Avian Census: Real-Time Bird Counting using Region-based Convolutional Neural Network.

Abstract

One of the ongoing challenges in avian ecology is tracking and monitoring bird populations, especially in real-time situations. Historically, counting birds reliably and quickly has proven to be complicated. Predicting bird populations in different areas by examining bird footage presents a viable solution to this problem. To achieve this, the suggested model uses deep learning's computing power, a prominent area of artificial intelligence known for its proficiency in image processing.

The suggested model uses neural network-based feature extraction to provide state-of-the-art, generic bird detection. Fast R-CNN (Region-based Convolutional Neural Network) provides the bird-bounding boxes for counting in real-time with the help of anchor boxes containing the detected bird. The counting will be done based on the in-out of the threshold line set in the frame's ROI (Region of Interest).

Such a video-based bird counting approach leverages deep learning to enable real-time bird census solutions and democratizes ornithological research through citizen scientist participation. In summary, this model demonstrates that real-time, video-based bird counting represents a pivotal advancement in avian ecology, with far-reaching implications for the conservation and understanding of bird populations.

Keywords: computer vision, machine learning, deep learning, bird detection, real-time bird counting, hierarchical feature extraction.

Introduction:

Accurately identifying and monitoring bird populations is a continuous difficulty in avian ecology, essential to comprehending and protecting biodiversity. Conventional techniques, such as manual observations and field surveys, require more efficiency for real-time monitoring and are labor- and time-intensive. The emergence of cutting-edge technologies, especially in deep learning and artificial intelligence, offers a viable path toward revolutionizing real-time bird population monitoring. Birds are essential to preserving the health and stability of ecosystems because of their vital ecological functions, which include pollination, seed distribution, and pest control (Wójcicki et al., 2023; Kavana et al., 2023). However, new research shows that human activity is causing a worrying reduction in bird populations, especially for raptors. Precise geographical and temporal data are essential for the conservation and management of bird species, which has led to the creation of novel monitoring techniques.

Geographic Information Systems (GIS) are becoming increasingly popular in bird observation. Studies have used GIS methods for density mapping and diversity evaluations (Nandipati & Abdi, 2009; Grenzdörffer, 2013;). Despite these developments, traditional methods of counting birds, including point counts, are still often employed. However, they are limited by their time-consuming nature, dependence on skilled observers, and sensitivity to environmental factors. We can employ automatic real-time bird counting using computer vision, machine learning, and deep learning to overcome these limitations. Utilizing the model architecture on video data in real-time helps reduce the requirement for extensive data storage.

Motivation

It is essential to accurately monitor bird populations to evaluate biodiversity, comprehend ecological processes, and implement conservation measures. Ornithological research has relied heavily on traditional methods of counting birds, such as field surveys and manual observations. These techniques, however, have certain drawbacks that impair their scalability, accuracy, and efficiency. Overcoming these obstacles and utilizing cutting-edge technologies for more fruitful avian ecology research is the driving force behind the switch to automatic bird counts.

The Drawbacks Of Conventional Methods:

1. Labor-Intensiveness: Manually recording bird sightings through professional observers is a common need of traditional bird counting methods, which can involve significant human work. For extensive monitoring periods or large-scale research, this labor-intensive technique becomes unfeasible.
2. Time-consuming: Manual bird counts take much time, mainly when there is a lot of bird activity, like migration bottlenecks. The requirement for repeated observations and long-term data collection further compounds the time limits of traditional approaches.
3. Subjectivity and Observer Bias: The accuracy of data obtained by manual counting depends on the observer's background, skill level, and surrounding circumstances. Data inconsistencies may arise from variations in individual observers' abilities and attention spans.
4. Weather Dependencies: Heavy cloud coverage, extreme rain conditions, or foggy weather can significantly constrain traditional methods. It will heavily affect the temporal data of the bird population and thus will account for inaccuracy in the measure.

5. Limited geographic coverage: Labour resources can only cover some census regions as they are limited. This constraint makes thoroughly studying bird populations across various habitats and geographical locations challenging.

