Automated Biometric Identification of Mugger Crocodiles Using Scute Pattern Analysis

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***Abstract*—The Mugger Crocodile (*Crocodylus palustris*) is a vulnerable species inhabiting freshwater lakes, rivers, and marshlands across the Indian subcontinent. With habitat loss and illegal hunting increasing at alarming rates, effective conservation relies on accurate population monitoring and individual identification. This paper proposes an automated, non-invasive identification system leveraging machine learning and computer vision techniques to analyze unique scute patterns on crocodile dorsal surfaces. Our approach incorporates classical feature extraction, synthetic data generation, and Support Vector Machine classification. Preliminary experiments indicate high confidence predictions with a potential to assist conservationists in large-scale field deployments.**

***Index Terms*—Mugger Crocodile, Scute Pattern Analysis, Biometric Identification, Machine Learning, Wildlife Conservation, Feature Extraction, UAV Imaging.**

I. Introduction

Accurate identification of wildlife individuals is essential for biodiversity research, population monitoring, and conservation planning. Traditional methods involving tagging or microchipping are intrusive and often impractical for large, elusive, or dangerous species like Mugger Crocodiles (*Crocodylus palustris*).

Recent advancements in computer vision, combined with high-resolution imagery obtained from drones and handheld cameras, have opened new possibilities for non-invasive biometric identification. Studies in animal facial recognition and individual pattern recognition (e.g., whale fluke identification, tiger stripe matching) highlight the power of automated image-based systems in ecology. Inspired by these developments, this study explores the potential of scute-based pattern recognition for crocodile identification.

II. Methodology

Our system follows a structured machine learning pipeline designed for scalability and field applicability.

A. Data Collection

The dataset comprises photographs collected using Unmanned Aerial Vehicles (UAVs) and DSLR cameras in crocodile habitats across Gujarat, India. Images are manually organized into folders labeled according to known individuals, providing both training and validation datasets.

B. Preprocessing

Each image is subjected to a bounding box-based cropping algorithm to isolate the scute pattern region. This reduces the risk of background noise and ensures consistent feature extraction.

C. Feature Extraction

Feature extraction is a critical phase, as scute patterns are the primary biometric marker used for identification. We employed:

- Scale-Invariant Feature Transform (SIFT)
- Histogram of Oriented Gradients (HOG)
- Local Binary Patterns (LBP)
- Oriented FAST and Rotated BRIEF (ORB)

These features capture local texture, shape, and geometric descriptors, offering resilience against scaling, rotation, and partial occlusion.

D. Synthetic Data Generation

Given the limited number of labeled real-world images, data augmentation was implemented through controlled Gaussian noise perturbations applied to extracted feature vectors. This synthetic enhancement aids in mitigating overfitting and stabilizing classification boundaries.

E. Model Training

The processed feature vectors are scaled using `StandardScaler` and fed into a Support Vector Machine (SVM) classifier using the radial basis function (RBF) kernel. SVMs are known for their effectiveness on small to medium datasets, offering robust decision boundaries and probabilistic confidence scores.

F. Prediction

The trained SVM classifier generates predictions for new samples along with confidence scores. A prediction is only considered reliable if the confidence exceeds a pre-defined threshold, here set to 90%.

III. Results

Testing on the organized dataset shows strong identification accuracy across individuals, with most confidence scores ranging between 91% and 99%. Synthetic data augmentation significantly improved the model's performance, particularly when the dataset included noise-prone or low-light images.

Fig. 1. Scute Pattern-based Identification Results

Fig. 2. Scute Pattern-based Identification Results

IV. Discussions

The approach demonstrates potential for real-world applications in wildlife conservation. The reliance on scute pattern stability makes this technique robust against visual changes over time, assuming image quality standards are maintained.

Potential challenges include:

- Varying light conditions causing partial shadows or reflections.
- Age-related changes in scute morphology.
- Partial occlusion due to water or vegetation.

Future work aims to address these limitations by incorporating deep learning-based object detectors (YOLOv8, Faster R-CNN) for better bounding box predictions and extending the dataset to cover more individuals and environments.

