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# BRIDGING ECOLOGY AND TECHNOLOGY: DEEP LEARNING FOR SMARTER BIRD DETERRENCE

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**Abstract**

Urbanization and technological advancements in the modern era have led to a conflict between nature and mankind. Safeguarding and protecting the interests of every living being is essential for maintaining the ecological balance of our planet. Avian creatures, with their vibrant colors and stunning patterns, are a beautiful ornament to nature. However, their natural behaviors such as foraging, roosting, and perching often collide with human activities, such as agriculture, windmill operations, and aircraft operations. These collisions result in significant financial losses and, in some cases, even the loss of life for both birds and humans. It is crucial, therefore, to adopt non-lethal methods to control bird activities, considering them as stakeholders in our environment.

Bird management is critical, and over the years, various methods have been tried, tested, and adopted to discourage these avian creatures from interfering with human endeavors, with the intention to safeguard every life involved. The choice of methods depends on the specific problem scenario, geographic location, and bird species involved. Technical support and innovative approaches have proven to be essential in enhancing the effectiveness of both active and passive non-lethal methods. As there is a foolproof effective generic solution for all species, implementing species-specific solutions, can mitigate birds' adaptability to new deterring measures that are adopted. However, the challenge lies in the timely and accurate identification of the species. Recent advancements in Computer Vision and Deep Learning techniques have made it possible to detect and identify objects, including bird species, making this otherwise cumbersome task more manageable.

This paper aims to highlight several active and passive methods that have been utilized over the years to deter birds from critical areas. By employing efficient species-specific actions, birds can be effectively driven away from areas such as farmlands, windmills, and airports, thereby guarding both bird populations and human interests.

**Keywords—** Bird Strikes, Audio Analytics, Image Analytics, Computer Vision, Object Recognition, Species Identification, CNN

## INTRODUCTION

Driving birds away from windmill farms, Solar panel parks, paddy fields, vineyards, and other cultivation areas is carried out in a range of economical as well as technically sophisticated methods. A bird hit by any machinery or by any man-made object could result in damage to the machinery. Therefore, birds have caused huge financial burdens to these industries, not to forget that by putting their own life unwittingly at threat.

Bird strikes in an airport scenario are an even greater concern as they could put hundreds of human lives at risk, apart from the monetary loss that is caused. Directorate General of Civil Aviation (DGCA) states that bird strikes

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by aircraft showed an exponential increase due to higher air traffic, the invention of quieter aircraft, and a huge rise in wildlife population, especially the synanthropic species such as crows, gulls, rock doves, and starlings, after the Covid pandemic (DGCA, 2022).

In Wind Turbine farms, around 5,38,000 deaths of birds every year in the US alone, and thousands of Bats die every year in North America alone, therefore is known as the Ecological Death Trap of birds. The hits are caused by the blades of the windmill that move with a speed of up to 180 mph, damaging the machine and killing the bird (US Wind turbine Database, 2021; Marques, 2014). The glossy blue reflection of the sky by the Solar Panels is mistaken for water by birds. This situation is known as the Lake Effect which kills approximately 1,38,000 birds per year in the US alone (Smallwood, 2022).

A highly fatal scenario is faced in airports and the bird strikes here are categorized ‘A’ among aviation hazards by the Federal Aviation Administration (Dolbeer, 2021). It affects travel, and security risks and brings in huge economic losses. The vast barren space with relatively minimal human disturbance and the absence of terrestrial animals makes the airfield very attractive to avian creatures. In a study conducted in an airport in Brazil, it was found that scavenger birds like vultures prefer the gradient of surface temperatures between the tarred runway and the other areas Novoselova, 2020). The reason is that many, several hundred species have made this human-possessed land to be their playground. This common airspace witnesses fatal collisions, thus making it a danger zone for man, the flying machine, and the flying creature.

