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Deep Learning for Avian Monitoring: Bird Detection at Chilika Lake

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Abstract

Chilika Lake serves as an important habitat for migrating birds. Located on the east coast of India, in Odisha, it is the largest wintering ground for migratory waterfowl in the Indian subcontinent, covering over 1,100 km^2. Manual counting and tracking can be a difficult task due to the vast area and the large number of birds and species visiting the lagoon throughout the year. This study focuses on a method to detect and classify Cormorant birds, specifically three species: the Little Cormorant (Phalacrocorax niger), the Great Cormorant (Phalacrocorax carbo), and the Indian Cormorant (Phalacrocorax fuscicollis). The ap proach involves analysing video files containing these birds and processing each frame using a custom parallel processing system. The method achieved an accuracy of 99.27% across the three species. This study pro poses an automated process for bird detection as an alternative to traditional manual counting methods.

Keywords: Deep Learning, Bird Detection, Avian Monitoring, Chilika Lake, Object Detection, Parallel Processing, Wildlife Conservation, Species Classification, Computer Vision

1. Introduction

Chilika Lake is the largest brackish water lagoon in Asia and the second largest coastal lagoon in the world, covering an area of over 1,100 km2, located in east-coast India, in Odisha [1]. The lake serves as an important wintering ground for migratory birds, during peak migration periods, over 160 species visit the lake. Birds from distant regions, such as the Caspian Sea, Lake Baikal, Siberia, Central Asia, and the Himalayas, travel thousands of kilometers to rest and breed in this ecologically rich ecosystem [2].

Chilika Lake is the largest wintering ground for migratory birds on the Indian subcontinent. A diverse range of species, including graylag geese, white ibis, brahminy ducks, shovellers, purple moorhen, flamingos, and jacan. Approximately 45% of the birds are terrestrial, 32% are waterfowl, and 23% are waders.

The lagoon is also home to 14 types of raptors. Migratory waterfowl arrive from regions as far as the Caspian Sea, Baikal Lake, Russia, Mongolia, Siberia, Iran, Iraq, Afghanistan, and the Himalayas [3].

In 2007, nearly 840,000 birds visited the lake, with 198,000 spotted in Nalbana Island. A census in January 2008 recorded 900,000 birds, of which 450,000 were sighted in Nalbana. The removal of invasive species, particularly water hyacinth, has contributed to the increasing attraction of birds to the lake [2,3].

Given the lakes importance in biodiversity and its role in bird migration. It's very essential for conservation and research. Manual counting and tracking can be a difficult task due to the large area and the huge number of birds visiting the lagoon throughout the year.

Identifying and classifying bird species has traditionally been a challenging task, even for expert biologists and ornithologists. The lack of experts and the limitations of manual methods further complicate bird identification and monitoring. Advancements in computer vision, particularly deep learning models using Convolution Neural Networks (CNN), have enabled automation in bird species identification [4-14]. Deep learning models such as SSD (Single Shot Multi-box Detector), YOLOv4, and YOLOv5 (You Only Look Once) have been used successfully for bird classification. Kumar et al. demonstrated that the YOLOv4 model achieved an accuracy of 95.43%, with 93.94% precision, 94.34% recall, and 94.27% F1 score across 20 bird species, along with a 96.99% mean Average Precision (mAP) score [4].

In this research, we aimed to develop a model using Convolutional Neural Networks (CNNs) with the EfficientNet architecture as the base. EfficientNet has been applied in

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various image processing tasks and has shown significant promise for this purpose [7]. The primary focus is for the model to detect and clasify the Cormorant species found in Chilika Lake. Specifically, we aim to classify three species of cormorants: the Little Cormorant (Phalacrocorax niger), the Great Cormorant (Phalacrocorax carbo), and the Indian Cormorant (Phalacrocorax fuscicollis).

2. Methodology

The primary objective of this research being, to develop an efficient deep learning model that can detect the Cormorant species. We needed both Images, and videos, of this 3 birds specifically. Where the individual Data collected must not have any other bird in it for sole purpose of training and testing this model.

