Machine Learning‑Based Approach for Automated Biometric Identification of Mugger Crocodiles

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***Abstract*—This paper presents a machine learning–based framework for the automated biometric identification of free-ranging mugger crocodiles using unmanned aerial vehicle (UAV) imagery. The approach employs a pretrained model to generate bounding boxes that localize individual crocodiles in high-resolution frames. Subsequent feature extraction is performed using classical methods—including Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Gray-Level Co-occurrence Matrix (GLCM)—to capture unique dorsal scute patterns. The experimental dataset consists of approximately 88,000 frames capturing 143 crocodiles across 19 locations in Gujarat, India. Preliminary results indicate that the proposed pipeline can serve as a non-invasive alternative for wildlife biometric identification. Future work will focus on ensemble learning strategies and the integration of multi-seasonal data to enhance the True Positive Rate (TPR).**

Index Terms—Biometric Identification, Mugger Crocodiles, Machine Learning, UAV Imagery, Feature Extraction, Ensemble Learning.

I. Introduction

Biometric identification plays a vital role in wildlife monitoring and conservation. Traditional methods such as tagging can be invasive and stressful for animals. With the advent of UAV technology and advanced machine learning techniques, non-invasive biometric identification has become increasingly feasible. This work addresses the challenge of identifying individual mugger crocodiles in free-ranging environments using a classical machine learning approach. The motivation is to reduce human intervention and improve monitoring accuracy without the high computational costs often associated with deep learning models.

II. Literature review

Recent studies have demonstrated the benefits of combining deep learning and machine learning for biometric applications. For instance, Kokal et al. [1] reviewed integrated deep learning frameworks for biometric mobile authentication, while Khan and Bhatt [2] explored hybrid recognition systems using stacked autoencoders and Random Forest classifiers. More specifically, Ghosal et al. [3] applied a UAV-based CNN model (YOLO-v5l) to identify mugger crocodiles with an accuracy of 89.2%. Additional work [4]–[6] has extended these methodologies to other wildlife species, highlighting the potential of aerial imagery in automated species recognition. However, there remains a gap in exploring classical feature extraction and machine learning methods for such applications.

III. Dataset description

The dataset consists of 88,000 UAV-captured frames obtained using a DJI Mavic 2 Zoom drone. Key aspects include:

Species: 143 free-ranging mugger crocodiles (approx. 1.5 m in length)

Locations: 19 distinct sites in Gujarat, India

Imaging Parameters:

- Frame resolution: 3840 × 2160 pixels at 96 DPI
- Optical zoom: 24–48 mm
- Flight height: 8–10 meters
- Recording duration: 30 seconds to 1 minute per session

Capture Protocol: Upon spotting a crocodile, the drone was maneuvered closer to capture detailed dorsal scute patterns. Frames were extracted from video clips using the OpenCV-Python library.

IV. Methodology

The proposed framework comprises three major components:

A. Bounding Box Generation

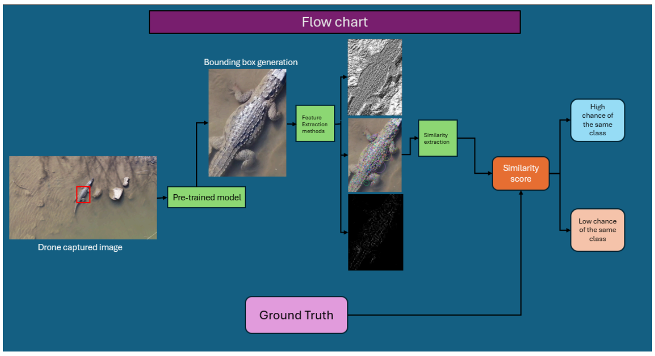
- A pretrained object detection model is utilized to automatically generate bounding boxes around crocodiles, ensuring that subsequent processing focuses on regions of interest [3].

B. Feature Extraction

- To capture the unique biometric markers on each crocodile, multiple feature extraction techniques are applied:
  - SIFT: Extracts scale- and rotation-invariant features.
  - HOG: Captures gradient orientation distributions, useful for texture analysis.
  - LBP: Encodes local texture information efficiently.
  - GLCM: Measures spatial relationships between pixel intensities to describe textural features.

C. Classification

After feature extraction, classical machine learning classifiers are employed to differentiate individuals based on their unique dorsal patterns. While initial experiments indicate promising performance, further optimization—potentially through ensemble learning—is planned to enhance the overall TPR.



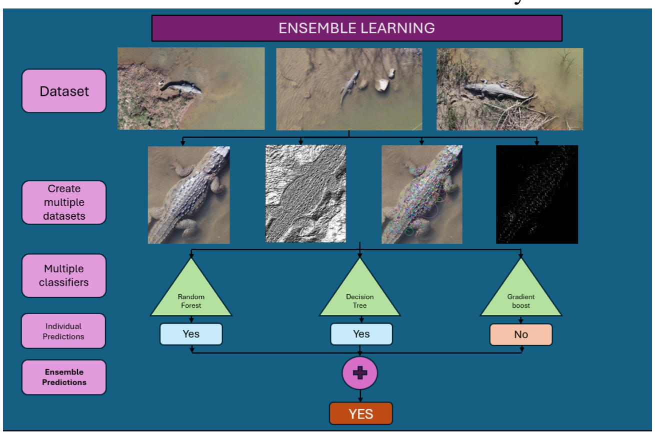
V. Experimental Results

Preliminary evaluations show that the integration of accurate bounding box generation with classical feature extraction methods yields distinguishable feature representations for individual mugger crocodiles. Although detailed quantitative metrics are still under refinement, early comparisons suggest that the classical approach may serve as a computationally efficient alternative to deep learning models in controlled conditions [3].

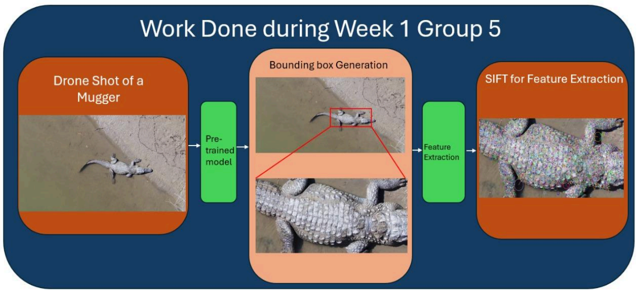
VI. Future work

Future research will concentrate on the following enhancements:

- Ensemble Learning: Combining multiple classifiers to improve prediction accuracy.
- Dataset Expansion: Incorporating multi-seasonal data to capture variations in environmental conditions and animal appearances.
- Feature Optimization: Refining feature selection and extraction methodologies to further increase the TPR and overall robustness of the system.



VII. Results



Similarity Scores	Value
SIFT Match Score	0.6050
LBP Chi-square distance similarity	0.97
HOG Histogram Intersection similarity	0.8857
GLCM Match Score	0.99

Table 2: Scores while comparing the same image

Similarity Scores	Value
SIFT Match Score	0.4928
LBP Chi-square distance similarity	0.9022
HOG Histogram Intersection similarity	0.7806
GLCM Match Score	0.9217

Table 3: Comparisions on the same image but different frame number

Similarity Scores	Value
SIFT Match Score	0.1975
LBP Chi-square distance similarity	0.4040
HOG Histogram Intersection similarity	0.7533
GLCM Match Score	0.4357

Table 4: Comparisions on different class

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