Beginning with the first-ever bird strike that happened in 1905 causing the death of Orville Wright, till the most recent bird hit, the damage and trauma that is caused are highly alarming. The year 1985 is considered to be the worst year in the history of Aviation with a death toll of over 2000 passengers. And by far, the most popular bird strike accident happened in January 2009 at New York airport, when an aircraft made a heroic landing on the Hudson River after hitting a flock of Geese causing dual engine failure. Between 1988-2020, 2,33,915 bird strike incidents happened, killing 293 people and destroying 21 aircraft (Thorpe, 2016). In India, a total of 974 bird strikes occurred in the first half of 2022 alone, reports DGCA. Major airlines like Air India, SpiceJet, Vistara, and Indigo have suffered damages and led to an emergency landing. The most recent was the strike on 15th October 2022, of the newly launched Akasa Air by a single bird causing radome damage. ( IABD, 2022)


*Fig 1: Human Innovations causing a threat to avian life*

### *1.1 Reporting*

Every bird strike is to be reported at the National level and the reports shall be collected and forwarded to ICAO (International Civil Aviation Organisation for inclusion in the Bird Strike Information System (IBIS) database (Metz, 2021). The culture of reporting Bird strike incidents has been very poor, in some countries. The rate of reporting in the USA increased from 41% in 1990 to 91% in 2013

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making 98.8% of reporting globally (Dolbeer, 2013). But in recent years, India has taken a heads-up on this matter, and therefore reporting such events is gaining a good habit. According to the Indian Aviation Safety Plan, whether damaging or non-damaging, every bird strike has to be reported per 10,000 movements by all Indian airports.
The increase in the Bird strike count could result from better reporting habits added to the increased flight operations in the post-pandemic phase. The rise in wildlife and avian creatures could be another reason for this exponential rise in bird strikes. DGCA has insisted all airports to implement a habitat management program that includes various active and passive methods like waste management, infrastructure management, and routine and random patrolling in the aerodrome.

### *1.2 Damages & Cost*

In Texas, A navy trainer aircraft was hit by a Black vulture in September 2021, causing 47 million dollars in damage. The 4.5-pound bird got ingested into the engine causing the plane to plummet into the neighbourhood. Till date around 618 hull loss has been faced by the Aviation Industry due to bird strikes. The annual loss faced by the industry worldwide is over 1 Billion USD. This includes the direct cost pertaining to Aircraft maintenance, airworthiness-related tests, and so forth. The Indirect cost is mostly associated with passenger rebooking, aircraft rescheduling, and lost revenue. In the statistics published by Dolbeer et. al. in 2013, the total cost for every non-damaging bird strike is US $22,417, and US $225,329 for every damaging strike (Dolbeer, 2013).

## EXISTING SOLUTIONS

After There are enough and more reasons to take this matter into serious consideration and be diligent enough to find an efficient solution. Several preventive methods have been adopted to suppress the problem by keeping the airport and its neighbourhood least attractive for bird habitation. Furthermore, it is found that 61% of bird strikes with civil aircraft occur during the landing phases of flight (descent, approach, and landing roll), and 92% of strikes happen below 3500 feet AGL (above ground level) (Metz, 2021) and 99% happen below 2000ft airport. Therefore, the surrounding area of the airport within a radius of at least 13 km from the runway is considered most critical and hazardous, as the aircraft reaches this altitude at this distance (Coccon 2015).
Limiting the possibilities of food, water, and shelter makes the birds less interested in foraging in airport areas. Though exclusion of avian creatures from the premises is not as easy as keeping away terrestrial animals, netting, porcupine wire, and sticky or chemical repellents are a few non-lethal techniques to prevent the birds from entering the area. Hydrological mitigation measures like the removal of drainage and other water bodies are a mandate for reducing the bird population in the airport area. A grass height of 1 meter is maintained as it is found to be less favourable for birds to perch. Periodical cleaning and disposal of overnight roosting areas like erections, and dryer-vent airflow lines, to remove nests, have to be carried out. Though not recommended by ecologists and bird lovers, a few harassment methods using gas exploders, alarms, distress calls, pyrotechnics, and visual repellents like effigies, lasers, reflecting materials, lights, mirrors, drones, trained dogs are also used in most of the airports. Some airports use natural enemies like falcons and dogs, which is a time-intensive and costly affair (Harris, 1998). Even model aircraft/drones imitating falcons and hawks called Ornithopters are used in a few airports.
Several acoustic methods such as Sonic bird repellers, emit synthetic, authentic sounds of raptors or frightened starlings signalling them to avoid the dangerous location. Sounds at frequencies audible and unpleasant to the birds cause a startle reflex compelling them to flee away from the risky location. Other pyrotechnics include various noise-making shells, fired shotguns, starter pistols, and flare pistols. The results are not that promising and effective only for a relatively short-term (Dolbeer 2013). Zon Mark4 Propane Bird Scare gas cannon has been employed in a few airports across the US and Canada. Though these methods are very economical, their effectiveness gradually decreases (Draulans, 1987)

