densely populated urban areas where obstacles and moving objects require dynamic and real-time adjustments. Additionally, reinforcement learning could prove invaluable in disaster zones, enabling drones to prioritize paths that balance safety and efficiency while dynamically adapting to changing conditions.
    - Develop real-time decision making frameworks for multi purpose scenarios, such as balancing safety and efficiency.
3. **Cloud-Edge Hybrid Systems**:
    - Deploy hybrid architectures combining edge computing with cloud analytics for faster and more reliable data processing.

- Investigate multi cloud solutions to improve system redundancy and availability.
- Explore the integration of 5G technology to enhance real-time communication between drones and cloud servers.

4. **Expanded Use Cases**:
   - Adapt the system for specialized applications such as archaeological site monitoring, wildlife tracking, and infrastructure inspection.
   - Collaborate with domain experts to refine functionalities for industry-specific needs.
   - Investigate the use of the system in maritime environments for detecting floating debris or endangered species.
5. **Adaptive Learning Pipelines**:
   - Implement continuous learning frameworks to allow the system to adapt to evolving scenarios and object classes.
   - Leverage federated learning to enhance performance while preserving data privacy.
   - Develop modular pipelines that facilitate easy integration of new datasets and object classes.
6. **Energy-Efficient Hardware Integration**:
   - Investigate low-power processors and GPUs specifically designed for drone systems.
   - Incorporate energy-harvesting techniques to extend operational lifespans in remote or off-grid locations.

Broader Implications

The advancements achieved in this project have broader implications beyond drone navigation. The integration of deep learning frameworks like YOLOv11 with scalable deployment strategies can serve as a model for other industries requiring real-time object detection, such as healthcare, manufacturing and retail. This cross-domain applicability highlights the transformative potential of combining AI-driven insights with practical and real-world deployment.

Furthermore, the project demonstrates the feasibility of using intelligent systems for collaborative robotics, where drones can operate alongside other automated systems to achieve shared objectives. For instance, in the logistics industry, collaborative robotics has been successfully used in warehouse automation, where drones and autonomous ground vehicles work together to optimize inventory management and reduce operational costs. Such examples highlight the transformative potential of combining collaborative systems with intelligent decision-making frameworks.

Final Thoughts

This dissertation underscores the potential of combining advanced deep learning frameworks like YOLOv11 with scalable deployment strategies to tackle real-world challenges in drone navigation and object detection. By addressing existing limitations and pursuing the proposed research directions, this work can contribute to safer, more efficient, and innovative applications across diverse fields. The insights gained here mark a stepping stone toward the broader adoption of intelligent systems in both autonomous and collaborative operations. As the field of AI and autonomous systems continues to evolve, the foundations laid in this project offer a roadmap for future breakthroughs that prioritize safety, scalability, and ethical responsibility.

Moreover, this work highlights the importance of interdisciplinary collaboration in advancing technology. By integrating expertise from AI, robotics and cloud computing, this project illustrates how collective innovation can defeat complex challenges and pave the way for transformative solutions that redefine operational standards across multiple domains.