How Automatic Bird Counting Solves These Issues:

1. Automation improves efficiency: Automatic bird counting, especially deep learning, and computer vision-based technologies, automates the process. It minimizes the need for considerable human labor, allowing for more efficient examination of massive datasets.
2. Real-time Monitoring: Using deep learning models on video data, bird populations may be monitored in real-time. It advances above old approaches, providing real-time insights into dynamic avian activities and behaviors.
3. Objectivity and consistency: Automation lowers the impact of observer bias, resulting in more objective and consistent outcomes. Once taught, deep learning models provide standardized detection and counting processes, minimizing the variability caused by human observers.
4. Solutions Unaffected by the Weather: Automatic bird counting technologies based on computer vision are less vulnerable to bad weather. Cameras utilizing infrared or other advanced imaging technologies can function well even in low-light or adverse weather conditions.
5. Extended Spatial Coverage: Automatic bird counting methods may comprehensively cover more significant spatial areas when deployed using unmanned aerial vehicles (UAVs) or fixed cameras. It enables a more comprehensive study of bird populations across varied habitats.
6. Data Storage Efficiency: By applying model architecture to video data, vital information can be extracted, eliminating the requirement for significant data storage.

This data management optimization improves the scalability of automatic bird-counting methods.

Background

Automatic bird counting is critical in nature-based tourism attractions, particularly in protected regions where visitor numbers are increasing, because it helps monitor and reduce the adverse effects of human presence on wildlife behavior, stress levels, and disease spread. Automated bird counting becomes critical in human-dominated landscapes such as the Katavi-Rukwa ecosystem for understanding avian community dynamics and applying effective conservation measures based on habitat heterogeneity and land-use cover (Wójcicki et al., 2023; Kavana et al., 2023).

Point count is a well-known technique in bird monitoring research, especially for on-the-ground land bird counting of flying migrant birds like storks, pelicans, and raptors. An observer stationed at fixed places using binoculars or telescopes monitors bird migration at suitable locations (Gregory et al., 2004). While point counts are widely used, they have both advantages and disadvantages. The method helps gather data on bird abundance and distribution, which may be used to help with avian community and migratory research. However, it has drawbacks, such as being time-consuming and frequently requiring more than one skilled observer. Point counts' success strongly depends on the observer's abilities, experience, and the characteristics of the surroundings. Weather, topography, and vegetation can all impact the detectability of birds, altering the overall effectiveness of point counts (Vansteelant et al., 2014; Fitzpatrick et al., 2009). Despite its shortcomings, point count methodology remains one of the best methods for detecting and counting birds, providing helpful information about avian populations and behaviors.

Geographic Information Systems (GIS) are critical in the advancement of bird counting procedures, providing a complete and spatially informed approach to wildlife monitoring. Researchers and ecologists use GIS in bird observation to improve the accuracy and efficiency of bird counting processes. For example, Nandipati and Abdi, and Grenzdörffer use GIS techniques for various objectives, including modeling bird species richness, constructing density maps, and using UAV imagery for bird detection and counting (Nandipati & Abdi, 2009; Grenzdörffer, 2013;). GIS gives bird observation a geographical context by allowing the integration of varied variables such as land cover, elevation, and habitat heterogeneity. This spatial information is essential for understanding bird distribution patterns, identifying critical habitats, and assessing the impact of environmental factors on bird behavior (Maharaj and Kushaal, 2023). Furthermore, GIS enables the creation of optimized bird-watching routes, assisting in the planning and managing ecotourism activities centered on bird observation. GIS allows for the mapping of bird species diversity, as illustrated in the example of the Kuala Bubon mangrove forest in West Aceh, providing vital insights for developing bird ecotourism by finding suitable spots and routes for bird-watching enthusiasts. Using GIS in bird counting enhances data precision and leads to more informed conservation and ecotourism planning (Ulhaq et al., 2023).

