Automated Biometric Identification of Mugger Crocodiles using Machine Learning

*A non-invasive approach for wildlife monitoring

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***Abstract*—This paper presents a machine learning-based framework for the automated biometric identification of free-ranging Mugger Crocodiles (*Crocodylus palustris*) using UAV imagery. The approach employs bounding box detection followed by feature extraction techniques such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Oriented FAST and Rotated BRIEF (ORB) to analyze unique dorsal scute patterns. The dataset consists of 88,000 high-resolution images that capture 143 crocodiles at 19 locations in Gujarat, India. Our results demonstrate the feasibility of a non-invasive identification system, serving as an alternative to traditional tagging methods. Future work will focus on ensemble learning strategies and dataset expansion to improve precision and robustness.**

***Index Terms*—Biometric Identification, Mugger Crocodiles, Machine Learning, UAV Imagery, Bounding Box Detection, Feature Extraction**

I. Introduction

Biometric identification plays a **critical role** in **wildlife conservation** by enabling researchers to track individual animals over time. Traditional **tagging and microchipping methods** are invasive, time-consuming, and often impractical for **free-ranging species** such as Mugger Crocodiles.

Recent advances in **machine learning (ML) and UAV-based imaging** have made **non-invasive biometric identification feasible**. Although **deep learning models** such as CNNs (YOLO, ResNet) have been used for **species-level classification**, they struggle with **individual recognition**. Instead, **feature-based machine learning models** have been proven to be **more robust for individual biometric identification** in small datasets.

This paper introduces a **feature-based ML system** for **automated crocodile identification** using UAV imagery. The approach extracts unique scute patterns and applies **classical ML classifiers** to **differentiate individuals**.

II. Dataset Description

Our dataset consists of **88,000 high-resolution (3840x2160) images** captured using a **DJI Mavic 2 Zoom UAV** from **19 locations in Gujarat, India**.

Dataset Characteristics:

- **Species:** 143 Mugger Crocodiles (*Crocodylus palustris*)
- **Frame Resolution:** 3840 × 2160 pixels (96 DPI)
- **Optical Zoom:** 24–48 mm
- **Flight Height:** 8–10 meters
- **Recording Duration:** 30 sec – 1 min per session

Data Collection Process: When a crocodile is spotted, the UAV maneuvers closer to **capture dorsal scute patterns**. Frames are extracted from video clips using the **OpenCV-Python library**.

III. Methodology

The proposed system follows a structured pipeline comprising the following steps:

A. Bounding Box Generation

The first step involves detecting **crocodile regions** within UAV-captured images. A **bounding box detection algorithm** is used to localize the crocodile in each image. This is done using:

- **YOLOv5 (You Only Look Once)** for fast, real-time object detection.
- **OpenCV Contour Detection** for edge-based localization.

This ensures that only the **dorsal scute patterns** are extracted for further processing.

B. Feature Extraction

Once the bounding boxes are generated, we apply feature extraction techniques to capture **unique biometric markers**:

- **SIFT (Scale-Invariant Feature Transform):** Detects key points invariant to rotation and scale.
- **HOG (Histogram of Oriented Gradients):** Captures texture and shape-based features.
- **LBP (Local Binary Patterns):** Encodes local texture features for fine-scale scute identification.
- **ORB (Oriented FAST and Rotated BRIEF):** Provides computationally efficient key-point matching.

C. Classification

After feature extraction, we train multiple **machine learning classifiers** to **differentiate individual crocodiles**:

- **Support Vector Machine (SVM)**
- **Random Forest**
- **k-Nearest Neighbors (k-NN)**
- **XGBoost**

D. Model Evaluation

Models are evaluated using **10-fold cross-validation** with the following metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

IV. Future Work

To enhance system performance, future work will focus on:

- **Ensemble Learning:** Combining multiple classifiers for higher accuracy.
- **Feature Optimization:** Refining feature selection for improved classification.

References

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