# IR-Based UAV Detection with Deep Learning for Monitoring No-Fly Zones

A Report Submitted
in Partial Fulfillment of the Requirements
for the Degree of
**Bachelor of Technology**
in
**Computer Science & Engineering**

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to the
**COMPUTER SCIENCE AND ENGINEERING DEPARTMENT**
MOTILAL NEHRU NATIONAL INSTITUTE OF TECHNOLOGY
ALLAHABAD PRAYAGRAJ
**November, 2024**

# UNDERTAKING

We declare that the work presented in this report titled "*IR-Based UAV Detection with Deep Learning for Monitoring No-Fly Zones*", submitted to the Computer Science and Engineering Department, Motilal Nehru National Institute of Technology Allahabad, Prayagraj, for the partial award of the ***Bachelor of Technology*** degree in ***Computer Science & Engineering***, is our original work. We have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, we accept that our degree may be unconditionally withdrawn.

November, 2024
Allahabad

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# CERTIFICATE

Certified that the work contained in the report titled "*IR-Based UAV Detection with Deep Learning for Monitoring No-Fly Zones*", by Shipra Chandra (20214090), Sundram Mishra (20214020), Shresth Sonkar (20214272), Setu Dineshbhai Patel (20214157), has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

(Dr. Shailendra Shukla)
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November, 2024

# Preface

The rapid adoption of drones in various domains, from recreational use to military applications, has brought both opportunities and challenges. Although drones offer remarkable benefits, their potential misuse has raised significant security concerns.

This has necessitated the development of efficient and reliable drone detection systems to mitigate threats and ensure public safety.

The use of infrared (IR) technology in drone detection offers a unique advantage, as it leverages thermal signatures that are less affected by environmental noise compared to traditional optical or acoustic methods.

Combining this approach with machine learning techniques further enhances detection accuracy, enabling systems to identify drones amidst complex and dynamic environments. Machine learning algorithms can process vast amounts of IR data, detect patterns, and differentiate drones from other objects with high precision.

# Acknowledgements

We extend our warm thanks to Dr. Shailendra Shukla, our project mentor, for guiding us through this project with his priceless advice and support that never wavered, as well as the feedback that has illuminated our way all along.

We owe a deep sense of gratitude to the Computer Science Department which laid down this path of exploration for us. The resource support, facilities, and intellectually vibrant atmosphere nurtured by the department have played a major role in helping bring this project to fruition.

We would like to acknowledge the Director, Dr. R.S. Verma for his visionary leadership — in the same way as expressing profound gratitude for the unwavering commitment to nurturing academic excellence.

And finally, we wish to thank all those who have played a part in any way towards the accomplishment of this project: your contributions have really been beneficial.

# Contents

# Chapter 1

# Introduction to Problem Statement

The emerging development and low cost of drone technology have made UAVs widely available and advantageous in a number of sectors, from agriculture to logistics, as well as disaster relief. However, there are also deeper, very serious concerns associated with these developments. High-resolution cameras on drones start raising privacy issues; they could be used for smuggling and as a weapon for terrorism.

Besides, they pose a threat to the safety of airspace and are relatively easier to hack. They are also increasingly becoming open to adversaries. Harsher regulations, enhanced cybersecurity, and anti-drone technologies are being developed as counter measures against these threats. Balancing benefit from drones with resultant robust protections is necessary in finding solutions for the misuse of drones and their safe utilization.

## 1.1 Background

Particularly vulnerable to issues caused by invasive unmanned aerial vehicles (UAVs) are the big public gatherings, such as Maha Kumbh Mela celebrations held annually, which has the potential to attract millions of participants from various parts of India, including:

- Privacy Invasion: Privacy of individuals is breached through 'lock-on' footage captured by drones mounted with cameras.

- Hostile Utilization: Enemy formations can use drones as Surveillance devices to get crucial information.
- Delivery Risk of Pay Loads: Drones can be used to deliver poisonous materials/snakes for the purpose of terror attacks.
- Interference of Space: Uninvited Drones may bypass or interfere with the drones' operators that are approved such as rescue units.

The safety of the airspace over large clusters of human beings for example the Maha Kumbh Mela is essential to ensure that catastrophes do not occur, privacy is maintained as well as the order.

## 1.2 Overview of UAV Detection Methodologies

At different points in time, different approaches have been used for the UAV detection depending on the specific requirements and the operational environment. Among these are [11]:

- Radar Systems:
  - These radar systems are used considerably for the detection of large aircraft.
  - While useful, their high costs and complexity of deployment make them less appropriate for temporary deployments.
  - While effective for detecting large aircraft, it struggles with small drones made of non-metallic materials, leading to false negatives.
- Visible Light Cameras:
  - These are based on optical imaging to detect and classify objects.
  - They experience significant deficiency in their performance when operating in poor lighting or during unfavorable weather conditions such as torrential fog or rain.

- Acoustic Sensors:
  - These systems detect drones based on their sound signatures.
  - These are susceptible to noise interference especially in urban regions hence affecting reliability.
- Infrared (IR) Cameras:
  - Emerging as a highly effective alternative, IR cameras detect thermal signatures, making them robust in low-light or night-time conditions.
  - They are unaffected by environmental noise or material composition, offering significant advantages over radar, visible light, and acoustic detection systems.

## 1.3 Objective

This project aims to create an IR-based UAV detection system. Advanced image processing and machine learning techniques are utilized in the system. Its key objectives are:

- Correct Classification: Distinguish UAVs from birds or any other flying objects.
- Real-time Alert: Notify security teams for immediate response.
- High-Risk Event No-fly Zone Security: Secure no-go zones during high-risk events. This will maintain public safety.

IR-based detection, combined with AI-driven classification models, provides a scalable and cost-effective solution, especially for high-security events like the Maha Kumbh Mela.

# Chapter 2

# Current Approaches

## 2.1 Radar Based Systems

### 2.1.1 Working of Radar

Radar systems operate by emitting electromagnetic waves and analyzing the reflections from airborne objects. By measuring the time delay and Doppler shifts of these reflections, radar can determine the object's distance, speed, and sometimes its size and shape. [12]

The process is simple:

- Emission: Radar provides pulses of radio waves.
- Reflection : Waves bounce back from objects.
- Analysis: The radar computes for time delay and Doppler shifts to infer object properties.

Key Components in UAV Detection:

- Detection and Tracking: Identifies objects in the radar's range.
- Classification: Distinguishes drones from other objects (e.g., birds, aircraft).
- Alert System: Warns operators of potential UAV intrusions.