Machine-learning-based computer vision and image recognition advancements have also potentially transformed bird counting approaches. As discussed earlier, traditional procedures, such as manual point counts, frequently include human observers and have drawbacks such as observer bias, time constraints, and substantial training requirements. Deep neural networks, in particular, provide a more automated and efficient solution to bird detection and counting (Hong et al., 2018; Weinstein et al., 2022). Unlike traditional methods that rely on hand-crafted features, deep learning algorithms may automatically learn beneficial characteristics from raw pixel values, making them versatile and suited for various applications, including bird monitoring (Hong et al., 2018; Weinstein et al., 2022). Chabot and Francis thoroughly examine bird detection methods, emphasizing the variety of methodologies, including standard image analysis techniques and segmentation methods. Integrating machine learning into these approaches can enhance accuracy and scalability, enabling the analysis of large-scale ecological systems. (Chabot and Francis, 2016)

Furthermore, machine learning and computer vision play a role in bird counting that goes beyond automating the detecting procedure. Creating generalized models that may be applied across diverse species and habitats overcomes the issues of large-scale ecological monitoring (Chen et al., 2023). These models have the potential to overcome the limitations of supervised models, which require a large amount of labeled training data and technical skill and are prone to overfitting. Researchers established the possibility of a generic bird detection model that achieves outstanding recall and precision rates on unique aerial data, even without local training, using a broad dataset from numerous projects worldwide (Liu et al., 2015). Because such generalized models eliminate the need for local annotations, the method becomes more efficient and applicable to many bird species and habitats.

Artificial intelligence (AI) is revolutionizing wildlife conservation efforts in Hong Kong by providing real-time, automated, and accurate species identification. Unlike traditional point counts, which take time and rely on human observers, AI bird counting provides a quick and efficient alternative, as demonstrated by joint initiatives such as the RoboticsCats collaboration with the Hong Kong Bird Watching Society and WWF-Hong Kong. Despite problems such as accuracy in complicated situations, continued advances in machine learning algorithms point to a bright future for AI bird counts (Andre, 2023). The Automated Bagworm Counter (Oto-BaCTM) in the agricultural landscape presents a pioneering integration of machine vision and image processing to monitor the Metisa plana bagworm species in Malaysian oil palm plantations. This technology uses deep learning with Convolutional Neural Networks to detect objects in real-time, eliminating human errors in census-taking and advancing precision agriculture methods. Both instances demonstrate AI's transformational potential in addressing problems in wildlife conservation and agriculture. (Ahmad et al., 2021)

Automatic bird counting, made possible by artificial intelligence (AI) and machine learning breakthroughs, is emerging as a game changer in bird population monitoring. Computer-aided bird counting provides a consistent, accurate, and efficient alternative using deep neural networks' capability, notably convolutional layers and max-pooling layers in image analysis. This is demonstrated in a study conducted in Turkey, which used yearly images to forecast bird counts and create distribution maps, showing the potential of AI in real-world bird monitoring applications (Akçay et al., 2020). This method helps overcome the issues associated with standard counting methods, allowing for more precise management decisions and enabling preemptive steps when necessary. Automatic bird counting performed by deep learning algorithms not only improves accuracy and efficiency but also shows promise for including citizen scientists in large-scale bird surveys, a significant achievement in avian ecology. (Akçay et al., 2020)

This methodology, which is effective in a variety of contexts such as marine bird detection from videos and tracking wild animals in the Serengeti, employs a variety of layers, including convolutional layers for feature extraction, max-pooling layers for grid-based output, and fully connected layers for comprehensive analysis (Norouzzadeh, 2018). Incorporating these layers into deep neural networks allows for the reliable detection of birds inside photos, demonstrating the adaptability of this method across a wide range of ecological monitoring settings (Akçay et al., 2020).