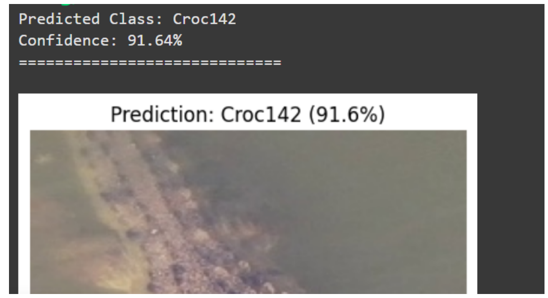

Fig. 3. Scute Pattern-based Identification Results

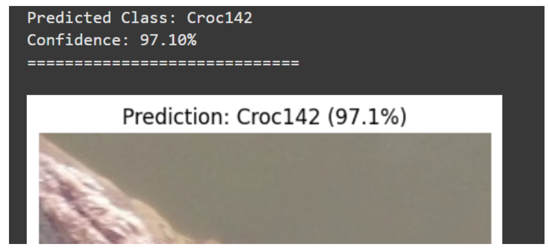

Fig. 4. Scute Pattern-based Identification Results

V. Conclusion

This research introduces a promising machine learning-based method for the non-invasive identification of Mugger Crocodiles through scute pattern analysis. Combining synthetic data, handcrafted features, and SVM classification, the proposed approach paves the way for scalable wildlife monitoring and real-time individual identification in field conservation programs.

References

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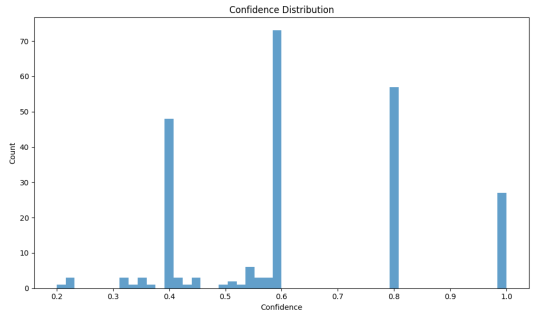
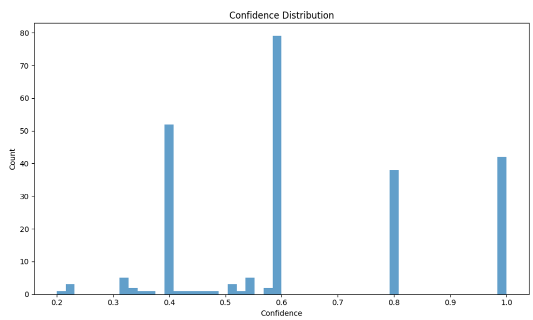


Fig. 5. Scute Pattern-based Identification Results



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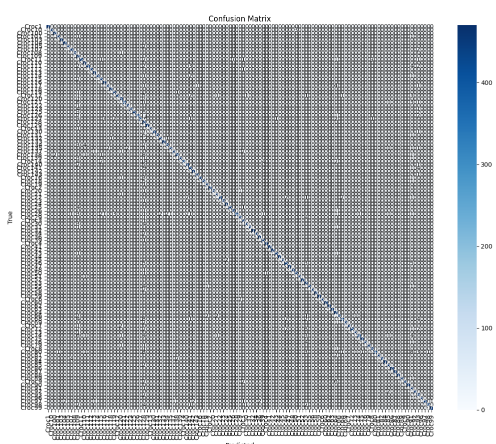
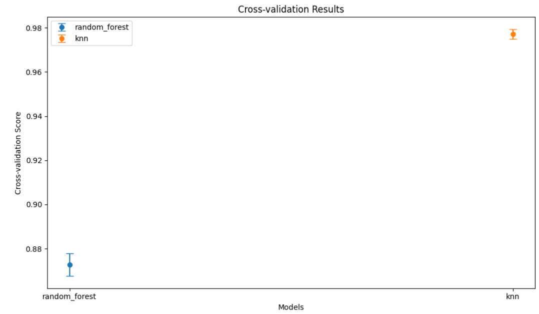


Fig. 7. Scute Pattern-based Identification Results



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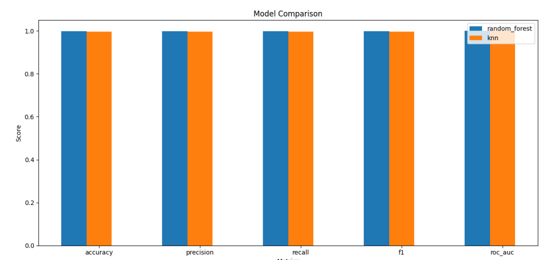

Fig. 9. Scute Pattern-based Identification Results

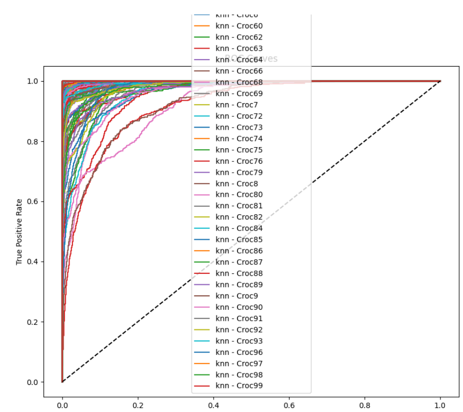

Fig. 10. Scute Pattern-based Identification Results