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Bird monitoring intelligence: Integrating Thermal UAV Imagery and Deep Learning Tools

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Abstract: Birds are excellent indicators of biodiversity and due to their selective association, are ideal for providing insights into the diversity of vegetation, insects, and aquatic life. Bird census, therefore, is an important tool for ecological monitoring. Birds, however, particularly migratory birds, often flock together in large numbers and bird count estimation of such congregations are herculean tasks, subject to large error margins. Computer vision tasks, such as object detection, tracking, and counting, immensely aid environmental monitoring. Despite many innovative techniques, there is still a lot scope for simplifying and improvising the count estimation process, especially through employing technology and artificial intelligences (AI). The integration of AI into drones for on-the-fly problem-solving is an evolving trend. This paper endeavors to offer a comprehensive compilation of potential studies on wildlife using low-altitude UAVs equipped with thermal sensor datasets found in the literature. Further, we tested the ability of a thermal drone to identify and count water birds in a fresh water habitat. The Unmanned Aerial System with an optical and thermal sensor was integrated with widely accepted detection models such as Detection Transformer, Yolo V7 and Yolo V8 to delineate and count the birds. Thermal imagery was found to be excellent in highlighting birds as bright/hot pixels especially against the cooler waterbody. Among the models, DETR achieved the highest precision score of 91.4%, followed closely by YOLOv8 with a precision score of 84.1%. Additionally, DETR exhibited a notable mAP of 89.2%, demonstrating its efficacy in object detection tasks. Interestingly thermal images are also effective in detecting birds even through canopy that otherwise camouflage well in vegetation. The birds didn't show much response to the presence of UAS particularly at late hours of the day. There is a huge scope of applications and research in the field of ecology. Our study illustrates how UAS, thermal imagery, and automated detection algorithms can be combined to efficiently detect and count birds, thereby offering a critical solution towards population count estimation essential for wildlife management.

Keywords: *Automatic bird detection, Computer Vision, Deep learning, Image and Video Processing, Thermal imagery, Subtropical wetland.*

1. Introduction

The health of ecosystems directly influences human well-being, and disruptions or abnormalities in ecosystems can have profound effects on human life. Early detection of such anomalies can provide warning, enabling timely mitigation measures. Birds serve as indicators of ecological health, reflecting changes in biodiversity composition, climate, and habitat quality. Studying bird populations and their habitats provides valuable insights into the overall environmental conditions. Methods of birds monitoring encompass methods such as point count [1], transect count, area search, pellet analysis, nest counts, photographic surveys, bioacoustics monitoring, aerial surveys, and citizen science [1] [2] [3] [4]. Notably, the aerial count method holds particular significance due to its ability to cover areas that are challenging for human access [2] [5]. Unmanned aerial vehicles (UAVs) or unmanned aerial systems (UAS), generally referred to as drones or flying robot, have shown to be extremely useful instruments in the field of wildlife conservation, especially when it comes to surveying and monitoring operations. It offers superior spatial and temporal resolution in imagery acquisition when compared to alternative data-gathering platforms [6]. UAS provide a novel method of gathering data, allowing scientists and environmentalists to efficiently and non-intrusively gather high-resolution pictures, real-time data, and geographical data. UAS armed with sophisticated sensors and cameras are able to take high-quality pictures and videos that provide conservationists remarkable precision in tracking animal migration patterns, monitoring populations, animal behaviours, and evaluating habitat conditions [7]. The use and capabilities of sensors that may be installed on UAS and are able to collect vital data for wildlife conservation have significantly increased in the last few years. Among these sensors are multispectral, hyperspectral, optical, infrared, and LiDAR sensors. A thermal sensor, sometimes referred

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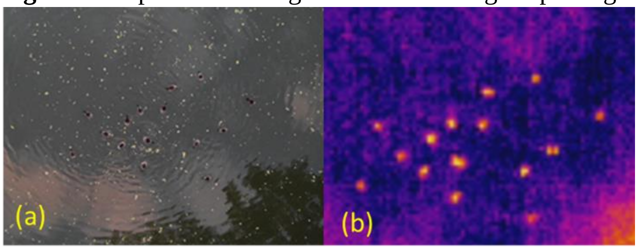
to as an infrared or thermal imaging sensor, picks up heat, or infrared radiation, that objects emit and transforms it into a contrast picture. Thermal sensors could be useful tool for efficiently and non-intrusively monitoring and analysing wildlife when used with drones for wildlife conservation (Figure 1).