Methodology

Model Overview

To modernize bird population monitoring, we investigated machine learning approaches, notably deep neural networks, for detecting birds in video frames carrying population data and location and timestamp information. We intend to use a robust and versatile technique for bird detection, drawing inspiration from successful applications in varied contexts such as sea bird detection from videos, Serengeti wild animal tracking, and wild bird detection using UAV footage (Jampens et al., 2016; Norouzzadeh et al., 2018; Hong et al., 2019; Bowley et al., 2016). Deep neural networks, which behave as complicated hypothesis functions, enable the translation of image information to desired outputs, such as pixel class labels and bounding boxes, via computations over numerous layers (Chabot and Francis, 2016).

Deep neural network architecture consists of several layers, including convolutional layers for feature extraction, max-pooling layers for grid-based output, and fully connected layers for thorough analysis (Goodfellow et al., 2016). The interaction of these layers allows for the recognition of birds inside photographs, underscoring the approach's versatility across many ecological monitoring contexts. In our investigation, the Faster R-CNN architecture, a form of CNN built for general object detection, is the foundation for mapping picture pixels to matching output bounding boxes containing birds (Ren et al., 2015). This approach is helpful in learning network parameters by using a stochastic gradient-descent (SGD)-based optimization technique , notably error back-propagation, to achieve convergence between expected output and true bounding boxes from a sequence of training images (Goodfellow et al., 2016).

The definition of a threshold line within the image frame, critical for accurate bird counting, is central to our research. This threshold line serves as a reference point or border, and birds traveling across it are tallied regularly. A similar notion was demonstrated in the YOLO 8 model for vehicle counting, where vehicles traveling through a designated transition line are precisely counted, proving the adaptability of this method in other domains (Girshick, 2015). Our research demonstrates the power of deep neural networks in automating bird detection and counting, giving a standardized and efficient solution to the issues provided by traditional counting approaches, which are frequently costly, time-consuming, and reliant on human observers.