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Visual methods like distributing glittering items on-premises use of reflectors that resemble the raptor's eye, holographic strips, and laser beams are also effective to some extent. Recently few aircraft-related mitigation measures (avian visual measures) like giving a bright colour scheme for the fuselage, coloured patterns on the propeller, and pulsing light on the aircraft are adopted to enhance the perceivability of the aircraft so that the bird can detect its approach and avoid a strike (Fernandez, 2011). With the advancement of material sciences and technology, engineers have attempted to minimize aircraft damage by introducing better materials for jet engine compressor blades, stronger windshield designs, and damage-resistant wings (Thorpe, 2008).
Another innovative system is the BirdTAMS, a customized German Air Force GAF (Luftwaffe) method NOTAMS (Notice to Airmen) a Long-range and Short-range radar used for military purposes. The BirdTAMS consists of area-wise warnings to restrict flight movements and helps in raising general situation awareness of pilots. This radar brought a dramatic decrease in bird strikes (Ruhe, 2008). The aircraft's rate of climb can be adjusted to pass critical zones quickly. In case of high collision risk, air traffic could be temporarily held back. More efficient and enhanced Avian RADAR with a better range of 11 km wide and 1.5 km and data quality are used these days. Airport Surveillance Radar (ASR) systems having a range of 15-20 km, detect bird concentrations relevant to flight safety in the approach and departure areas (J. A. Bruder, 1997).
The bird species causing bird strikes differ depending on geographical and demographic factors. In Indian airports, Black Kites and Red Wattled Lapwings pose the greatest risk. From 1980 to 1988, black kites alone were involved in 55 incidents. However, there has been a noticeable and alarming rise in strikes to 85 over the past thirteen years which also includes two fatal IAF accidents in 2005 and 2014. This escalation raises serious concerns (Srinidhi, 2021). Ornithology centres such as SACON (Salim Ali Centre for Ornithology and Natural History) under the Ministry of Environment, Forest, and Climate Change, have actively engaged in the study of bird hazards to aircraft. They have collaborated with the Indian Air Force to comprehensively investigate bird strikes and implement effective measures for their management. By conducting case studies at airports nationwide, they provide valuable guidance for adopting tailored bird strike mitigation strategies (Pramod, 2020). This collaborative effort is a commendable initiative, fostering a deeper understanding of the specific reasons behind bird strikes at each airport. It not only offers localized solutions to minimize such incidents but also encourages airports to develop good reporting practices, thereby enhancing overall safety.