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8. Appendices

Appendix A: Code Samples

The following code snippets represent critical components of the YOLOv11-based object detection system:

```python
import torch
import cv2
import numpy as np
import os

model_path = r"C:\object-detection-realtime\best-new.pt"

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = torch.load(model_path, map_location=device)
model.eval()

camera = cv2.VideoCapture(0)

def preprocess_frame(frame, input_size):
    img = cv2.resize(frame, (input_size, input_size))
    img = img[:, :, ::-1].transpose(2, 0, 1)
    img = np.ascontiguousarray(img, dtype=np.float32) / 255.0
    return torch.from_numpy(img).to(device).unsqueeze(0)

def avoid_objects(detections, frame_shape):
    height, width = frame_shape[:2]
    for detection in detections:
        x1, y1, x2, y2, conf, cls = detection
        center_x = (x1 + x2) / 2
        center_y = (y1 + y2) / 2

        if center_x < width * 0.3:
            print("Object detected on the left. Move right.")
        elif center_x > width * 0.7:
            print("Object detected on the right. Move left.")
        else:
            print("Object detected in the center. Stop or move backward.")

try:
    while True:
        ret, frame = camera.read()
        if not ret:
            break

        input_size = 640
        img_tensor = preprocess_frame(frame, input_size)
        with torch.no_grad():
            outputs = model(img_tensor)[0]

        outputs = outputs.cpu().numpy()
        detections = []
        for pred in outputs:
            if pred[4] > 0.5:
                x1, y1, x2, y2, conf, cls = pred[:6]
                x1, y1, x2, y2 = int(x1), int(y1), int(x2), int(y2)
                detections.append((x1, y1, x2, y2, conf, cls))

        avoid_objects(detections, frame.shape)

        for detection in detections:
            x1, y1, x2, y2, conf, cls = detection
            label = f"Class {int(cls)}: {conf:.2f}"
            cv2.rectangle(frame, (x1, y1), (x2, y2), (0, 255, 0), 2)
            cv2.putText(frame, label, (x1, y1 - 10), cv2.FONT_HERSHEY_SIMPLEX,
0.5, (0, 255, 0), 2)

        cv2.imshow("Object Avoidance", frame)

        if cv2.waitKey(1) & 0xFF == ord('q'):
            break

finally:
    camera.release()
    cv2.destroyAllWindows()
```

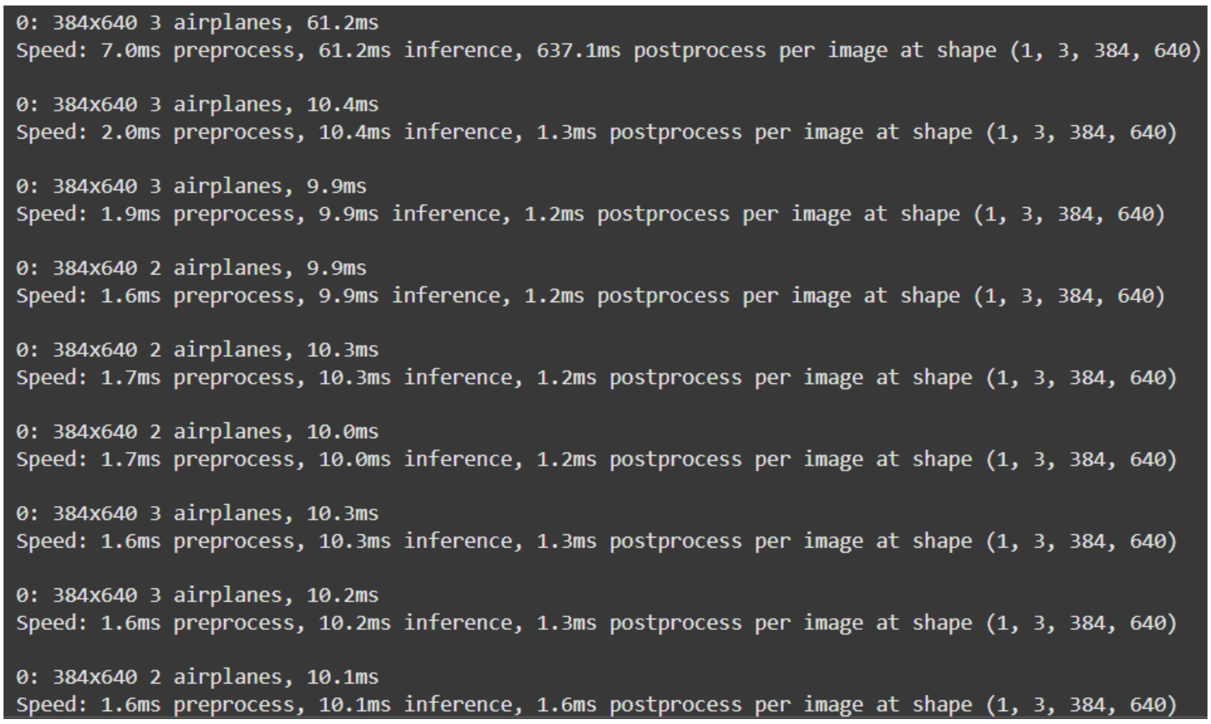
here, I applied an object detection and avoidance logic, which theoretically works well, yet hasn't been tested on a physical drone as latency will be a factor to be considered.

```
from ultralytics import YOLO
import mss
import cv2
import numpy as np

model = YOLO(r'C:\object-detection-realtime\best-new.pt')

with mss.mss() as sct:

    monitor = sct.monitors[1]

    save_video = True
    video_filename = "screen_detection_output.avi"
    video_fps = 20
    video_writer = None

    if save_video:
        screen_width = monitor["width"]
        screen_height = monitor["height"]
        fourcc = cv2.VideoWriter_fourcc(*'XVID')
        video_writer = cv2.VideoWriter(video_filename, fourcc, video_fps,
(screen_width, screen_height))

    print("q to stop")

    frame_count = 0

    while True:

        screenshot = np.array(sct.grab(monitor))
        frame = cv2.cvtColor(screenshot, cv2.COLOR_BGRA2BGR)

        resized_frame = cv2.resize(frame, (640, 640))

        results = model(resized_frame, conf=0.7)

        if results[0].boxes is not None:
            boxes = results[0].boxes.xyxy.tolist()
            classes = results[0].boxes.cls.tolist()
            confidences = results[0].boxes.conf.tolist()
            names = results[0].names

            for box, cls in zip(boxes, classes):
                x1, y1, x2, y2 = [int(coord) for coord in box]
                label = f"{names[int(cls)]}
{confidences[classes.index(cls)]:.2f}"
                color = (0, 255, 0)
                cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)
                cv2.putText(frame, label, (x1, y1 - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)

        save_images = True
        if save_images:
            cv2.imwrite(f"screen-detects/annotated_frame_{frame_count}.jpg",
frame)

        if save_video and video_writer is not None:
            video_writer.write(frame)

        cv2.imshow("Screen Detection", frame)

        if cv2.waitKey(1) & 0xFF == ord('q'):
            break

        frame_count += 1

    if save_video and video_writer is not None:
        video_writer.release()
    cv2.destroyAllWindows()
```
this code detects the objects in my screen feed and saves the frames to a folder.