### 2.1.2 Types of Radar

1. Mono-Static Radar:
   - Single location for both transmitter and receiver.
   - Commonly used in short-range applications.
   - Challenges: Terrain masking and difficulty with low-altitude drones.
2. Multi-Static Radar:
   - Separate locations for transmitter and receiver(s).
   - Reduces terrain masking effects and enhances low-altitude detection.
3. MIMO Radar (Multiple-Input Multiple-Output):
   - Uses multiple antennas to improve resolution and accuracy.
   - Effective in distinguishing drones in cluttered environments.
4. Passive Radar:
   - Relies on existing radio signals (e.g., TV, GSM).
   - Difficult to jam but may have lower accuracy compared to active radar.
5. Micro-Doppler Radar:
   - Analyzes the unique motion patterns (e.g., drone rotors).
   - Useful for classifying drones versus birds.
6. Cognitive Radar:
   - Dynamically adjusts parameters (e.g., frequency, waveform) to optimize detection.
   - Effective in complex environments with high interference.

### 2.1.3 Drawbacks of Radar

Despite its wide use, radar has limitations when it comes to detecting small, low, and slow-moving UAVs (LSS air threats) [12]:

- Small Radar Cross Section (RCS): Drones often have low RCS values due to their small size and non-metallic materials, making them difficult to detect.
- False Positives: Birds and other objects can trigger false alarms as their radar signatures overlap with drones.
- Terrain and Clutter Effects: Low-altitude drones are obscured by ground clutter or terrain masking.
- Unconventional Flight Patterns: Slow speeds and hovering positions create challenges for traditional radar systems.
- Active Detection Vulnerability: Active radar systems can be detected and jammed by adversaries.
- Cost and Complexity: High-performance radar systems require significant investment and complex deployment, making them impractical for temporary setups.
- Limited Identification Capability: While radar can detect objects, classifying UAVs accurately (e.g., identifying the number of rotors or payload) is challenging without auxiliary sensors like cameras or infrared systems.

## 2.2 Existing Systems in Active Usage

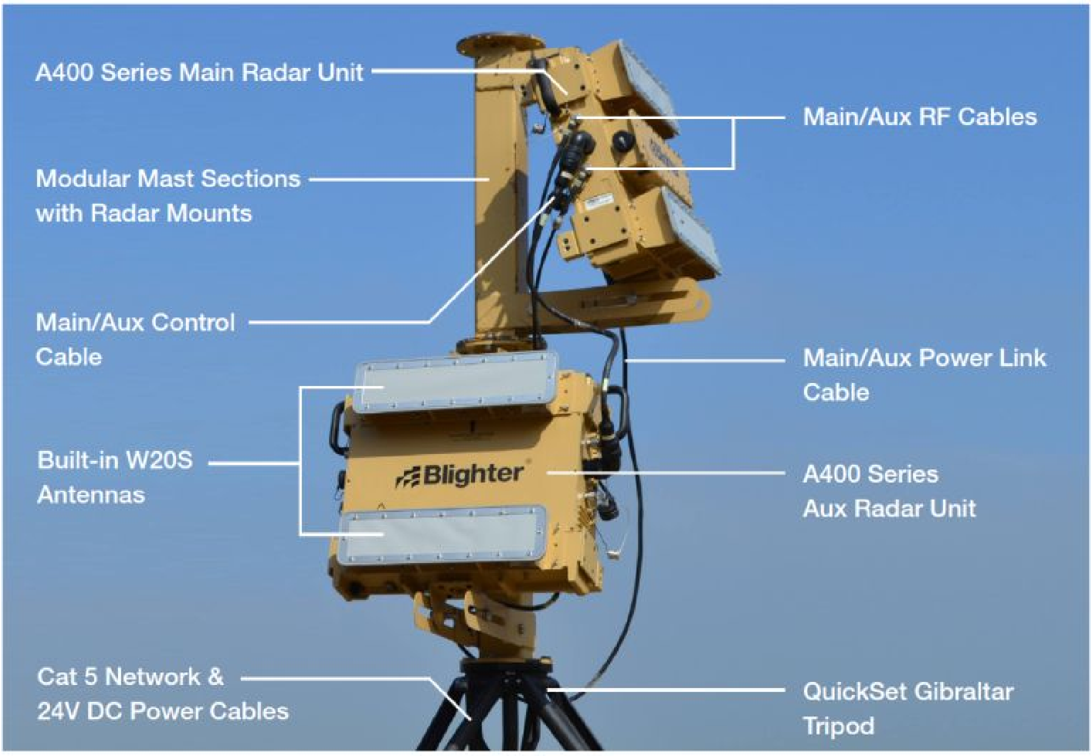


**Fig.1**: Blighter X400 [10]

**Fig.2**: Bharat Electronics Limited DDR [3]

# Chapter 3

# Transition to Infrared Based Drone Detection

## 3.1 Infrared (IR) Cameras for UAV Detection

IR cameras are a breakthrough development in drone-detecting systems which other detection technologies are limited. IR Cameras have certain advantages over all other technologies [2]:

- Dependable Performance at Night or in Dark Environments: Unlike the optical systems, the attempt to use infrared cameras does not suffer from night or poor lighting.
- Construction Material Lattice: They don't care what the construction material is, be it metallic, or non-metallic, they detect UAVs.
- Reduced False Positives: Precisely distinguishes UAVs from birds or other objects based on their heat signatures.
- Lower Quite Rate: As they are able to detect heat, IR Cameras can more easily eliminate or distinguish between a UAV and a bird, or other objects that may be in close range.
- Light Weight: This makes them great for temporary security arrangements for example at the Maha Kumbh Mela as they combine lightweight design and low cost.

- Cost-Effective Deployment: Compact and scalable for temporary installations like those required at the Maha Kumbh Mela.

## 3.2 Need for Image Processing

Key Advantages of Image Detection Systems [6]:

1. Enhanced Precision and Speed :
    - Advanced algorithms analyze patterns and features with high accuracy, reducing human error.
    - Real-time processing enables rapid decision-making, critical for applications like autonomous vehicles and emergency response.
2. Automation and Scalability :
    - Automates tasks such as object recognition, defect detection, and behavior analysis, improving efficiency.
    - Handles vast amounts of data in real-time, making it ideal for large-scale applications like traffic monitoring or industrial production.
3. Versatility Across Applications :
    - Effective in various spectra (e.g., infrared, X-ray), supporting fields like security, healthcare, and manufacturing.
    - Adapts to diverse use cases, from heat detection to anomaly identification.
4. Improved Security and Monitoring :
    - Enables advanced surveillance systems for threat detection, access control, and anomaly detection in sensitive or crowded areas.
    - Non-invasive observation ensures safety and minimal disruption in applications like medical imaging and wildlife tracking.
5. Cost-Effectiveness and Insight Generation :

- Reduces dependence on manual labor in repetitive or hazardous tasks, cutting costs while maintaining safety.
- Provides actionable data insights for trend analysis, operational efficiency, and informed decision-making.