Fig. 1. Example showcasing an unaltered image capturing a



lake in both UAV optical and thermal modes, featuring the presence of birds. Thermal image provides a clearer depiction of the presence of birds in the lake.

Thermal sensors use infrared light generated by objects to detect changes in temperature. More infrared light is released by warmer things than by colder ones as shown in Figure 1(b). The lake appears as a cooler area contrasting with warmer surroundings, such as land or vegetation. Birds appear as bright, hot spots against the cooler water background. Furthermore, the sensor converts the temperature variations into a visual representation, which is typically displayed as a colour gradient or in grayscale [8]. This makes it possible for users to distinguish between warm and cool regions in the scene that was photographed. Infrared and radiometric sensors are the two major types of thermal cameras. Radiometric cameras provide precise temperature readings for in-depth quantitative research, while infrared cameras record infrared radiation for visual representation of temperature fluctuations. For exact measurements, radiometric cameras are the ideal choice, which makes them appropriate for applications in science and other fields requiring precise temperature data. Studies utilizing thermal imagery, either independently or in conjunction with optical sensors, facilitate wildlife surveillance, search and rescue, animal monitoring, bird counting, habitat assessment, anti-poaching efforts, and fire detection [15]. A recent study has demonstrated significant effectiveness in aerial scanning and detection of important animal species and the monitoring of their behaviours using UAV equipped with a 160 × 120 pixel FLIR thermal sensor, and 12 MP RGB camera, and a 24 mm lens [10]. The results of these studies show that animals/habitats with noticeable color contrasts can be easily measured. Drone imagery analysis with Object-Based Image Analysis (OBIA) and Machine Learning (ML) allows for the effective extraction of insights that support a variety of industries, including wildlife management. One subset of machine learning that has shown to be quite effective is deep learning, particularly for tasks like object detection.

Object detection models fall into two primary categories: two-stage detectors, which identify objects in two passes, emphasizing high localization and recognition accuracy (examples include DEtection TRansformer (DETR), Faster Region- Convolutional neural network (R-CNN), Mask R-CNN, Cascade R-CNN, Feature pyramid network (FPN), R-Feature convolutional network (FCN), and one-stage detectors designed for speed and real-time detection, including various versions of YOLO, SSD, and RetinaNet [11] [12] [13].

This study has reviewed available literature to understand the current trend of Thermal UAV applications in the field of wildlife and ecology. We assessed the efficiency of thermal and optical dataset for deep learning (DL) based object detection algorithms to count the birds in a subtropical lake. This study utilises the widely accepted detection models such as Detection Transformer, Yolo v7 and Yolo v8 to delineate and count the Indian Spot billed duck '*Anas poecilorhyncha*' which is a winter migrant at this location.

2. Material and Methods

2.1. Study Area

The research area, which is a waterbody, 400 m^2 in size is located in Uttarakhand, India, under the Dehradun District administration, geographically between 30°17'8'' to 30°17'13'' North and 77°58'26" to 77°58'31'' East (Figure 2). The lake is located within the Wildlife Institute of India campus, nestled amid the valleys of the Himalayan foothills and the Shivalik mountain range [9], at an elevation of 607 m above sea level. The region experiences a moist tropical environment with annual rainfall of roughly 2051 mm (Directorate of Environment, 2013), February - March being the lean seasons, July to August, being the wettest month. The dominant vegetation comprises of Sal forest and associated species such as Paper Mulberry (*Broussonetia papyrifera*), *Murraya koenigii*, Karaunda (*Carissa opaca*) Kamini (*Murraya paniculata*), Jasmine (*Jasminium angustifolium*) occupy the ground canopy. Few trees of Peepal (*Ficus religiosa*), Semal (*Bombax ceiba*), Jamun (*Syzygium cumini*), Kamala tree or Rohini (*Mallotus philippensis*), Jungli Beri (*Zizyphus nummularia*), Wild Himalayan Pear (*Pyrus pashia*), Castor (*Ricinus communis*), Dhak/ Palash (*Butea monosperma*), Chinese Tallow (*Sapium sebiferum*), *Albizia prosera*, *Albizia lebback*, Crocodile Bark tree (*Terminalia alata/T.Tomentosa*), Kachnar/ Camel Foot tree (*Bauhinia purpurea*, *Bauhinia variegata*) are also present along with *limbrs Smilax wightii* and *Passiflora superosa*. Invasive species *Lantana camara*, *Parthenium hysterophorus*, Chromolaena odorata and Ageratum conyzoides; Grasses like Khus (*Vertivaria sp.*) and aquatic plants like the leafy *Polygonum sp., Ipomea carnea* buffer the banks of the lake.