Considering the importance of the quality and authenticity of the data, different sources were consulted to obtain the required information. For training, static images of the three Cormorant species were used, with each image containing only one species. A variety of backgrounds was selected for each bird to improve the model's detection capabilities. A total of 1,511 images were collected: 400 of the Little Cormorant, 584 of the Great Cormorant, and 527 of the Indian Cormorant. For testing, 44 videos were collected: 15 of the Little Cormorant, 13 of the Great Cormorant, and 16 of the Indian Cormorant. The majority of

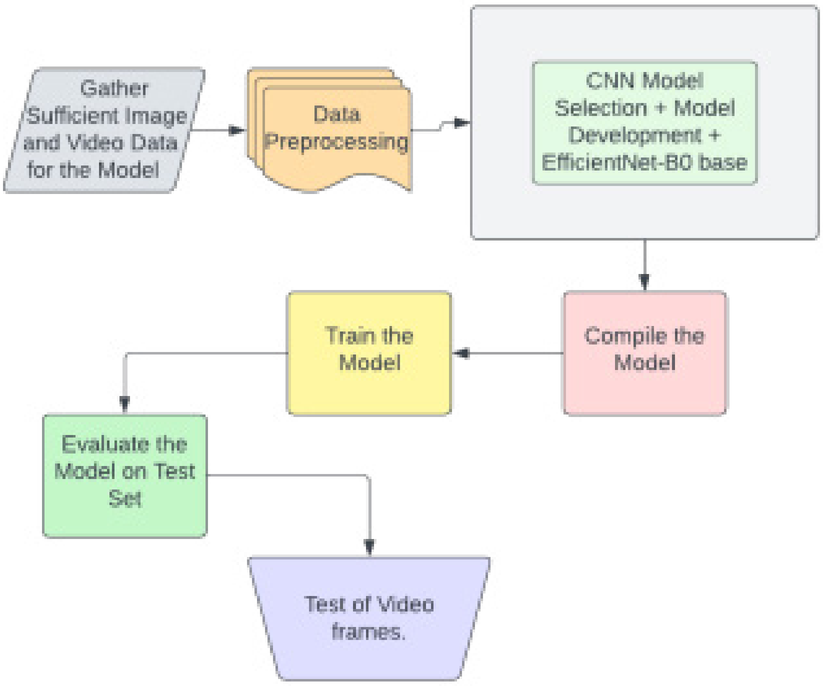

Figure 1: Methodology Process Flow Chart

this data was sourced from the *eBird Media Library* (media.ebird.org), which provides a large collection of bird images captured in diverse environments. Additional videos with varied backgrounds were obtained from other open sources on the web.

The overall methodology followed in this research is summarized in Figure 1. The collected data was processed using standard methods to ensure consistency:

• **Data Cleaning:** Images and videos with poor resolution or excessive noise were removed.

• **Resizing:** All images and video frames were resized to 224x224 pixels. – Normalization: Pixel values were scaled to [0, 1] by dividing by 255.

3. Model Selection

EfficientNet was selected as the foundational architecture due to its demonstrated performance in image classification tasks [8–10,14]. The EfficientNet family's compound scaling technique optimizes depth, width, and resolution, making it particularly effective for processing high-resolution video frames of birds in diverse environments.

The pre-trained EfficientNet-B0 model serves as the spatial feature extractor, chosen for its computational efficiency in resource-constrained field environments. It effectively captures the distinctive features of Cormorant species, including their characteristic silhouettes, plumage patterns, and movement behaviors from video frames.

The architecture of the model is shown in Figure 2. While the current implementation processes individual frames, future work will incorporate temporal analysis across frame sequences using 3D convolutions or recurrent neural networks (RNNs). This enhancement will enable the model to capture species specific flight patterns and diving behaviors, providing more accurate species classification through combined spatial-temporal analysis.

3.1. Implementation

The technology stack used for developing the deep learning model included Python as the programming language and the TensorFlow library for defining, compiling, and training the model.

To handle video processing efficiently, a custom multi-threaded parallel pro cessing application was developed using Rust. The architecture of this model is shown in Figure 3. This application extracts frames from videos, processes each frame for species detection, and saves the output for evaluation. The primary goal of the multi-threaded application is to minimize overhead and computation required for frame extraction, preprocessing, and processing, thereby improving efficiency.