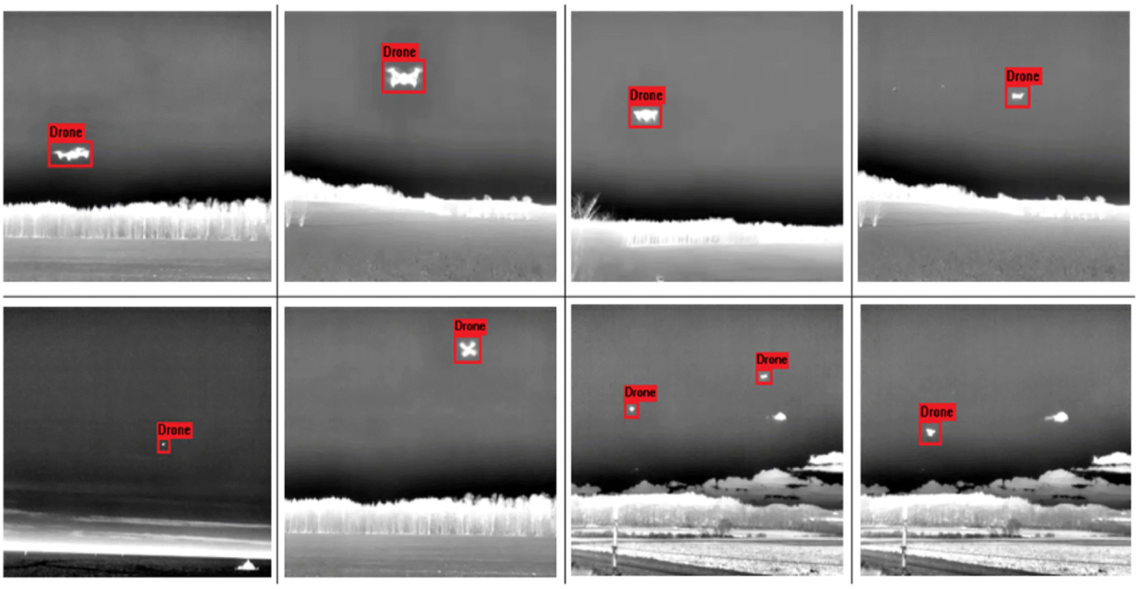


**Fig.3**: Infrared Drone Detection [1]

# Chapter 4

# System Overview for IR-Based UAV Detection System

The proposed system utilizes cutting-edge technologies to detect and classify UAVs (unmanned aerial vehicles), such as drones, in real-time.

## 4.1 System Architecture

The system integrates both hardware and software components designed to perform efficient and automated UAV detection and classification in real-time. This section provides a comprehensive overview of the system's architecture, key components, and operational workflow.

By combining infrared (IR) imaging, edge computing capabilities, and deep learning models, the system ensures high accuracy and reliability in monitoring airspace, particularly in restricted or no-fly zones.

### 4.1.1 Description

The object classification mechanism in this system heavily depends on the Deep Learning Model. It is designed to differentiate between drones, birds, and helicopters in thermal imaging.

The model comprises a combination of architecture and augmentation techniques which enable discrimination between the different classes as the system is trained on enhanced thermal images which are in great numbers.

Once again, the training procedure employs the Adam optimizer that helps in updating the model's parameters during training and categorical cross-entropy loss for classification-based training.

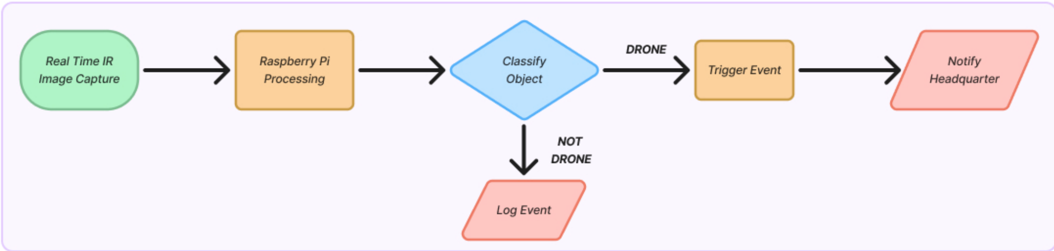


**Fig.4**: Image Recognition [9]

Evaluation of the model during the course of training is done using the accuracy metric, while other techniques such as early stopping and learning rate scheduling are employed to avoid overfitting, and for tuning performance respectively.

Finally, when the model has been fully trained, objects are outputted with associated confidence levels, such that drones prompt an alert system, whereas birds and helicopters do not, and are simply recorded.

## 4.2 Hardware

1. Infrared (IR) Camera: Image Capture Functionality: The foremost requirement in identifying UAVs is the Infrared (IR) camera, which will take IR images of the sky. It detects heat signals from objects within a 1.5 km radius, it works extremely well in low light or at night, which is difficult for traditional cameras. In addition to this, it is made to work precisely in a variety of weather scenarios, and is unaffected by environmental factors like low-visibility. It is designed to function dependably in outdoor environments, such major gatherings like the Maha Kumbh Mela, where crowd monitoring and surveillance are crucial Specifications:

    - Range: 1.5 km radius.

- Weatherproof (IP66-rated) for reliable performance in outdoor environments like the Maha Kumbh Mela.

2. Raspberry Pi In the central hub of the system the processing unit is a Raspberry Pi for Data Processing Operation:

   - From the camera it receives the Infrared images and analyzes it with a deep learning model that is present on chip.
   - The processed objects in the IR images are recognized and classified by the processor based on the pre-stored information, thus it is fast and efficient in image processing

   Hardware Enhancements : Raspberry Pi can be improved with the use of Graphics Processing Unit or special purpose graphics segment accelerators such as Coral TPU or NVIDIA Jetson Nano which increase the computing power necessary for analysis to be done in real time.

3. Communication Module: Alert Generation Functionality: It is a critical component of the system because it allows for the automatic issuance of alerts whenever a drone is sighted within the vicinity. Options: This module supports multiple means of communication including GSM, Wi-Fi and LAN which allows deployment flexibility of the system. Alert Types:

   - These notifications can take different forms and include visual or sound alerts on the monitoring screen, SMS or an application notifying deployed security personnel.
   - These alerts are very important in ensuring there is no wasted time should there be a need to respond to a security issue.
   - It ensures real-time notification of the relevant persons for prompt action.