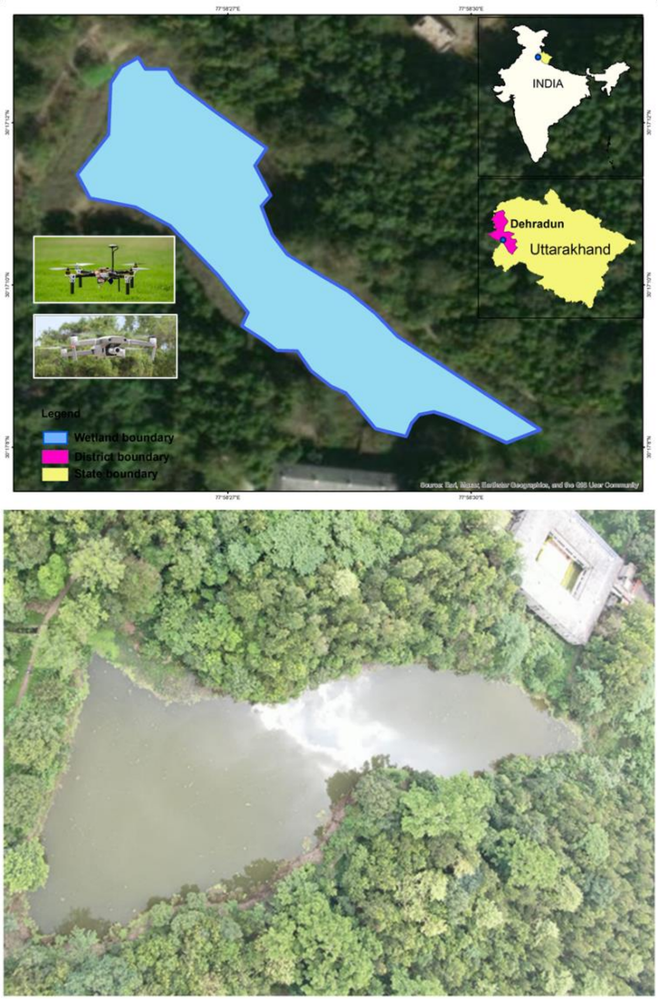


Fig. 2. The map representing the study area within the city of Dehradun, India. It also illustrates the drones utilized in this study and showcases the orthomosaic map of the selected area, surveyed using a UAV.

The lake provides shelter for various migratory water birds during the winter season. Apart from supporting many species of fishes, amphibians, reptiles and turtles, the lake also plays an important hydrological role being at the headwater of Asan River, a tributary to Yamuna River. The lake is a good representation of a sub-tropical wetland with many winter migratory birds such as Mallard, Gadwall, Northern Pintail, Little Grebe, Common Coot, Common Moorhen, and Black-winged Stilt etc. The Wildlife Institute of India campus, within which the lake is situated, harbours a total of 310 Birds species belonging to 49 families, migratory as well as residential (https:// www.ebird.org, accessed on 15 November 2023). Among these, the spot-billed ducks are early arrivals during the winter migration, and hence the study experiments were focused on this particular species. These birds are easily distinguishable based on the bright yellow spots on their beaks.