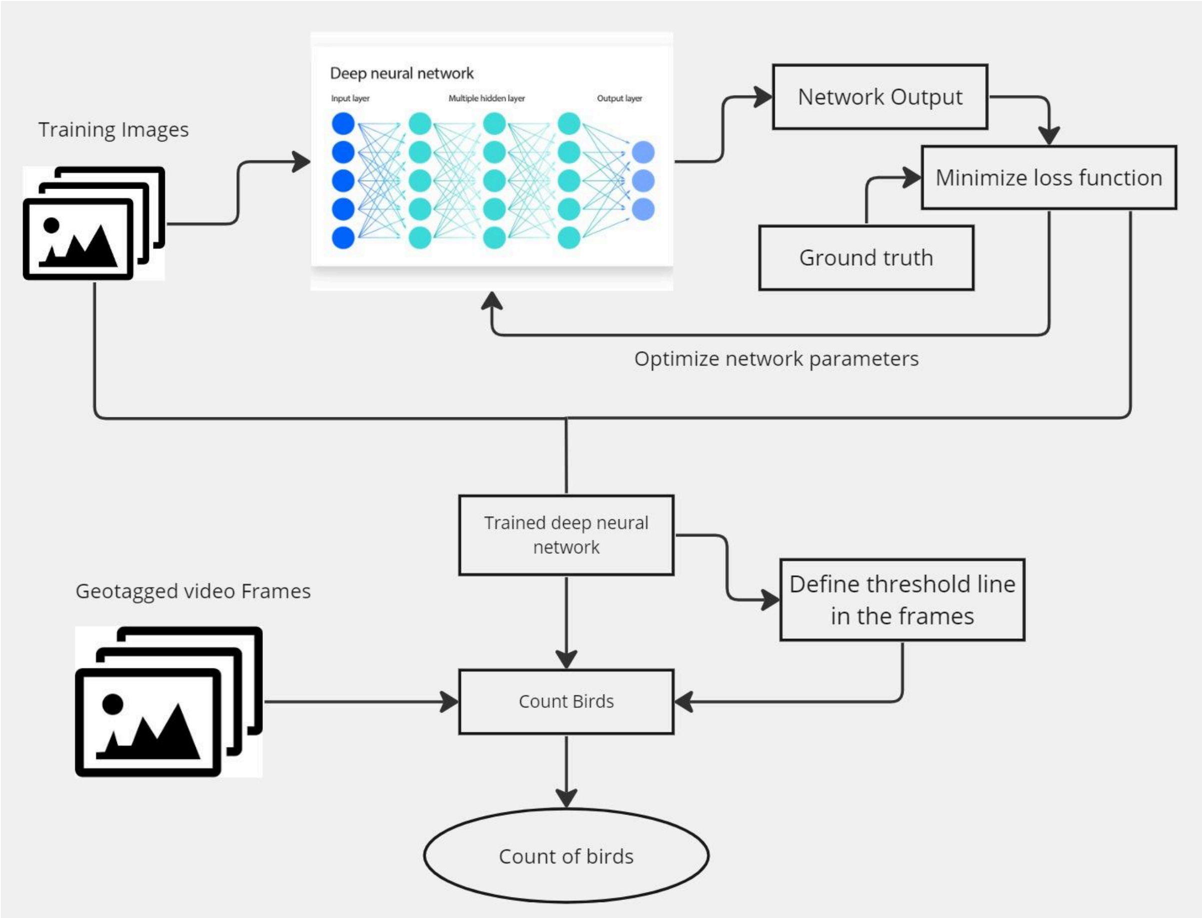

Figure 9.2.1. Overview of the methodology followed.

So, deep neural networks, specifically the Faster R-CNN architecture, are used in our study to transform bird population monitoring. This model demonstrates its capabilities by mapping image pixels to accurate bounding boxes containing birds, demonstrating its adaptability in various ecological monitoring scenarios. The breakthrough is defining a strategic threshold line within the visual frame to serve as a reference boundary. Birds that cross this threshold are counted methodically, similar to the YOLO 8 model's application in vehicle counts, highlighting the model's adaptability. This synergistic combination of deep neural network architecture and the novel threshold line approach provides an efficient, standardized, and automated solution that mitigates the limitations of traditional bird counting methods while promising to revolutionize real-time bird monitoring applications with increased accuracy and scalability.

Data Set

The dataset used in this study consists of 3436 natural bird scenarios meticulously filmed from 2010 to 2019, providing a wide variety of bird species with significant within-species and low between-species volatility. The photographs were shot at 21 separate observation stations (OPs) in 12 locations throughout Turkey, all intentionally placed near migration bottlenecks to capture the dynamic avian activity. These OPs include Tekirda-Kyköy (OP1), Vize (OP2), Balabanl (OP3), and others, each picked for their importance in avian migration. The dataset, available on the Kaggle data repository (Akçay et al. 2020), depicts a diverse range of bird habitats, behaviors, and poses in various biological contexts, including water surfaces, beaches, woodlands, and farmlands. (Akçay et al., 2020)

This investigation used a Canon 7D Mark II body and a Canon EF 100-400 mm f/4.5-5.6 L IS II USM telephoto zoom lens to capture photos with a resolution of 5184 X 3456 pixels (Akçay et al., 2020). The camera settings are tuned for the intricate task of capturing birds in diverse locations and activities, with a focal length of 200 mm, a sensor size of 22.4 mm X 15 mm, and a shutter speed of 1/1000 s (Akçay et al., 2020). Multiple images were taken to ensure thorough coverage of bird flocks when a single shot could not catch the entire flock, reducing overlap between succeeding shots. (Akçay et al., 2020)

The dataset's richness extends to the range of bird backgrounds influenced by observation sites, weather conditions, and bird activities. The different positions and actions of birds, such as flying, standing erect, and bending, add to the dataset's complexity and authenticity. Each photo's metadata includes GPS coordinates, which provide critical location information for each bird situation. The dataset's duration and geographic diversity make it an excellent resource for training and assessing machine learning models, particularly in bird detection and counting, furthering the study of ornithology and ecological monitoring (Akçay et al., 2020)

(a) Train Data

(b) Test Data

Figure 9.2.2 Example photos from the dataset.