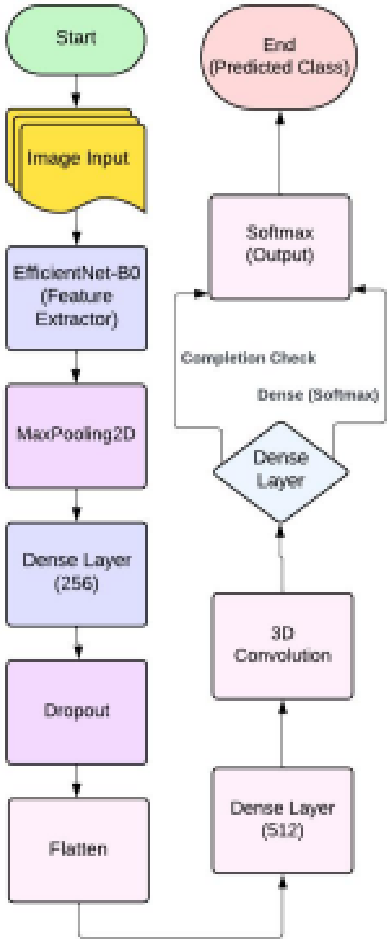

Figure 2: Custom Model Architecture

Although the first phase of this project focuses solely on detecting bird species, the design and development of the multi-threaded application, along with the choice of EfficientNet as the base architecture, were made with future improvement in mind.

Recent studies have demonstrated the effectiveness of multi-threaded approaches in video processing for object detection. For instance, one study proposed a multi-threaded approach using YOLOv3 to handle large-scale video streams, improving detection performance by 26% in terms of frames per second (fps) without compromising accuracy [5]. Another approach optimized system resources by introducing a multi-thread frame tiling model for concurrent pro cessing of video streams, achieving a 116.6 fps detection rate, significantly higher than the original YOLOv3 [6]. These advancements in parallel processing techniques influenced the architecture designed for this study in terms of real-time bird species detection.

3.2. Model Training

The training process was configured with the following parameters:

• **Optimizer:** Adam with a learning rate of 0.0001.
• **Loss Function:** Categorical Crossentropy, suitable for multi-class classification.
• **Metrics:** Accuracy to monitor model performance.

The model was trained over 10 epochs with a batch size of 4, using a split dataset comprising training and validation sets. Regularization techniques such as dropout (rate of 0.5) were applied to prevent overfitting. The training and validation loss and accuracy were tracked throughout the process, as illustrated in Figure 4 and Figure 5.

To evaluate the model's effectiveness, the test set was used to compute the confusion matrix shown in Figure 6.

3.3. Results

The model's performance was evaluated by classifying images of three different Cormorant species: Little Cormorant, Indian Cormorant, and Great Cormorant. The images below show the predictions for each bird species, along with the respective probability distributions for each classification.

3.3.1. Little Cormorant

Figure 7 shows the image of the Little Cormorant along with the prediction probabilities for each class. As shown in the following Table 1 is the probability distribution for the prediction of the Little Cormorant:

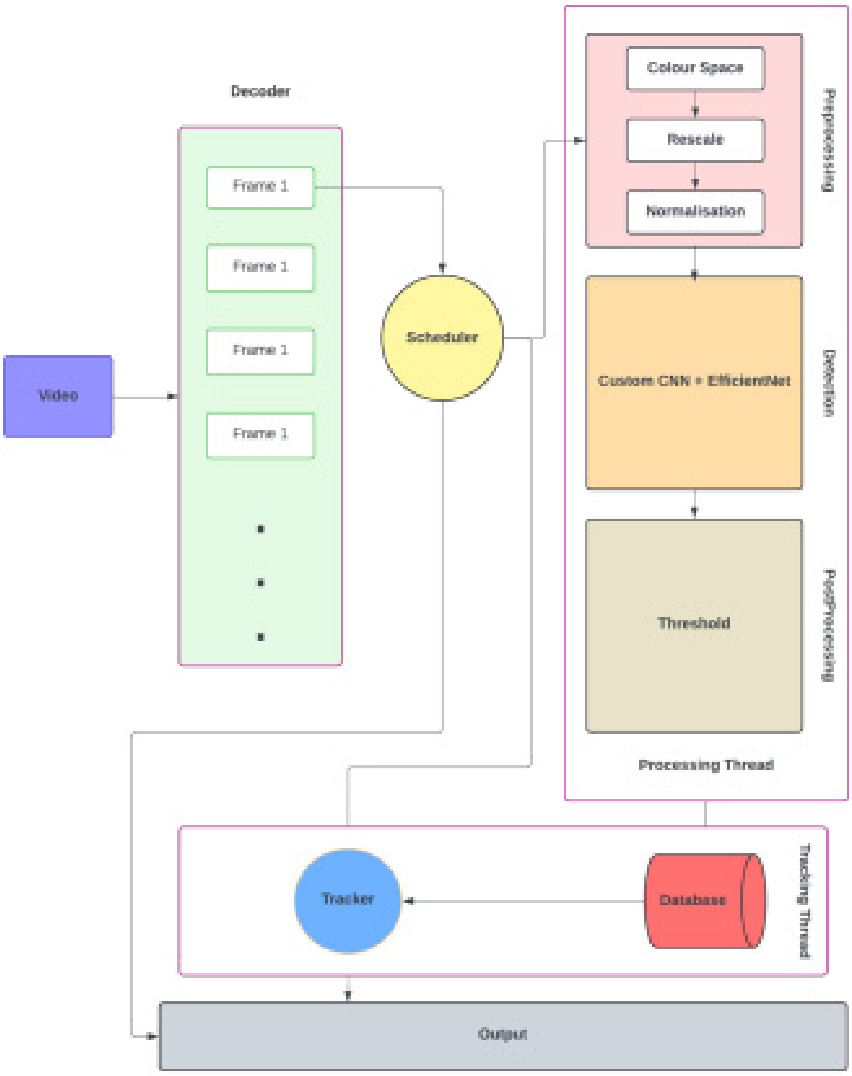

Figure 3: Architecture of Video Frame Extraction and Multiprocessing

Species	Probability
Little Cormorant	0.7433
Indian Cormorant	0.2520
Great Cormorant	0.0047