2.2. Data Preparation and Processing

Two Quadcopter drones were employed for data acquisition: a DJI Mavic 2 Enterprise Zoom equipped with an optical sensor featuring 12MP resolution (4000 x 3000 pixels) and a 1/2.3" CMOS sensor, and a DART 60 drone equipped with a radiometric thermal camera—specifically, the FLIR Vue Pro R, with a resolution of 640 and operational frequency of 9 hertz. The details of UAV specifications are provided in Table 1. The DJI Pilot app was utilized for gathering RGB images, while OpenDroneMap and the FLIR UAS 2 application were employed for capturing thermal images. This dual-drone approach facilitated comprehensive data collection, incorporating both visual and thermal perspectives for enhanced analysis and interpretation. We conducted the flights between 7:30 PM to 9:00 PM in each grids of the lake. The entire flight was done in two ways: autonomous and pilot mode. For monitoring, an autonomous flight was performed at various height range from 35 to 90 m. The data collection was performed at vertical angle flight of 90 degrees. The collected data was preprocessed and ortho-mosaiced in the AGIS Metasoft professional Software. While approaching the birds, a minimum noise-producing flying speed of less than 8 m/s was maintained.

Table 1. Key specification of UAVs used in this study.

Specification	**DART 60**	**DJI Mavic 2 Enterprise Zoom**
Take-off weight	4.12 kg	899 g
Operating Frequency (GHz)	2.400 - 2.483, 5.725 - 5.850	2.400 - 2.483 5.725 - 5.850
Battery	30000 mAh	3950 mAh
Charging time	Approx. 4 h	Approx. 2.5 h
Flight time on non-windy, good weather day	55 minutes	31 minutes
Sensor	FLIR Thermal Imaging Camera Vue Pro R 13 mm, 9 Hz	1/2.3" CMOS; 12 megapixel , HD 4K ： 3840×2160 30p
Format type include image and video	.rJPEG, .JPEG, (.MPEG-4 AVC/H.264), .MOV, and .MP4	.JPEG, MOV .(MPEG-4 AVC/H.264), and .MP4

Figure 3, illustrates the proposed methodology for avian detection, structured into three principal stages. In the initial phase, the study design was meticulously planned, encompassing aspects such as drone flight paths, camera angles, altitude, and suitable time frames. Subsequently, aerial photographs of birds were acquired using a thermal-equipped UAV, with selective optical images captured for detailed bird observation. The data preprocessing phase involved the verification of auto orientation for each image to ensure consistent alignment. Subsequently, images underwent resizing, to a standardized size of 640 x 640 pixels. Auto adjustment of contrast was then applied using a contrast stretching technique to enhance the visibility of features within the images. Finally, the images were partitioned into a grid format, specifically into 2 rows by 2 columns, facilitating efficient and systematic processing during subsequent stages of the analysis. Then all preprocessed data were labelled through an online platform, Roboflow (https://roboflow.com/annotate, accessed on 14 September 2023). In the process of augmenting data, various techniques were employed to enhance the diversity and richness of the dataset. Initially, rotation operations were applied to the images, involving clockwise, anticlockwise, and upside-down rotations. Subsequently, cropping was implemented at varying zoom levels, ranging from 1% to 9%. Additionally, shearing was introduced both horizontally and vertically, with angles spanning from -15 degrees to +15 degrees. Further, adjustments were made to the hue, spanning from -19 degrees to +19 degrees. The augmentation process extended to modifying brightness levels, encompassing a range from -15% to +15%. These sequential augmentation techniques collectively generated a multitude of sub-images derived from the original aerial photographs dataset, thereby diversifying and expanding the dataset for subsequent analysis and training. Following augmentation, the annotated image dataset underwent conversion to a .txt format, adhering to the YOLO v7, v8 PyTorch format for YOLO models and the COCO dataset format for the DETR model. In the conclusive stage, training procedures were executed across three distinct models—YOLO v7, YOLO v8, and DETR. A comprehensive evaluation of each model's bird detection performance ensued through rigorous testing processes.

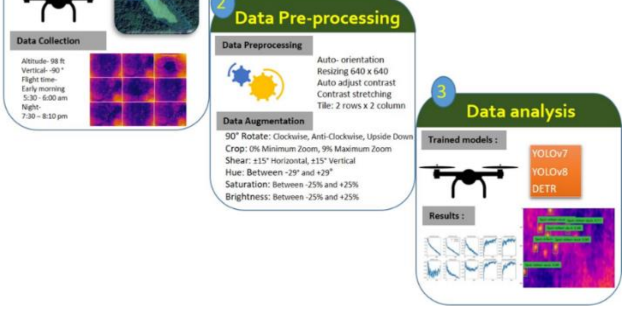


Fig. 3. Represents the proposed methodology flow diagram of how different models are used to detect bird using thermal mounted UAV following three steps namely, Data collection, preprocessing, and analysis.