4. Monitoring System: Purpose: It is an integrated platform that allows controlling alerts and providing visual information in real time. Features:

   - It features the 'Network Overview', which illustrates the live images of all connected cameras and their operational status within the premises.

- Furthermore, every incident is stored in the system for further post-incident analysis for better future operations and quick response improvement.
- On the other hand, there is a mobile version that enables security officers to be notified on their mobile devices for them to act fast against any looming danger.

5. Response: The monitoring system places security teams in a better position to act decisively where there is a need to use s precautions, summon local law enforcement officers or change surveillance activities in line with the current situation.
6. UAV Altimeter Radar : Drones often use altimeter radars to maintain stable flight altitudes. These systems rely on bouncing radio waves off the ground to measure height, making them highly effective for flight stability but not for detection by external radar systems.

## 4.3 Deep Learning Model

The objective of the deep learning model is to classify objects using IR images into multiple classes, including drones, birds, and helicopters. [4]

It is designed to differentiate between drones, birds, and helicopters in thermal imaging. The main objective of this model is to distinguish drones from other aerial objects, including birds and helicopters, and identify them as potential security threats.

The model then learns upon the thermal emissions recorded by IR cameras, which detect heat from objects residing in their field of view. Drones are recognized by their unique heat profiles, which immediately generate warnings.

However, birds and helicopters are only recorded for monitoring purposes and these do not trigger warnings (i.e are ignored), even though they are sighted. This ensures that only relevant threats are communicated to security personnel and reduces the chances of false positives.

### 4.3.1 Data Preprocessing

The step at the beginning of any machine learning pipeline is preparing the data. The videos are broken into frames-the input images for training the model, frames extracted at regular intervals from the videos to be reduced in redundancy and to manage an appropriate size for the dataset.

```
Processing AIRPLANE videos...
100% ████████████████████ 74/74 [00:19<00:00,  2.89it/s]

Processing BIRD videos...
100% ████████████████████ 79/79 [00:11<00:00,  7.58it/s]

Processing DRONE videos...
100% ████████████████████ 157/157 [00:18<00:00,  8.84it/s]

Processing HELICOPTER videos...
100% ████████████████████ 55/55 [00:06<00:00,  8.41it/s]

Dataset Statistics:
Total frames extracted: 22986
Training images: 16090
Validation images: 4597
Test images: 2299

Verifying dataset structure:
train:
  Images: 16090
  Labels: 16090
val:
  Images: 4597
  Labels: 4597
test:
  Images: 2299
  Labels: 2299
```

**Fig.5**: Preprocessing

In this case, every fifth frame is extracted from the video files. After extracting the frames, they are converted to grayscale images in order to minimize data complexity. This works such that it prevents the model from focusing on color variations rather than on key features. The grayscale images are then transferred back into 3-channel images since YOLOv8 is a 3-channel image requirement for training.

These processed images are stored with a directory structure that separates train, validation, and test data. Additional labels generated in the YOLO format corresponding to the images are provided. Each label file contains class index, along with bounding box information, for the object in the given image.

Labels for the respective files are placed in separate directories for each split of the dataset, namely train, val, test. The subsequent process entails splitting the dataset into training, validation, and test sets by using particular ratios. This ensures that there is sufficiently trained data for the model while still allowing the model to validate and test its performance with unseen data.

### 4.3.2 Training the Model Using YOLOv8

The You Only Look Once (YOLO) framework, introduced in 2016, revolutionized object detection by offering a unified approach capable of swiftly and accurately detecting objects in images and video streams. [8]

Its single-pass processing through a convolutional neural network (CNN) enables rapid detection without sacrificing accuracy, making it a popular choice in various applications requiring real-time detection capabilities.

With the dataset properly preprocessed, the next step is to train a machine learning model. For this project, YOLOv8 (You Only Look Once) is used for object detection. YOLO is a popular deep learning model known for its speed and accuracy in detecting objects in images and videos.

With training the YOLOv8 model, starting from the pre-trained model is used, through which knowledge extracted from already known other data sets accelerates learning time in the model.

There are specified hyperparameters for training, like epochs-most iterations on entire data, batch size-number of images processed in one step, and input image size. In our project, the model is trained over 25 epochs at a batch size of 16 and 640x640p images.

```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      24/25      2.16G    0.01993    0.03427     0.8614         10        640: 100%|██████████| 1006/1006 [04:54<00:00,  3.42it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 144/144 [00:35<00:00,  4.03it/s]
                   all       4597       4597          1      0.999      0.995      0.995

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      25/25      2.16G        inf     0.0299     0.8595         10        640: 100%|██████████| 1006/1006 [04:52<00:00,  3.44it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 144/144 [00:34<00:00,  4.16it/s]
                   all       4597       4597      0.999          1      0.995      0.995

25 epochs completed in 2.347 hours.
```

**Fig.6**: Successful Execution of 25 epochs

Instead, by minimizing the loss function, which calculates how far away its predictions are from the actual locations of objects, the model learns to detect objects. Through this, the model adjusts parameters during training in order to optimize its prediction and eventually to learn and detect drones, airplanes, birds, and helicopters from the frames in the dataset.

Adding a GPU (via the cuda device), the training is accelerated considerably so that it becomes feasible to train the model in a reasonable amount of time. During training, the performance of the model is monitored using metrics such as mAP mean Average Precision which describe how well the model can approximate the intersection over union (IoU) thresholds for bounding boxes that measure good object detection efficiency.

### 4.3.3 Testing and Evaluating the Model

Testing performances of the trained model on unseen data are used by maintaining the validation dataset. There are evaluation metrics such as mAP50 (mean Average Precision at IoU threshold 0.5), and mAP50-95, which are mean Average Precisions averaged over multiple IoU thresholds. These effectively translate to a good quantitative description of how well the model detects objects and localizes those objects within an image. [5]

The performance of the trained model is then tested against a completely independent test dataset. The test set is the final evaluation of how well a model will actually perform in the wild. In this experiment phase, it feeds inferences on the images from the test set with the generation of predictions for each one. The results are visualized, with drawn bounding boxes surrounding detected objects or other items as well as an associated confidence score (probability) for each detection.