Table 1: Prediction Probabilities for Little Cormorant

Figure 4: Training and Validation Accuracy Over Epochs

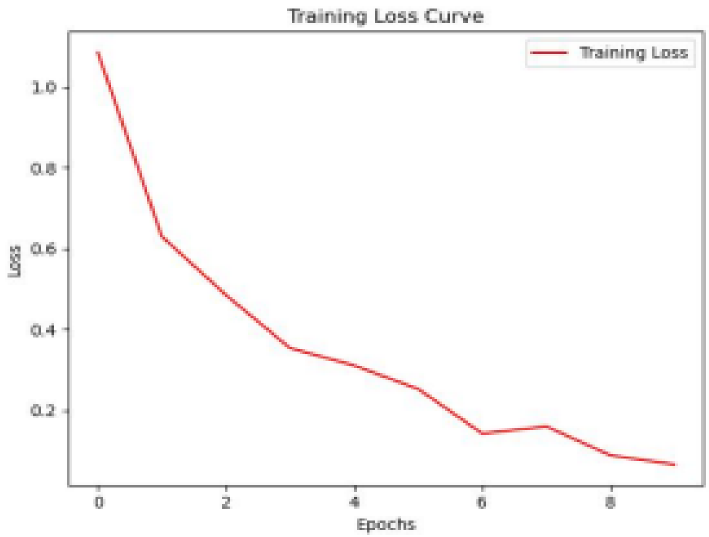

Figure 5: Training and Validation Loss Over Epochs

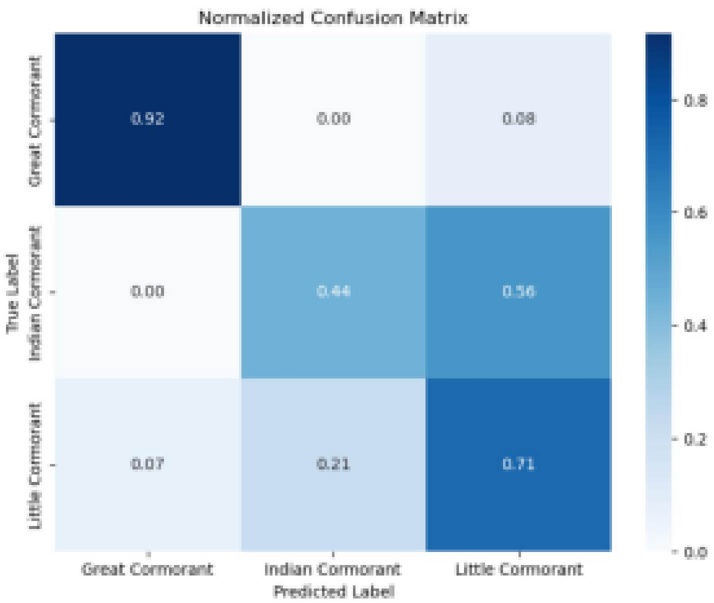

Figure 6: Confusion Matrix for Test Set Classification.

Figure 7: Prediction for Little Cormorant with Probability Distribution

Figure 8 shows the image of the Indian Cormorant along with the prediction probabilities for each class.

Figure 8: Prediction for Indian Cormorant with Probability Distribution

As shown in the following Table 2 is the probability distribution for the prediction of the Indian Cormorant:

3.3.2. Great Cormorant

Figure 9 shows the image of the Great Cormorant along with the prediction probabilities for each class.

As shown in the following Table 3 is the probability distribution for the prediction of the Great Cormorant:

The model's overall accuracy was found to be 99.27% based on the number of correct predictions.

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Species	Probability
Little Cormorant	0.2327
Indian Cormorant	0.7646
Great Cormorant	0.0017

Table 2: Prediction Probabilities for Indian Cormorant

Figure 9: Prediction for Great Cormorant with Probability Distribution

Species	Probability
Little Cormorant	0.0284
Indian Cormorant	0.0006
Great Cormorant	0.9710

Table 3: Prediction Probabilities for Great Cormorant

4. Future Work and Discussion

This particular model demonstrates the capability to classify Cormorant species. Several extensions to this study can be envisioned:

4.1. Analysis of Migration Patterns

The LSTM networks can be employed for temporal modeling to achieve the following:

• Predict seasonal migration patterns of Cormorant species at Chilika Lake.
• Analyze historic migration data to develop forecasting models for arrival and departure times.
• Identify environmental factors influencing migratory behaviors.

4.2. Automatic Counting of Populations

• Develop algorithms for real-time counting of birds in video streams.
• Apply crowd detection techniques to handle large flocks.
• Create daily and seasonal tracking systems for population monitoring.

4.3. System Improvement

• Generalize the system to recognize other species beyond Cormorants.
• Enhance capabilities for processing real-time streams from multiple video inputs.
• Build interfaces to facilitate collaboration between wildlife researchers and conservationists, allowing multi-user interactions.

4.4. Data Collection Improvements

• Develop a comprehensive video dataset covering the entire migration process.
• Include diverse weather and lighting conditions in the dataset.
• Incorporate drone footage for aerial perspectives of bird migrations.

5. Conclusion

This research presents a deep learning approach for automated detection and classification of Cormorant species at Chilika Lake, achieving an accuracy of 99.27%. The implementation of the EfficientNet architecture combined with cus tom parallel processing demonstrates the feasibility of automated bird monitoring systems. This approach reduces the manual effort required for bird counting and classification while maintaining high accuracy. The model's success in distinguishing between Little, Great, and Indian Cormorants provides a foundation for expanding to other species and implementing real-time monitoring systems. The proposed methodology contributes to efficient wildlife monitoring and establishes a framework for future advancements in automated avian monitoring systems. This work supports conservation efforts at Chilika Lake and can be adapted for similar ecosystems worldwide.

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