Model Architecture

The Faster R-CNN (Region-based Convolutional Neural Network) architecture is a powerful model designed for object detection, and its application to bird detection involves a series of critical components. The architecture comprises three main modules: the Feature Extraction Network, the Regional Proposal Network (RPN), and the Fast R-CNN Detector.

The Feature Extraction Network is the backbone, employing a fully convolutional neural network (CNN) to extract hierarchical features from input images. Trained on a dataset designed explicitly for bird detection (Akçay et al., 2020), this network undergoes a series of convolutions that progressively capture general to more specific features. Lower layers focus on fundamental features such as edges and blobs, while upper layers discern finer details like wings, legs, the median body, and the beak. The highest layers encapsulate semantic features, understanding the entire bird's body.(Akçay et al., 2020)

The Regional Proposal Network (RPN) operates on the output feature map from the Feature Extraction Network, generating rectangular object proposals with associated scores. The RPN utilizes a sliding window approach, considering anchors at various scales and aspect ratios to propose candidate object regions. Each anchor's likelihood of containing an object is predicted, along with adjustments to the anchor's position. After sorting and non-maximum suppression, the top-ranking proposals proceed to the next stage. (Akçay et al., 2020)

Following RPN, the Fast R-CNN Detector refines and classifies the proposed regions. The detector takes anchors of different sizes, utilizing Region of Interest (RoI) pooling to extract fixed-length feature vectors. This ensures uniformity in CNN feature map usage across all anchors. The feature vectors undergo fully connected (FC) layers for classification and regression tasks. The final output of the detector includes binary class labels indicating the presence of a bird and regressed bounding box coordinates for accurate localization. (Akçay et al., 2020)

As shown in Figure 9.2.3, The input to the algorithm is a bird scene image. Firstly, a CNN generates a context-aware feature image on which the Regional Proposal Network (RPN) generates candidate regions of interest (ROIs) (Akçay et al. 2020). Inside each candidate, a Fast R-CNN is run to decide whether that ROI contains a bird and if so, adjust its coordinates and scale (Akçay et al., 2020). So, the Faster R-CNN for bird detection integrates a robust hierarchy of feature extraction, precise region proposal generation through RPN, and efficient classification and localization by the Fast R-CNN detector. This architecture demonstrates the model's ability to understand and differentiate bird species within natural scenes, offering a comprehensive solution for bird detection in diverse environments. The detailed design of this architecture ensures adaptability to varying bird poses, sizes, and environmental conditions, making it a versatile and effective tool for avian ecology research and monitoring (Akçay et al., 2020).