This step further aids in visual verification of how accurately the model can identify drones, planes, and so on.

```
Ultralytics 8.3.36 🚀 Python-3.10.12 torch-2.5.1+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 3,006,428 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/dataset/labels/val.cache... 4597 images, 0 backgrounds, 0 corrupt: 100%|██████████| 4597/4597 [00:00<?, ?it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 288/288 [00:40<00:00,  7.15it/s]
                   all       4597       4597      0.999          1      0.995      0.995
              AIRPLANE        915        915      0.996          1      0.995      0.995
                  BIRD       1039       1039          1      0.999      0.995      0.995
                 DRONE       2001       2001      0.999          1      0.995      0.995
            HELICOPTER        642        642          1          1      0.995      0.995
Speed: 0.2ms preprocess, 3.0ms inference, 0.0ms loss, 1.3ms postprocess per image
Results saved to runs/detect/drone_detection2

Validation Metrics:
mAP50: 0.995
mAP50-95: 0.995
```

**Fig.7**: Model Accuracy (99.5%)

In testing, outputs of the model are overlaid onto the test images to determine to which extent bounding boxes covered the correct object locations. These results are useful for understanding the model's strengths and areas that might need improvement, such as misclassifications or false positives.

### 4.3.4 Model Performance Results

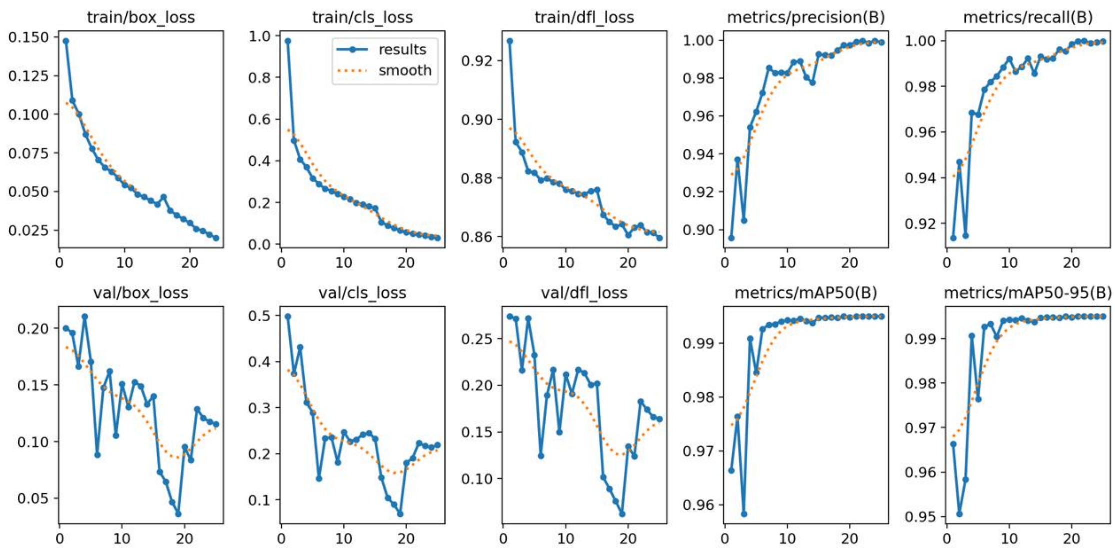


**Fig.8**: Trend Analysis

Fig.8 shows training and validation performance metrics over epochs for a machine learning model.

- train/boxloss: Decreasing trend indicates improved bounding box predictions.
- train/clsloss: Decreasing trend shows reduced classification errors.
- train/dflloss: Decline suggests better distribution focal loss performance.
- metrics/precision(B): Increasing precision, nearing 1.0.
- metrics/recall(B): Increasing recall, also nearing 1.0.
- val/boxloss, val/clsloss, val/dflloss: Fluctuating but generally decreasing, indicating validation improvements.
- metrics/mAP50(B), mAP50-95(B): Increasing mean Average Precision (mAP), approaching 1.0.

The model is improving consistently in both training and validation, achieving high precision and recall, with mAP values close to 1.0.

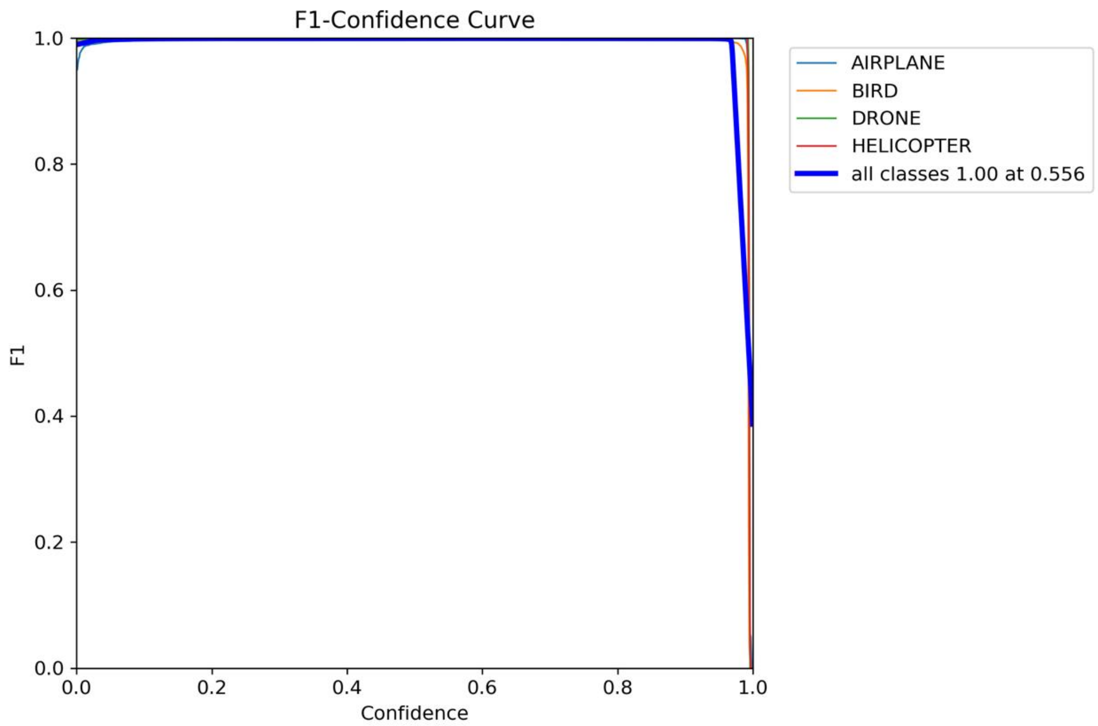


**Fig.9**: F1 Confidence Curve

Fig.9 shows F1-Confidence Curve, plotting the F1 score against prediction confidence for four classes: AIRPLANE, BIRD, DRONE, and HELICOPTER. Key Points:

- F1 score is consistently high ( 1.0) across all confidence levels.
- The blue line represents the overall F1 score for all classes.
- The model achieves perfect performance (F1 = 1.0) at a confidence threshold of 0.556.