## SPECIES IDENTIFICATION

In all the diverse problem areas such as windmill farms, solar parks, and airports, various passive and active, technical and non-technical measures have been adopted and aborted over the years. No techniques can be used regularly for a long period of time, as birds are smart enough to adapt to new and unpleasant environments very easily. Measures taken have to be species-specific to avoid a monotonous and anticipated action. The adapting capability of birds has pushed for further advancement to the development of intelligent systems that bring out actions that are less bland and unpredictable and which depend on the species that are in subject.
As stated by ICAO in Annexure 15, the ATC is obliged to report current information on the presence of birds in the airport area which is likely to be risky for flight operations (ICAO, 2017). They have to be highly cautious in every bird activity observed and bird strikes that occur. Such manual observation by ATC and pilots is cumbersome, yet very vital for safe aircraft operations. The use of additional surveillance of BIRDTAMs to an extent helps them to avoid flying in the route of bird flight (Cilulka, 2013). As mentioned by Metz et. al, a combination of avian radars together with thermal and video imaging can be promising data for real-time intelligent bird strike prevention. The implementation of video imaging is efficient for a flock of birds and thermal imaging is efficient for birds in close proximity. False alarms are in plenty for a thermal sensor as the sensors are not able to discern between birds and other objects. These false predictions can reduce the operational capacity

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of a busy airport and increase the overhead of the alarm system. Thermographic imaging techniques have drawbacks such as field of view, the distance between the item and the thermal imaging camera, and meteorological variables such as humidity, rain, sun radiation, etc. (Metz, 2020).
Methods should be adopted according to the species in that particular airport area (Allan, 2006). A generalized approach to deter birds will only work for a very short period of time, after which the birds get adapted to it. A more species-specific, real-time intelligent approach has to be built to make the action less predictable and to sustain the response of the bird every time the action takes place.
Species identification is a primary requirement for an efficient bird-deterring system. Though parameters such as the location of the airport, landscape, altitude, time of the day, weather, and season could also be vital for predicting the species, they cannot be accurate. Audio analysis is performed on the bioacoustics captures from the area, which provides a good prediction. But information like the position of the bird and the number of birds is not addressed. Here is where images can be more helpful in analysing the shape and visual features of the bird. Sounds and visual inputs are used for the identification of birds. Videos go a step further in helping analyse the flying and behavioural patterns of the bird.

### A. *Audio Analytics*

Birds produce vocal sounds for alarm calls, begging, and fighting. They sing songs for mating, wooing, and territory defence. Apart from this they also produce non-vocal sounds which are generated during wingbeat, clapping, trilling, and Bill drumming. Each species has a distinctive call and different songs during different times of the day. Pitch, tone, rhythm, and quality are the various parameters used for positive identification. (Kroodsma, 1991)
Since the early 90s, bird species identification using audio signals has been largely carried out for studying the decreasing bird population and protecting certain endangered species (Blondel, 1990). These bioacoustics monitoring approach is a passive and cost-efficient strategy that requires less human effort. The use of Machine Learning techniques makes it, even more cost-effective and less cumbersome. Many models have been developed that can process continuous audio data and recognize them after training them using preexisting audio data sets. Several online libraries with audio data sets are available such as Xeno-canto, Cornell's Macaulay Library, Avibase, the Western Soundscape Archive, and the BirdDB which can be used for obtaining training data and data for validation. Due to a lack of efficient tools for extraction and analysis, only a minor portion of this data has been used. Yet there are a number of apps to identify species like ChirpMatic, BirdSngID, MerinBird, and Warblr for identifying birds, Cicada Hunt for identifying insects, Plantsnap, Plantifier, and NatureGate for identifying plants.
BIRDCLEF, a bird identification challenge organized by the Cornell Lab of Ornithology together with Google Bioacoustics Group and LifeCLEF has been conducted every year since 2014 to bring out the best models for Auto Auditory identification of birds. Each year more effective tools with better performance are developed which helps to advance the science of bioacoustics and support ongoing research to protect endangered Hawaiian birds. (BirdCLEF, 2022). Mario Lasseck performed an Audio-based Bird Species Identification with Deep Convolutional Neural Networks on the Xeno-Canto dataset containing images of 1,500 different species. It outperformed previous models achieving a mean reciprocal rank (MRR) of 82.7% and 74.0% on the official BirdCLEF subtask1 test

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set. InceptionV3 architecture performed better than ResNet152, DualPathNet92, InceptionV4, DensNet, Xception, and NasNet (Lasseck, 2018).
The main advantages of auditory identification are that the bird need not be in the line of sight of the receptors and inputs can be obtained in a 360-degree direction at any time of the day irrespective of lighting conditions. But these factors are overshadowed by the limitations that signals obtained are very sparse and contaminated and counting the number of birds of the same species is quite unlikely (Briggs, 2009; Neal, 2011; Lopes, 2011; Bardeli, 2010).

