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

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***Abstract*—This study introduces a machine learning framework for automated biometric identification of free-ranging mugger crocodiles using unmanned aerial vehicle (UAV) imagery. A pretrained model generates bounding boxes to localize individual crocodiles in high-resolution frames, followed by feature extraction using classical techniques such as 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 dataset comprises approximately 88,000 frames of 160 crocodiles across 19 locations in Gujarat, India. An ensemble learning approach, integrating XGBoost, Deep Learning, and Random Forest classifiers, was employed to classify the 160 individuals by fusing GLCM and LBP features, achieving enhanced accuracy and robustness compared to individual classifiers. This non-invasive pipeline demonstrates potential for wildlife biometric identification. Future efforts will aim to incorporate multi-seasonal imagery and investigate deep learning-based feature fusion to further improve 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: 160 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.[Fig.1]

This method had yielded an accuracy of 56% so another ensemble approach was used:

A. Feature Extraction using GLCM and LBP

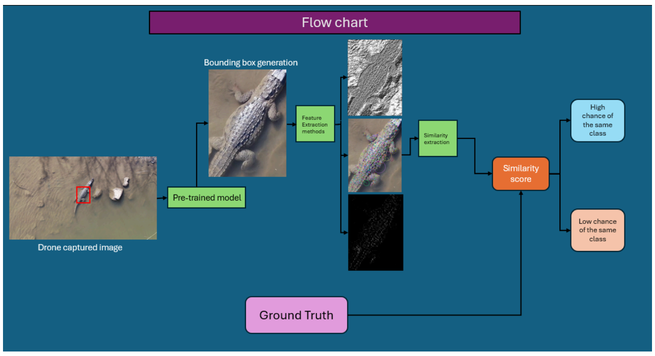
- A robust feature vector is constructed by integrating outputs from the Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) and concatenating them. This combination is effective due to the complementary strengths of GLCM, which captures spatial relationships and texture relationship among pixel intensities, and LBP, which encodes local texture patterns. These texture descriptors exhibit strong similarity scores and adeptly detect diverse textural variations, resulting in a unified feature vector that comprehensively represents each sample.

B. Probability Estimation using XGBoost and Multi Layer Perceptron

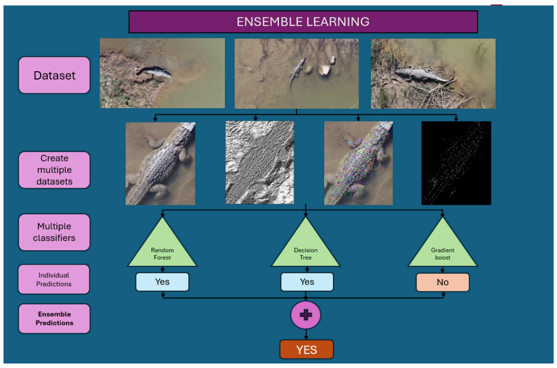
- The extracted feature vector is processed through two distinct classification models: XGBoost and a MLP. These models independently generate probability estimates for each input:
- XGBoost is selected for its superior performance on structured data, excelling in capturing complex nonlinear relationships.
- The MLP model leverages its capacity for intricate pattern recognition, offering a contrast to XGBoost's approach.
- Both models produce probability distributions across possible classes for each sample, enhancing predictive diversity.

C. Final Classification using Random Forest and XGBoost Ensemble

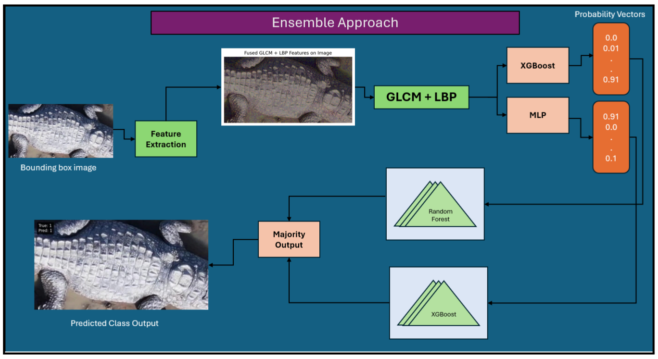
The probability outputs from XGBoost and MLP are given to form the input for an ensemble of five Random Forest classifiers where the random forest gets the input from XGBoost and four additional XGBoost classifiers get the input from the MLP Model. Each Random Forest classifier processes the same probability data with unique random seeds to foster prediction diversity, while the XGBoost classifiers further enhance robustness. The final classification for each sample is determined through majority voting across all nine classifiers, reducing decision errors and improving overall classification reliability.



[Fig.1 Structural Similarity Between Images]



[Fig.2 Ensemble Approach-1]



[Fig.2 Final Ensemble Approach]

V. Experimental Results

Extensive testing of the proposed classification method involved using a dataset containing 160 distinct classes. Performance metrics analyzed the results by measuring overall accuracy and per-class accuracy as well as confusion matrix analysis and F1-score and class-wise precision and recall.

A. Overall Performance

- The model reached an 85.94% accuracy value through analysis of correct predictions among total prediction attempts. The model proves its capability in performing multi-class classification tasks successfully for a variety of categories although only achieving 85.94% accuracy. The model obtained 85.94% True Positive Rate along with 99.86% True Negative Rate in cumulative rates.

B. Confusion Matrix Analysis

- All 160 classes received confusion matrix visualization through the Figure which used normalized values. The majority of predicted instances cluster together on the diagonal part of the matrix which indicates strong accuracy in class identification. Most of the predictive values appear along the diagonal line yet few off-diagonal points indicate that classification errors happen between classes with overlapping features.

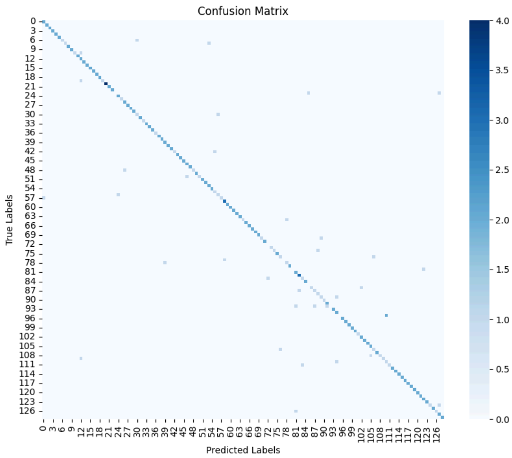


Figure-1.

C. Per-Class Accuracy

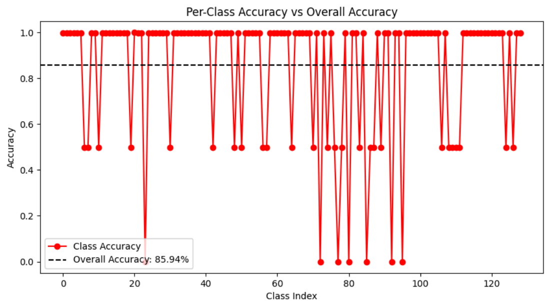


Figure-2.

VI. Future work

Future work can replace YOLO v11-based bounding box detection with advanced image segmentation methods, enabling more precise localization and improved accuracy in classical machine learning-based mugger identification . Moreover the future work also involves system deployment for identifying the muggers.

References

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