The dataset comprises a total of 9580 images, consisting of 4918 thermal infrared images and the remaining 4662 are RGB images. Within the subset of 4918 thermal images, the data was partitioned into distinct sets for training (4820 images), validation (108 images), and testing (60 images) to facilitate robust model development and evaluation.

Three models named Detection Transformer (DETR), YOLO v7, and YOLO v8 (You only look once) were trained for the detection of Spot-billed ducks in UAV-based thermal infrared (TIR) images and videos. DETR based on Niels Rogge (https://github.com/NielsRogge), provides an object detection notebook that helps in fine-tuning a custom dataset. Transformers, a dominant deep learning architecture, are widely used in the field of natural language processing, language modeling, speech recognition, and machine translation. DETR (Detection transformers) is a new approach in object detecting and panoptic segmentation tasks. This architecture combines elements from both transformer models, which are commonly used in natural language processing (NLP), and traditional convolutional neural networks (CNNs) used in computer vision tasks. It simplifies architecture, matching Faster R-CNN's performance on Common Objects in Context (COCO) dataset. YOLO v7 is a single-shot object detection system, featuring a notable enhancement, higher resolution, detection of smaller objects and thereby achieving higher accuracy. Yolo v7 presents notable improvements in minimizing gradient propagation during back-propagation, resulting in reduced memory consumption for network layer storage and enhanced learning speed. A version of the YOLO model known as YOLOv8 for its remarkable accuracy and real-time processing powers with its efficiency and precision.

The precision of a model's positive predictions is its accuracy. It is computed as the ratio of the model's total number of positive predictions, which includes both true positives and false positives, as shown in equation 1 to the number of genuine positive predictions. Recall, also referred to as True Positive Rate or Sensitivity, quantifies a model's capacity to accurately discern every pertinent instance from the total number of real positive instances in the dataset represented in equation 2. Equation 3, illustrates the F1 score, a metric that provides a fair evaluation of a model's performance in binary classification tasks by combining precision and recall into a single value. A higher number on the F1 score, which goes from 0 to 1, denotes a better balance between recall and precision.

$$\boldsymbol{P} = \sum \boldsymbol{True\ positive} \div \sum(\boldsymbol{true\ positve} + \boldsymbol{false\ positive}) \quad \textbf{.....(1)}$$

$$\boldsymbol{R} = \sum \boldsymbol{True\ positive} \div \sum(\boldsymbol{true\ positve} + \boldsymbol{false\ negative}) \quad \textbf{....(2)}$$

$$F1\ score = \sum(P \times R) \div \sum\frac{(P+R)}{2} \quad ......(3)$$

Where, P is precision, R is recall. True Positive represents the number of correctly predicted positive instances (correct detections), while, False Positive represents the number of instances that were predicted as positive but were actually negative (incorrect detections). False Negative is the number of instances that belong to class but were not detected (missed detections).

$$mAP = \frac{1}{N}\sum AP \quad .....(4)$$

N is the total number of Intersection over Union (IoU) thresholds considered. AP is the Average Precision calculated at the Corresponding IoU threshold.

3. Results

A total of 4,220 research papers spanning the last 15 years, were indexed through, specifically concentrating on the utilization of drones equipped with thermal or combined use of thermal and optical sensors. Out of this dataset, a subset of less than 5% papers (n=175) were identified, specifically constrained to topics related to environmental studies, wildlife monitoring, species monitoring, and habitat management [14] [15] [16]. Utilizing thermal remote sensing with drones emerges as a powerful and effective tool for wildlife monitoring [17] [18] [19], Habitat management [20] [21] [22], forest fire and disease management [23] [24] [25] [26]. In recent years, drones mounted with thermal sensor have been found to be beneficial in detecting species and habitat in real time utilizing artificial intelligence techniques [12] [27] [27] [28].