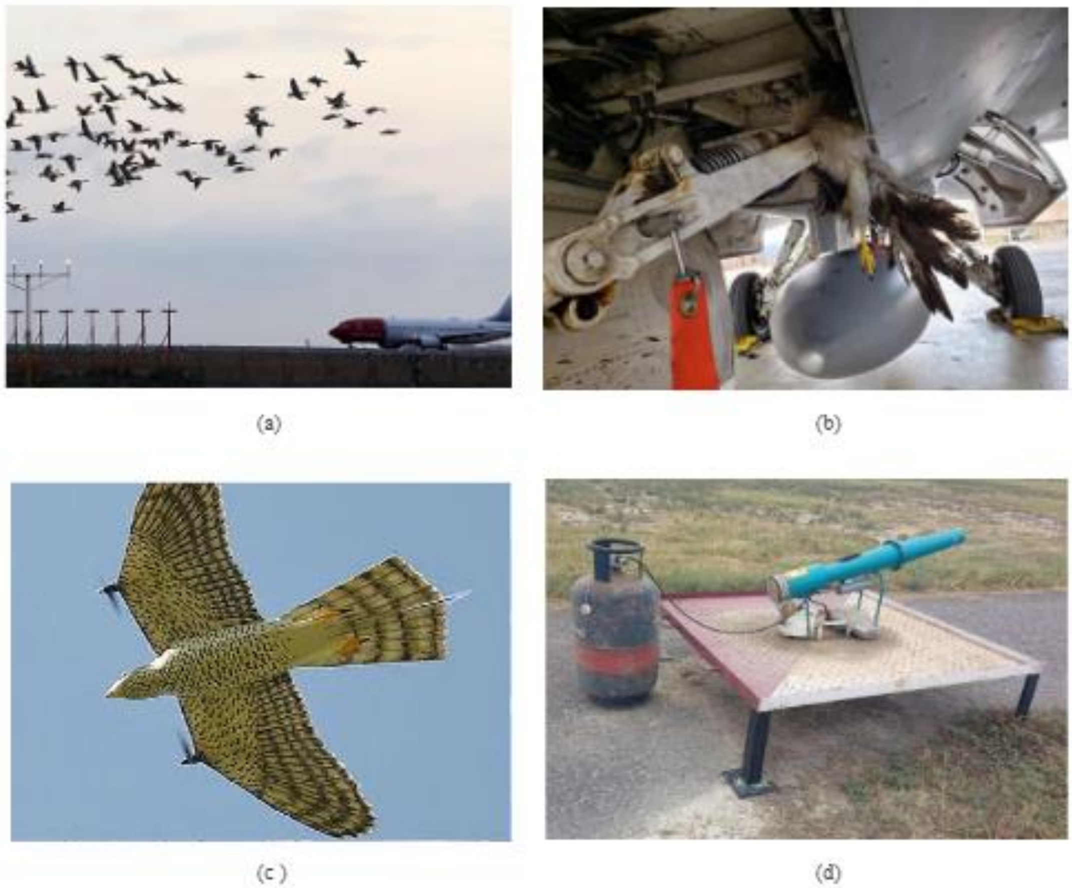

*Fig 2: (a) The Presence of Birds at Airports. Image Retrieved from https://aertecsolutions.com/ en/2017/09/18 /the-presence-of-birds-at-airports/. (b) The remains of a Swainson's hawk that hit an F-16 landing at Hollowman Air Force Base on April 17, 1995. Air Force amn/nco/snco Facebook page. (2019, May 23). Retrieved from https://www.airforcetimes.com/news/your-air-force/2019/05/23/this-is-the- hefty-toll-bird-strikes-have-inflicted-on-the-air-force-since-1995/.(c) The RobotFalcon was developed by the University of Groningen in the Netherlands. Credit: Twitter/AusSMC) Retrieved from https://www.deccanherald.com/india/robotic-falcon-built-to-prevent-bird-strikes-why-indian-airports-need -it-1157359.html (d) Lucknow airport deploys scarecrows, zon guns to keep birds away from flights. Hindustan Times (2023, September 11). https://www.hindustantimes.com/cities/others/lucknow-airport -deploys-scarecrows-zon-guns-to-keep- birds-away-from-flights-101687270300499.html*

### B. *Image Analytics*

There is an obesity of data in the digital world, especially images. With every individual having high-resolution easy-to-use cameras in their pocket, a huge number of data is clogged in the cloud every day. Around 50 billion images have been uploaded to Instagram itself.
'Vision' being the most amazing and complex sense of all, the scope of image analysis is limitless and the outcome is perfect. Computer vision is one of the most trending technologies with its application in Robotics, Autonomous cars, and face recognition, etc. It uses colour, shape, texture,

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and behaviour to infer objects in the image. Computer vision when powered with Artificial Intelligence exponentially increases the efficiency, repeatability, and accuracy of image analysis. AI-based algorithms enable machines to understand the patterns and regularities of pixels and recognize the image. Objects, people, and even situations in images can be classified, identified, and interpreted. It has been proved that computer vision reduces 8.4 hours of human effort making it a cutting-edge technology for object detection and object identification (Norouzzadeh, 2018). Advancements in computer vision skyrocketed since 2010, with limitless storage and high-definition visual sensors. Many machine learning techniques such as scale-invariant feature transforms (SIFT), Viola-Jones object