The classifier performs exceptionally well across all classes, maintaining high F1 scores even at lower confidence thresholds.

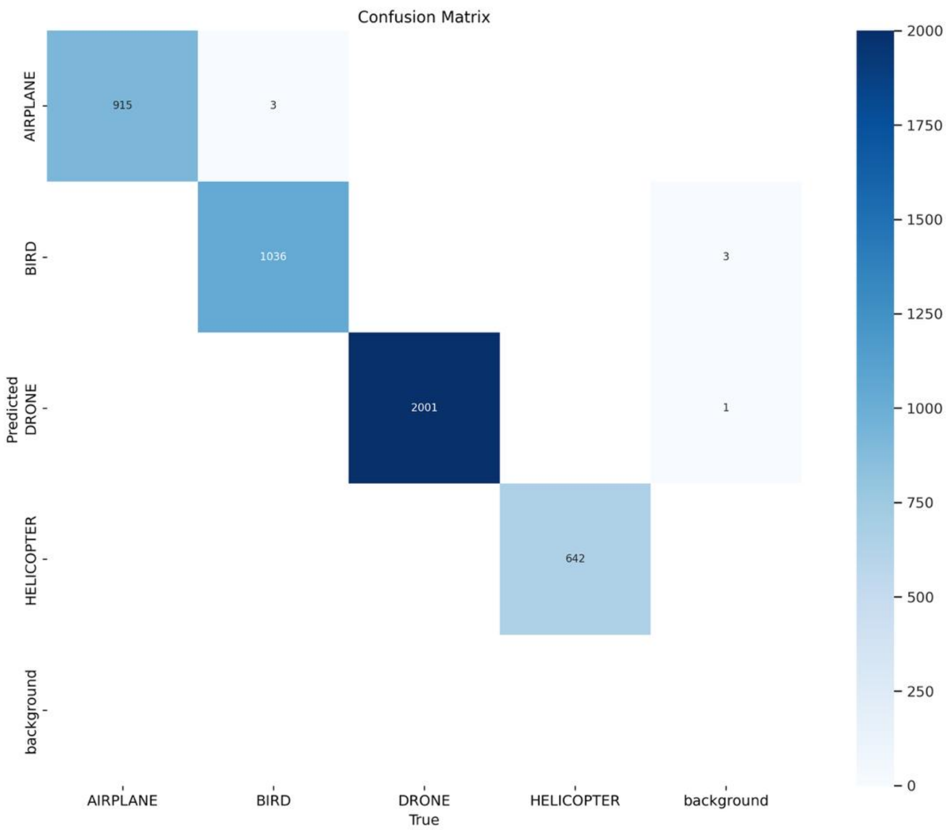


**Fig.10**: Confusion Matrix

Fig.10 is a confusion matrix used to evaluate a classification model's performance across five classes: AIRPLANE, BIRD, DRONE, HELICOPTER, and background. Diagonal values (correct classifications):

- AIRPLANE: 915
- BIRD: 1036
- DRONE: 2001 (highest accuracy)
- HELICOPTER: 642

### 4.3.5 Exporting the Model for Deployment

The model is exported for deployment after final testing and ensuring that the model performs well, i.e, the trained YOLO model was converted into the ONNX (Open Neural Network Exchange) format. This format allows it to be deployed across different platforms and environments, enabling its usability in real-world applications, such as drone detection in surveillance systems or monitoring systems.

The model is exported to ONNX, which allows it easy integration with a variety of software tools and hardware accelerators, such as GPUs or edge devices, to allow for faster inferencing. Once exported, the model is ready for deployment in a production setting where it can be used for real-time detection of drones.

# Chapter 5

# Case Study : Maha Kumbh Mela

## 5.1 Hardware Requirement

Going by the above estimates, with a detection radius of 1.5 km, each camera can cover roughly 7.07 square kilometers, thereby at least 7 infrared (IR) cameras are needed to cover a 45-square kilometer area, like the Maha-Kumbh Mela :

$$\text{Area Per Camera} = \pi r^2 = \pi(1.5)^2 \approx 7.07\,\text{sq. km}$$

$$\text{Cameras Required} = \frac{\text{Total Area}}{\text{Area per Camera}} = \frac{45}{7.07} \approx 7 \text{ cameras (rounded)}$$

This eliminates blind spots by guaranteeing full coverage of the event space with overlapping fields of view.

## 5.2 Specifications

- For the cameras to survive severe weather conditions, such as rain, fog, and other unfavorable weather, they need to have an IP66 or higher waterproof classification.
- The cameras must also be able to identify the thermal signatures of objects, such drones, birds, and helicopters, that are within a 1.5 km radius.
- Each camera is attached to an NVIDIA Jetson Nano or Raspberry Pi 4 for real-time imagine processing. To manage the deep learning model inference,

these processing units must have a quad-core CPU, 4 GB of RAM, and an accelerator (such the NVIDIA GPU or Coral TPU).

- Real-time object classification and local processing of the thermal images will be done by each of the Raspberry Pi, which will then transmit the results to a central monitoring system for faster alarm generating if drone is detected.