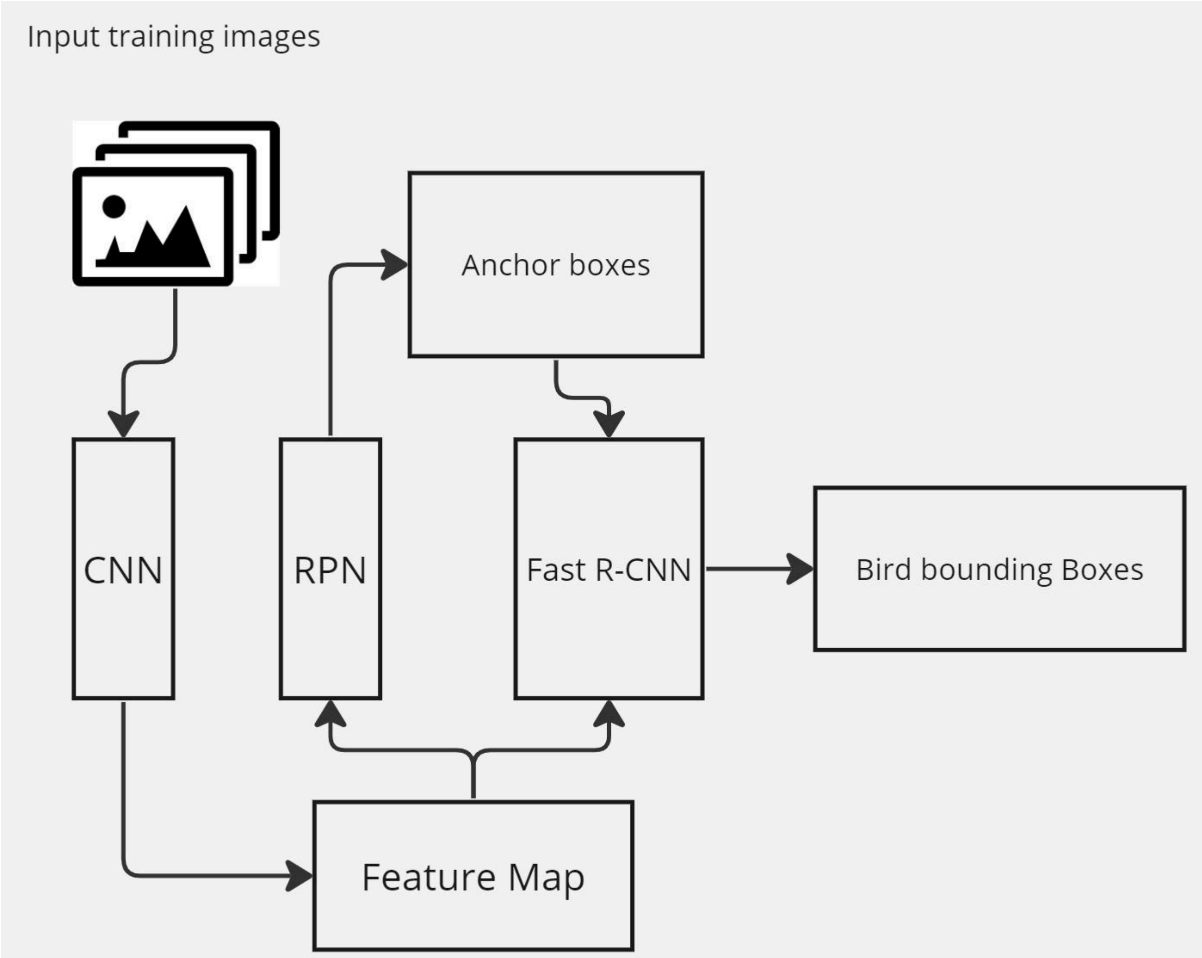

Figure 9.2.3 Faster R-CNN architecture.

Bird Counting

Counting birds using Computer Vision (CV) involves harnessing image processing techniques to detect and track birds within a live camera feed. Implementing a threshold line in this context serves as a reference point to accurately tally the number of birds as they traverse the line in the feed.

Computer Vision in Bird Counting:

Computer Vision, a field of Artificial Intelligence, facilitates extracting information from visual data, enabling the recognition and analysis of objects within images or videos.

Employing a CV for bird counting typically involves the following steps:

1. Image Acquisition: A live feed from a camera serves as the input. The continuous stream of frames captures the bird movements and actions within the designated area.
2. Preprocessing: The incoming frames undergo preprocessing steps such as noise reduction, resizing, and normalization to enhance the quality of the images and facilitate easier feature extraction.
3. Object Detection and Tracking: CV algorithms, like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), or Faster R-CNN (Region-based Convolutional Neural Networks), are used to detect and track birds in each frame. These algorithms identify birds based on learned features and provide bounding boxes around them as discussed previously.
4. Implementing the Threshold Line: Defining a threshold line within the frame is crucial in this process. This line serves as a reference point or boundary where birds passing it are counted. It can be a horizontal or vertical line set at a specific position in the frame.
5. Bird Counting: Their positions are continuously monitored as birds are detected and tracked within the frames. When a bird's trajectory intersects or crosses the threshold line, it triggers an event to increment the bird count.

Threshold Line Creation and Functionality:

Creating a threshold line involves determining its position within the frame. This line is established using coordinates corresponding to its location in the video frame. It's crucial to ensure that the line doesn't impede the birds' natural movements but is strategically placed to count their passage accurately.