detection techniques, and Histogram of oriented gradients (HOG), have been developed to extract information from diverse data types to solve computer vision problems. Since 2006, various object recognition techniques have been applied for species identification among birds. Zivkonic & Heijden used a background Gaussian mixture model to extract bird silhouettes (Zivkovic, 2006). Gavves performed unsupervised alignment of bird images which received a good classification rate but required user interaction (Gavves, 2013).

By 2015, with the advent of deep learning algorithms, Computer vision had shown significant progress in its efficiency with an accuracy as high as 95%. The major highlight of the deep learning model is that it can perform semi-supervised or unsupervised feature extraction on huge datasets, and this is achieved by using neural network architectures like RetinaNet, YOLO, CenterNet, R-CNN, EfficientNet, etc. For most of the models, the working and accuracy highly depend on the size of the training data set. But for classification problems with limited datasets or no dataset for training, can use synthesized data generated by a game engine.

### C. *Video Analytics*

Video analytics is generally more complex than image analytics because it involves processing a sequence of images (i.e., frames) rather than just a single image. It often involves analysing the motion and behaviour of objects over time, which requires more advanced algorithms and techniques than analysing a single image. Actions and events can be discerned to enhance experiences, reveal insights by image segmentation, get visual insights in real-time, and Identify objects with precision (Marini,2015; Cullinan, 2015; Wah, 2011; Atanbori, 2018, Huang,2019; Branson,2014).

***A few specific challenges with video analytics include***,

Massive data volume, which makes processing and storage very difficult. A very robust computational power and efficient storage including techniques like compression, encoding, and parallel or distributed processing is required when dealing with video analytics.

Temporal Coherence: Motion blur, camera movement, object occlusion, and changes in lighting make it difficult to maintain temporal coherence between frames. This makes it hard to track and analyse the movements of objects accurately. Optical flow estimations, object tracking, and interpolation can be used to maintain object motion constancy between frames.