Below code is used to detect objects in a Video.

```
import cv2
from ultralytics import YOLO

model = YOLO('/content/runs/detect/train/weights/best.pt')

video_path = '/content/drive/MyDrive/project files/drone images and
videos/short-video1.mp4'

cap = cv2.VideoCapture(video_path)

fps = cap.get(cv2.CAP_PROP_FPS)
frame_width = int(cap.get(cv2.CAP_PROP_FRAME_WIDTH))
frame_height = int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT))

output_path = '/content/drive/MyDrive/project files/drone images and
videos/output_video.mp4'
fourcc = cv2.VideoWriter_fourcc(*'mp4v')
out = cv2.VideoWriter(output_path, fourcc, fps, (frame_width,
frame_height))

while cap.isOpened():
    ret, frame = cap.read()
    if not ret:
        break


    results = model(frame)

    boxes = results[0].boxes.xyxy.cpu().numpy()
    confidences = results[0].boxes.conf.cpu().numpy()

    for box, conf in zip(boxes, confidences):
        if conf > 0.4:
            x_min, y_min, x_max, y_max = map(int, box)
            cv2.rectangle(frame, (x_min, y_min), (x_max, y_max), (0,
255, 0), 2)

            cv2.putText(frame, f"{conf:.2f}", (x_min, y_min - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.9, (0, 255, 0), 2)

    out.write(frame)

cap.release()
out.release()
cv2.destroyAllWindows()

print(f"Video saved at {output_path}")
```