Challenges and Considerations:

Several challenges need to be addressed in this process as follow.

1. Varied Bird Sizes and Orientations: Birds come in various sizes and might have different orientations while crossing the threshold line. The algorithm must account for these size, direction, and speed variations.
2. Background and Environmental Changes: Different backgrounds and environmental conditions might affect bird detection accuracy. Algorithms should be robust enough to differentiate between birds and ecological elements like trees, clouds, or other moving objects.
3. Real-Time Processing: The system processes the live feed in real-time to ensure accurate counting without significant delays. Optimization of algorithms and hardware acceleration might be necessary to achieve this.
4. Validation and Accuracy: Regular validation and accuracy checks are essential to ensure the system reliably counts birds crossing the threshold line without missing or double-counting.

Implementing a threshold line in a live feed for bird counting using Computer Vision presents a robust and efficient method to track and tally bird movements. With its continual advancements and fine-tuning, this technology holds promise in aiding ecological studies, wildlife monitoring, and conservation efforts by providing accurate and automated bird counting capabilities.

Conclusion and Future scope

The combination of deep learning methods and the analysis of videos has opened up possibilities in bird symbiosis, revolutionizing how we monitor and understand bird populations. The model's smart use of networks allows it to carefully study visual data and accurately identify and track birds in real-time situations.

By using Fast R-CNNs power, this approach enables us to create anchor boxes around birds, which forms the basis for efficient and reliable counting within particular areas of interest. Also, incorporating threshold lines within these edges helps streamline the counting process by making it easier to identify birds as they move through these defined line. This method does provide real-time census abilities. Also establishes standardized rules of conduct for consistent and similar population evaluations across different ecological areas. What's more, the involvement of citizen scientists in research has brought about a time in the history of group data collection and analysis. This approach improves the scale of data collection. Also, develop a sense of community responsibility and engagement, strengthening conservation efforts.

The effects of this model go beyond the world of college. Its ability to help accurately evaluate bird populations is important for policymakers, ecological researchers worldwide, and people trying to protect the Earth. This new and interesting approach serves as a ray of hope for preserving bird-related biodiversity and their communities by providing a tool for supervising and managing bird populations. It makes sure of a living together between humanity and the natural world.

Looking ahead, real-time bird counting through video analysis and deep learning has strong promise. Developments in this field enabled birds to even fine-tune and expand neural networks, boosting recognition speed and accuracy. Adding different data sources like noise or environmental factors will improve the accuracy of population guesses (of a number). Also, developing computer programs with relatively user-friendly interfaces and mobile apps can improve the interface's convenience. A larger group of citizen scientists will then participate in bird-related research.

Also, the scalability of this method opens up possibilities for ecological computer programs not limited to bird populations. Maybe almost the same methods could be applied to monitor different wildlife species so we can grab all of the communities. ecologists teaming up with computer scientists and people who try to reduce pollution and protect the Earth can only improve creative ideas. Naturally, there will be more advanced, complete, and thorough tools for wildlife supervision at the world level.

The future scope of the Bird Detection System based on vision presents exciting opportunities for advancements in three key areas. First, there is a need to explore and develop a lightweight and deployable model architecture. This involves optimizing the existing model to reduce its computational complexity, making it more efficient and adaptable to various hardware platforms, including those with limited resources. Second, continuous efforts should be directed toward enhancing the accuracy of bird counting. This can be achieved through the refinement of machine learning algorithms, the incorporation of more extensive and diverse datasets, and the exploration of advanced computer vision techniques. Lastly, to make this solution accessible and user-friendly, the development of a user interface is crucial. Creating an intuitive and interactive interface will enable a broader audience, including conservationists and researchers with varying technical backgrounds, to deploy and benefit from the bird detection system easily. These future endeavors aim to make the system more robust, accurate, and user-friendly, fostering its widespread adoption for avian ecology studies and wildlife conservation efforts.

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