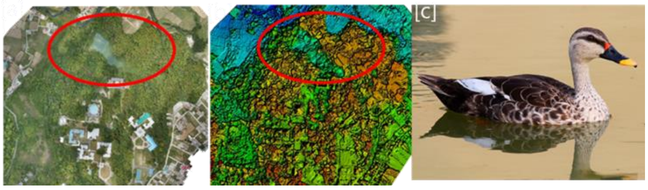


Fig. 4. Represents the Orthomosaic image (a), Digital Terrain map in (b), and inage depicting Spot-billed duck in (c) of the Lake.

Based on orthomosaic and digital terrain model imagery (as depicting in the Figure 4. a and b), the Indian Spot-billed ducks measured on an average 50–65 cm in length as shown in Figure 4. A thorough survey using deep learning-based object detection methods on low-altitude UAV datasets has been presented in our proposed work. It was also observed how the presence of drones affected the behaviour of the animals. As seen in Table 2 and Figure 5, the combined results reveal that the employment of deep-learning-based detection techniques along with UAV aerial photography is quite adequate for bird detection in a variety of situations.

Table 2. Object detection results of YOLOv7, YOLOv8 and DETR with different architectures. The best and second-best precision scores are underlined and highlighted.

Models	Precision	mAP	Recall	F1 Score	Time (hrs.)
YOLO v7	83.1	86.9	87.9	85.43	3.01
YOLO v8	**84.1**	87.3	89.4	86.17	4.01
DETR	**91.4**	89.2	81.2	86.04	4.10

This approach indicates that employing DL based deep detection technique in conjunction with UAV mounted with thermal sensor is a viable approach for effectively detecting birds.

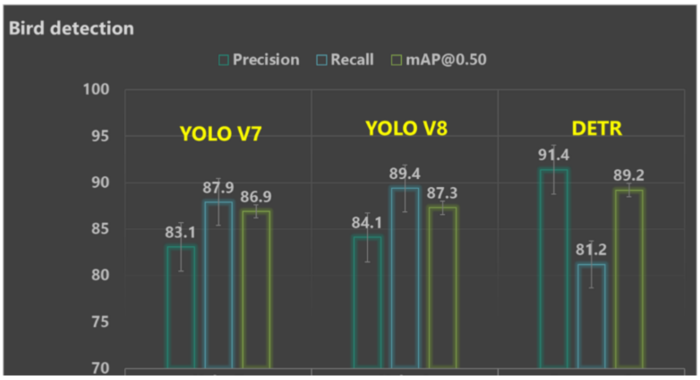


Fig. 5. The precision, recall, and mean average precision graphs illustrating bird detection are presented for three models. DETR successfully detected birds, as indicated by its accuracy.

The outcomes from employing three distinct models for bird detection shown in Figure 6(a) and (b), specifically focus on the results obtained using Yolo v7 and Yolo v8.

The visual representation underscores instances in which ducks marked with circles were not successfully identified by the models. Conversely, in Figure 6(c) provides a contrasting scenario using DETR model, where all ducks were accurately detected by the employed model. In our result DETR demonstrated superior performance compared to Yolo v7 and Yolo v8.