## 5.3 Component View

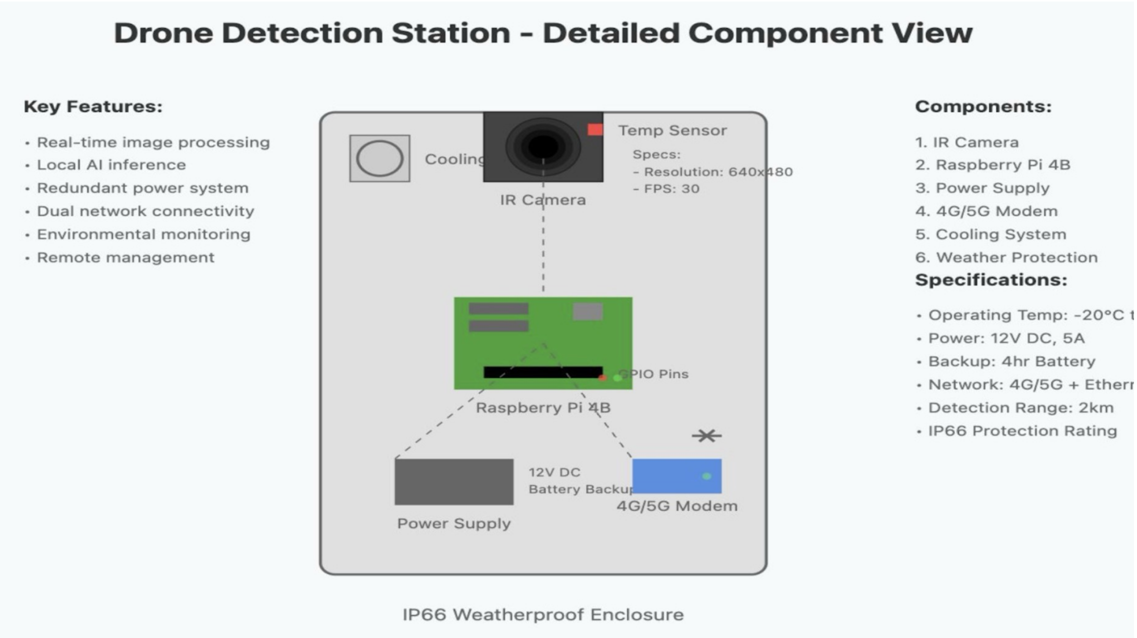


**Fig.11**: Component Layout of each module [9]

## 5.4 Deployment Diagram

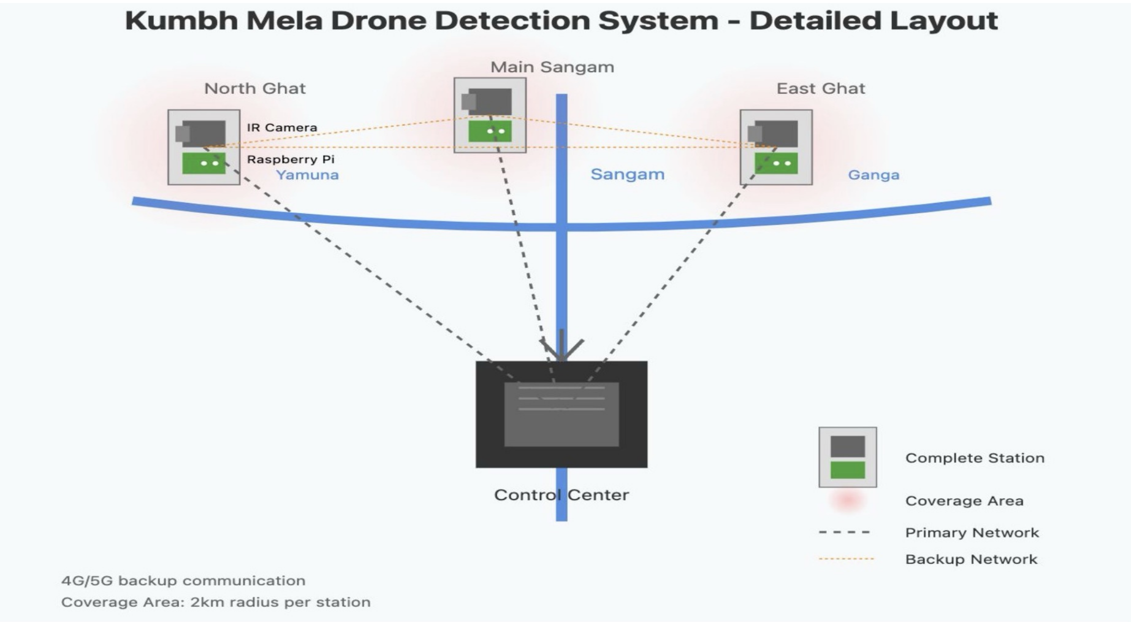


**Fig.12**: Deployment of Camera Array [9]

# Chapter 6

# Future Scope

The project in its current state has huge opportunities of being expanded to incorporate other features in future such as :

1. Deployment of camera on Drone
2. AI for Trajectory Prediction and Multi-Object Tracking
3. Cloud Computing for Drone Detection
4. Scalability for Large-Scale Deployment

## 6.1 Deployment of Camera on Drone

Instead of using fixed cameras in surveillance area, we can also deploy the infrared (IR) camera on a drone to detect other drones. Further, the processing hardware can also be mounted on the drone.

By deploying cameras on drone, the number of cameras required can be reduced as fewer number of drones can cover the entire area of interest.

1. Deployment :
   - Mounting Location: Place the IR camera with minimal vibration and obstruction.
   - Field of View (FoV): Ensure the camera's range covers the desired detection zone.

- Communication: Optional—if part of a swarm or networked system, detected data could be shared across units.

2. Applications :

   - Surveillance: Military or security applications to monitor airspace.
   - Anti-Drone Defense: Detecting unauthorized drones around critical infrastructure.
   - Swarm Coordination: Preventing collisions within drone swarms by detecting nearby units.

## 6.2 AI based Trajectory Prediction and Multi-Object Tracking

The same drone detection hardware for identification, can also be used for predicting drone trajectories and tracking multiple objects simultaneously, even in areas which have no restrictions for drone flights.

By utilizing AI, we can significantly enhance threat assessment and facilitate preemptive actions in dynamic environments, such as defense, security, or traffic management where an explicit No Fly Zone is not ordered.

AI-based trajectory prediction and multi-object tracking promises easier monitoring and control of drones and objects similar to them, even where the use of drones is restricted. Using the same detection hardware, AI predicts the future paths of drones, tracks multiple objects in real time, and evaluates possible risks. [13]

- Predicting Drone Path: AI performs this using past flight data, environmental factors, and drone movement patterns that predict where the drone is likely headed. It includes collection of real-time data, cleaning the data, applying models such as RNN to recognize patterns, and predicting future positions for unusual behavior detection.

- Tracking Multiple Objects: AI can track multiple drones or objects in a busy area with the help of tools for predictive movements, deep learning for real-time tracking, and to detect and recognize objects quickly from video streams.
- Enhancing Threat Assessment: AI can identify potential dangers by knowing how objects move and categorizing them as friendly, neutral, or hostile. It uses models like CNNs to recognize patterns and detect unusual behavior, such as sudden speed changes or entering restricted areas. Real-time risk is assessed by comparing object behavior with known flight plans or rules.

In the future, these systems will become even more intelligent, help with defense, security, and traffic management by improving situational awareness, and eliminate potential threats.