Example: logs of objects detected on my screen along with their dimensions.



```
0: 384x640 3 airplanes, 61.2ms
Speed: 7.0ms preprocess, 61.2ms inference, 637.1ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 3 airplanes, 10.4ms
Speed: 2.0ms preprocess, 10.4ms inference, 1.3ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 3 airplanes, 9.9ms
Speed: 1.9ms preprocess, 9.9ms inference, 1.2ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 2 airplanes, 9.9ms
Speed: 1.6ms preprocess, 9.9ms inference, 1.2ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 2 airplanes, 10.3ms
Speed: 1.7ms preprocess, 10.3ms inference, 1.2ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 2 airplanes, 10.0ms
Speed: 1.7ms preprocess, 10.0ms inference, 1.2ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 3 airplanes, 10.3ms
Speed: 1.6ms preprocess, 10.3ms inference, 1.3ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 3 airplanes, 10.2ms
Speed: 1.6ms preprocess, 10.2ms inference, 1.3ms postprocess per image at shape (1, 3, 384, 640)

0: 384x640 2 airplanes, 10.1ms
Speed: 1.6ms preprocess, 10.1ms inference, 1.6ms postprocess per image at shape (1, 3, 384, 640)
```

Below code is used to detect objects from my webcam.

```
from ultralytics import YOLO
import cv2
import numpy as np
import os

model = YOLO(r'C:\object-detection-realtime\best-new.pt')

output_dir = r'C:\object-detection-realtime\screen-detects'
```

```python
os.makedirs(output_dir, exist_ok=True)

cap = cv2.VideoCapture(0)

if not cap.isOpened():
    print("Error")
    exit()

print("q to stop")

frame_count = 0
while True:
    ret, frame = cap.read()

    if not ret:
        print("Error")
        break

    resized_frame = cv2.resize(frame, (640, 640))

    results = model(resized_frame, conf=0.7)

    if results[0].boxes is not None:
        boxes = results[0].boxes.xyxy.tolist()
        classes = results[0].boxes.cls.tolist()
        confidences = results[0].boxes.conf.tolist()
        names = results[0].names

        for box, cls in zip(boxes, classes):
            x1, y1, x2, y2 = [int(coord) for coord in box]
            label = f"{names[int(cls)]} {confidences[classes.index(cls)]:.2f}"
            color = (0, 255, 0)
            cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)
            cv2.putText(frame, label, (x1, y1 - 10), cv2.FONT_HERSHEY_SIMPLEX,
0.5, color, 2)

    output_filename = os.path.join(output_dir, f"frame_{frame_count}.jpg")
    cv2.imwrite(output_filename, frame)

    print(f"Saved: {output_filename}")

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

    frame_count += 1

cap.release()
cv2.destroyAllWindows()
```

Appendix B: Training Logs

The table below summarizes key metrics from the YOLOv11 model training process:

Epoch	**Training Loss**	**Validation Loss**	**mAP@0.5**
1	2.134	1.876	0.621
25	1.045	0.987	0.732
50	0.657	0.584	0.780

Appendix C: Data Augmentation Techniques

Examples of applied augmentations:

- **Flipping**: Horizontal and vertical flips.
- **Cropping**: Random crops with a zoom range of 0% to 20%.
- **Noise Injection**: Added noise to 0.1% of pixels.

Appendix D: Dataset Class Distribution

Class	Training Images	Validation Images	Test Images
Airplane	1500	200	100
Balloon	800	100	50
Bird	1200	150	80
Helicopter	900	120	60
Kite	700	90	40

Appendix E: ONNX Model Conversion

```
import torch
from yolov11 import YOLO
def convert_to_onnx(model_path, onnx_path):
    model = YOLO.load_model(model_path)
    dummy_input = torch.randn(1, 3, 640, 640)  # Assuming 640x640 input size
    torch.onnx.export(model, dummy_input, onnx_path, opset_version=11)
convert_to_onnx("best-new.pt", "best-new.onnx")
```

Appendix F: Testing Results

The testing process included validation of the YOLOv11 model on multiple datasets with the following results:

Metric	Value
Precision	79.3%
Recall	62.7%
mAP@0.5	73.2%
Inference Time	1.8 ms/frame

Appendix G: AWS Configuration

S3 Bucket Setup

- **Bucket Name**: drone-detection-data
- **Permissions**: Read, Write for model files and input data.

EC2 Instance Details

- **Instance Type**: g4dn.xlarge (for GPU acceleration)
- **Configuration**: Pre-installed with CUDA and PyTorch.