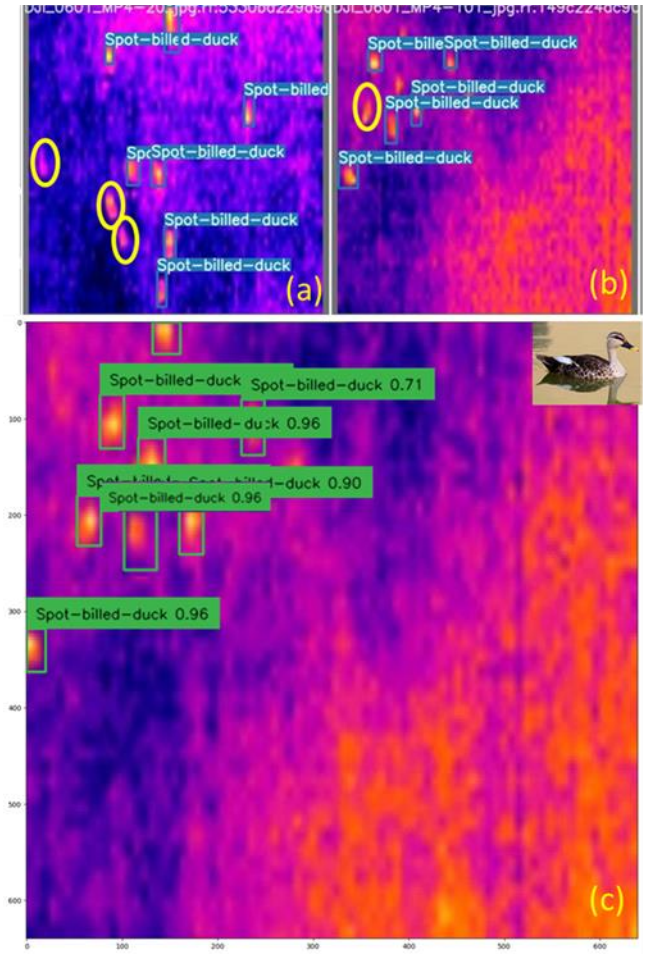


Fig. 6. The detection outcomes of three models are presented. In sub-images (a) and (b), illustrating the results of Yolo v7 and Yolo v8, it is evident that some circled ducks were overlooked. Conversely, in sub-image (c), all ducks were successfully detected.

4. Conclusion and Discussion

India's drone policy is formalizing UAVs in government and research institutions, leading to a notable increase in their civil applications [29]. Utilizing Optical camera, at heights exceeding 30 meters, birds that effectively camouflage in sunlight are challenging to detect, while flying below 25 meters can disturb many birds [30], potentially causing them to take flight or pose a threat to the UAV. Daytime operations are particularly vulnerable to bird attacks. However, during night or early morning, when water bird activity is reduced, using a thermal camera proves advantageous. The thermal camera's ability to capture thermal radiation makes birds more visible, mitigating the risk of counting errors and enhancing accuracy, especially in low-light conditions and when birds are less active.

The field of wildlife and biodiversity conservation with utilizing UAVs are growing and demonstrating its efficacy as a new, more accurate, and easily accessible alternative. Since our DL-based method is intended to function with every single image during the entire process, we did not include the mapping step in our analysis. In aerial pictures, the models prioritise detection over counting.

Bird count estimations, annual or seasonal are essential events undertaken by the Government departments or NGOs for not just evaluating habitats, calculating species richness, mapping distributions, nesting and feeding behavior but also to qualify Ramsar sites, IBAs, Heritage sites, Flyways etc. Despite its significance and requirement, the process of count and estimation is still a herculean task subject to large error margins. Our study highlights the significant advancements made in bird monitoring through the integration of thermal UAV imagery and deep learning tools. By leveraging state-of-the-art detection models such as Detection Transformer, YOLOv7, and YOLOv8, we demonstrated the effectiveness of thermal imagery in detecting and counting birds, particularly in challenging environments such as dense vegetation and water bodies. Our results showcase the potential of unmanned aerial systems equipped with thermal sensors to provide efficient and accurate bird census data, which is crucial for ecological monitoring and wildlife management. This study paves way towards bird abundance assessments in larger inaccessible wetlands. This paper investigates the application of both deep learning and thermal equipped drone for object detection. Additionally, it delves into the details of the dataset used and the evaluation metrics employed. Looking ahead, there is immense potential for further research and application in this field. Computer vision, machine learning, and sensor technology hold promise for enhancing the scalability, accuracy, and efficiency of avian monitoring systems. Future studies could explore the scalability of our approach across multiple bird species and habitats, as well as investigate the integration of additional sensor modalities for comprehensive ecological monitoring. Additionally, efforts to optimize detection algorithms and enhance the robustness of thermal imaging techniques will be crucial for maximizing the accuracy and reliability of bird population estimates. Thermal variations in inter and intra species heat signatures is an exciting research arena to explore. Our future work will involve the development of a secure onboard real-time framework for object detection and counting, specifically targeting multiple birds.

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6. Author Contribution

Ravindra Nath Tripathi - performed "Writing – Original Draft, Methodology, Formal analysis, and Visualization". **Aishwarya Ramachandran** - performed "Formal Analysis, Writing, Conceptualization, and Methodology, Software, and Data curation". **Vikas Tripathi** - performed "Validation, Methodology, and Visualization". **Ruchi Badola** - performed "Validation, Resources and administration". **Syed Ainul Husssain** - performed "Validation, Methodology, Conceptualization, Resources and administration".

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Conflicts of interest

The authors declare no conflicts of interest.