## 6.3 Cloud Computing for Drone Detection

Replacing the Raspberry Pi with cloud computing offers strong advantages with regards to scalability and processing power. Offloading data storage and processing tasks that the raspberry pi has to handle currently for the drones with virtually unlimited computational resources is offered by cloud computing. This shift will enable more complex and resource-intensive operations, such as real-time image and video processing, object recognition using AI and machine learning models, and data-intensive tasks like predictive analytics and geospatial mapping. By storing data on the cloud, drones can access historical and real-time data from anywhere, facilitating large-scale data management and improving decision-making.[7]

This will also enable real-time collaboration across multiple drones and control centers, allowing multiple drones to be controlled at the same time while allowing simultaneous data sharing. Cloud-based remote monitoring is extremely liberating since it would enable operators to control and track drone missions over thousands of miles of distance without the constraints of local hardware. Moreover, cloud integration increases the capability of drones: soft updates and model training can now be done without taking care of the physical intervention, which in turn increases the flexibility and adaptability of the system itself.

## 6.4 Scalability for large-scale implementation

All processing operations must be handled locally, hence the system must be designed for scalability to allow robust on-device computing. By doing this, dependence on network infrastructure, edge devices, or cloud systems is removed and each detection module is guaranteed to function independently. We can use the following strategies to scale the system:

1. Analytics and Processing on-Device: Equip each IR module a high performance CPU (such as an ARM-based or ASIC) so that it can process images in real time, recognize patterns, and analyze trajectories. Use AI models that are optimized for drone identification and are small enough to run directly on the device. Use techniques for real-time thermal image processing to identify and categorize drones according to heat patterns.

2. Scalability through Modular Design : Create standalone detection devices that include infrared sensors, a computing unit, storage, and a power source. These modules need little upkeep and are capable of functioning independently. Use interchangeable parts (such as processors or infrared sensors) to enable upgrades and accommodate different deployment scenarios. To ensure ongoing operation even in the absence of external data transfer, use local storage (such as solid-state drives) to retain detection logs and important data.

3. Sophisticated On-Device Detection Techniques : Use computer vision methods designed specifically for identifying heat signatures, such as edge-detection algorithms or convolutional neural networks. Use self-learning techniques to gradually increase the accuracy of detection. For increased accuracy, combine thermal imaging and motion analysis. To differentiate drones from other heat sources (such as birds or cars), use on-device filtering.

4. Sustainability and Energy Efficiency: For off-grid deployment, incorporate solar panels or rechargeable batteries and use low-power components. Deploy intelligent power management that only turns on processing in response to motion or temperature abnormalities.

Thus, there is a huge opportunity to continue the project and extend its functionality and versatility

# Chapter 7

# Conclusion

This project offers a cost-effective, scalable, and reliable solution for drone detection, particularly in no-fly zones such as the Maha Kumbh Mela. The system's key benefits include:

1. Enhanced Public Safety: By using IR cameras with deep learning capabilities, the system can accurately identify drones in real-time, ensuring public safety during large-scale events.

2. Superior Detection Capabilities: Infrared technology outperforms traditional radar and visible light cameras, offering reliable detection in low-light and adverse weather conditions.

3. Scalable and Cost-Effective: The modular design allows for easy scalability, covering large areas, while the use of affordable components, like Raspberry Pi, ensures a cost-effective solution for widespread deployment.

4. Real-Time Alerts and Response: The system provides instant classification and alerts, enabling swift action and reducing potential risks in crowded or sensitive locations.

5. Weatherproof and Reliable: With an IP66-rated enclosure, the system is designed to withstand harsh environmental conditions, making it suitable for outdoor use at events like the Maha Kumbh Mela.

In conclusion, this project provides an innovative, efficient, and scalable design of a Drone Detection System, which uses an IR camera for taking aerial images. This ensures it operates ideally under various lighting and weather conditions.

It uses a pre-trained deep learning model that runs on a Raspberry Pi to classify images as helicopter, bird, or drone, continuously monitoring airspace for real-time detection. Automated warning messages are sent to the monitoring team whenever unauthorized drones are detected.

The system is designed to be portable and scalable, allowing deployment at various event locations as well as security-sensitive areas. It does not involve reliance on expensive and complex detection technologies, thereby easily accessible for wider use, enhancing airspace security and public safety in critical no-fly zones.

# References


[1] *Multimedia Tools and Applications*. Accessed: 2024-06-14.

[2] Bentamou, A., Zein-Eddine, A., Messai, O., and Gavet, Y. Real-time drone detection and tracking in distorted infrared images. In *2023 IEEE International Conference on Image Processing Challenges and Workshops (ICIPCW)* (2023), pp. 3594–3598.

[3] Bharat Electronics Limited. Drone Detection Radar (DDR). https://bel-india.in/product/drone-detection-radar-ddr/. Accessed: 2024-06-14.

[4] Bhattacharya, P., Nowak, P., Ahlers, D., and Zölzer, U. A dataset of infrared images for deep learning based drone detection. In *2023 17th International Conference on Signal-Image Technology  Internet-Based Systems (SITIS)* (2023), pp. 130–137.

[5] DroneDetectionThesis. Drone detection dataset. https://github.com/DroneDetectionThesis/Drone-detection-dataset, 2023. Accessed: 2024-11-22.

[6] Islam, M. T., Karim Siddique, B. N., Rahman, S., and Jabid, T. Image recognition with deep learning. In *2018 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)* (2018), vol. 3, pp. 106–110.

[7] Lee, J., Wang, J., Crandall, D., Šabanović, S., and Fox, G. Real-time, cloud-based object detection for unmanned aerial vehicles. In *2017 First IEEE International Conference on Robotic Computing (IRC)* (2017), pp. 36–43.

[8] Redmon, J., Divvala, S. K., Girshick, R. B., and Farhadi, A. You only look once: Unified, real-time object detection. *CoRR abs/1506.02640* (2015).

[9] Shipra, Sundram, Shresth, Setu. Major Project Images, 2024. Accessed: 2024-06-14.

[10] Surveillance, B. Blighter x400 series radar system for drone detection, 2024. Accessed: 2024-11-22.

[11] Svanström, F., Englund, C., and Alonso-Fernandez, F. Real-time drone detection and tracking with visible, thermal and acoustic sensors. *CoRR abs/2007.07396* (2020).

[12] Wellig, P., Speirs, P. J., Schuepbach, C., Oechslin, R., Renker, M., Boeniger, U., and Pratisto, H. S. Radar systems and challenges for c-uav. *2018 19th International Radar Symposium (IRS)* (2018), 1–8.

[13] Wu, T., Liu, J., Liu, J., Huang, Z., Wu, H., Zhang, C., Bai, B., and Zhang, G. A novel ai-based framework for aoi-optimal trajectory planning in uav-assisted wireless sensor networks. *IEEE Transactions on Wireless Communications 21*, 4 (2022), 2462–2475.