Background Modelling: Fluctuation of lighting conditions and object occlusion makes it difficult to detect objects in videos. Modelling the scene's background and subtracting it from each frame is required for video analytics.

Real-time processing: The sheer size of video data can lead to longer processing times, making real-time analysis and decision-making more difficult. Quick processing and low-latency algorithms are required in real-time video analytics applications like traffic monitoring and surveillance.

The application of video analytics techniques can be mainly for object detection, motion analysis, and behaviour identification. While similar techniques used in image analytics, such as convolutional neural networks (CNNs), can be applied to video analytics, additional methods like optical flow, background modelling, and object tracking are often required to analyse motion and behaviour over time. Several studies are referenced, including one from 2001 by Cutler and Davis that focused on human motion identification using self-similarity and time-frequency analysis (BenAbdelkader,

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2001). Ayyildiz and Conrad (2011) approached image classification through repetitive movements' main frequencies, while Betke et al. utilized wing beat frequency and thermal imaging for bird species detection (Ayyildiz, 2011).

Betke et al. utilized wing beat frequency and Fast Fourier Transforms (FFT) techniques to extract signals from thermal imaging and pose templates, overcoming signal noise. Despite limitations in long-distance detection and all-weather conditions, thermal imaging was employed by Betke et al., Cullinan et al., Matzner et al., Hristov et al., and Lazarevic et al., achieving an accuracy of up to 82% in highly humid and rainy conditions, particularly in offshore wind farms (Betke, 2008; Cullinan, 2014; Matzner, 2015; Hristov, 2010; Lazerevic, 2010). Real-time classification of birds and bats achieved an 81% detection rate using 2D flight tracks, reducing video from a single thermal source, with a dataset containing 18 birds and bats (Cullinan, 2015; Duberstein, 2012). A method developed in 2019 demonstrated improved speed and accuracy in video object detection by adaptively selecting the input image scale, suggesting that lower resolution scaling can enhance accuracy. Real-time classification of birds and bats was achieved using 2D flight tracks and thermal imaging, with subsequent developments in 2019 that adaptively select input image scales for improved speed and accuracy in video object detection (Chin, 2019). The use of video analytics extends to motion detection for analysing wing beat frequencies and flight trajectory patterns of birds, as well as fish species classification based on swimming trajectories (Beyan, 2013).

## CONCLUSION

Over the years, implementing non-technical passive and active methods has contributed to reducing bird strikes. These methods include habitat management, wildlife control measures, acoustic and visual deterrents, radar and detection systems, and collaborative education efforts. Managing airport habitats, employing trained personnel and predator-prey relationships, and using audio and visual disturbances help discourage birds from airport areas. Radar systems and bird detection technologies assist in monitoring bird activity. Collaborative efforts raise awareness and provide education on bird strike prevention. While it's challenging to attribute the reduction in bird strikes solely to non-technical methods, their implementation has played a role in mitigating bird-strike risks.

Similar to Birders, who use both their eyes and ears to identify birds in the field, which proves that audio and video inputs are equally responsible and collectively beneficial for the identification of bird species. Yet, video analytics plays a major role in this purpose. The emergence of Deep learning algorithms has escalated video analysis or video surveillance using computer vision. It has shown powerful learning capability and remarkable performance in handling background switches, occlusion, and scale transformation. Videos can be analysed for the continuous position of the object, behaviour, and other physical features that are not derived from image analysis.

To conclude, it is evident that, even though non-technical methods play a crucial role in bird strike prevention, the combination of technical methods and AI-based innovations, especially those leveraging computer vision, provides enhanced capabilities for early detection, proactive monitoring, and data-driven decision-making. These advancements significantly contribute to minimizing bird strike risks and enhancing safety in aviation environments. Technical methods and AI-based innovations, particularly those utilizing computer vision, provide enhanced capabilities for early detection, proactive monitoring, and data-driven decision-making in bird strike avoidance. These advancements significantly contribute to minimizing bird strike risks and enhancing safety in aviation environments.

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