Open-Set Biometric Algorithm (Complete Methodology)

1. Problem Definition

The objective of this project is to design an **Elephant Re-Identification (Re-ID) system** capable of recognizing **individual elephants** from field images under **open-set conditions**. Unlike closed-set classification, the system must:

- Correctly identify **known elephants**
- Explicitly detect **unknown / new individuals**
- Support **incremental enrolment without retraining** This problem is therefore formulated as an **open-set biometric recognition task**, analogous to human face recognition systems (e.g., Face-ID).

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2. Why Open-Set Biometric Recognition (Not Classification)

Closed-Set Classification (Rejected)

A closed-set classifier answers:

> "Is this elephant ID-1, ID-2, or ID-N?"

This approach fails because:

- The number of identities is **not fixed**
- Only **2–3 images per elephant** are available (few-shot)
- New elephants appear continuously
- Adding a new elephant requires **retraining the entire network**
- Retraining risks **catastrophic forgetting**

Open-Set Biometric Recognition (Adopted)

In the biometric paradigm:

- The model **does not learn identity labels**
- It learns a **similarity function**
- Each image is mapped to a **fixed-length embedding vector**
- Similar elephants → embeddings close together
- Different elephants → embeddings far apart New elephants are enrolled by **storing embeddings**, not retraining the model.

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3. Dataset Overview

3.1 Dataset Composition

The dataset consists of **high-resolution field images** and is divided into two main groups:

Makhna Dataset

- Adult male elephants (tuskless bulls)
- Each folder corresponds to **one individual Makhna**
- **Highly imbalanced number of images per individual**:
  - Some individuals have **very few images** (e.g., 2–3)
  - Others have **moderate to large collections** (e.g., 20–30+ images)
- Example:
  - *Makhna_9* → ~36 images
  - *Makhna_10* → ~5 images This natural imbalance reflects **uneven field sightings** and must be handled explicitly during training.

Herd Dataset

- Elephants observed in **social (herd) settings**
- Organized hierarchically by:
  - **Herd number**
  - **Demographic group**:
    - Adult_Female
    - **Sub_Adult**
    - Juvenile
    - Calf
- Each lowest-level folder corresponds to **one individual elephant** This structure preserves both **social context** and **individual identity**.

3.2 Image Characteristics

- Resolution:
  - Mostly ~4608 × 3456
  - Some ~5184 × 3456
- High variability in:
  - Pose
  - Lighting
  - Occlusion
  - Background This is **uncontrolled, real-world field data**.

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4. Key Dataset Challenges

1. **Few-shot learning** (2–3 images per ID)
2. **No bounding box annotations**
3. **Multi-elephant scenes**
4. **High inter-individual similarity**
5. **Large biological variation across age and sex classes**

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5. Weak Supervision via Red Arrow

What the Arrow Is

- Digitally painted
- Solid red
- Same shape across images
- Appears **only in multi-elephant images**
- Points to the **target elephant**

What the Arrow Is NOT

- Not a bounding box
- Not a head locator
- Not a biometric region indicator

Correct Interpretation

> **The arrow is an identity selector, not a localization signal.**

It answers:

> "Which elephant in this image is the one of interest?"

6. Phase A — Data Understanding (Frozen Assumptions)

ID	Assumption	Status
A1	Arrow is digitally painted and consistent	☑
A2	Arrow always points to target elephant	☑
A3	Arrow position varies (head/back/side)	☑
A4	Images are high resolution	☑
A5	Open-set recognition required	☑
A6	Identity unit = individual elephant	☑
A7	Robustness > speed	☑

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7. Phase B — Preprocessing & MegaDetector Integration

7.1 Objective

Convert raw images into **elephant-centric inputs** suitable for biometric learning using automated detection.

7.2 MegaDetector Integration (UPDATED)

Key Breakthrough: Integrated MegaDetector v5a for automated elephant detection

- **100% detection rate** (validated on sample set)
- Works with or without arrows
- Provides precise bounding boxes around elephants
- Eliminates manual cropping heuristics

Validated Parameters:

- MegaDetector Model: **v5a**
- Confidence Threshold: **0.4** (validated through exploration)
- Padding Ratio: **15%** around bounding box (validated)
- Arrow Detection: Retained for **multi-elephant selection**

7.3 Detection-Based Preprocessing Strategy

Step 1: Elephant Detection

1. Load MegaDetector v5a model (once at startup)
2. Run detection on each image
3. Filter for animal category (category '1')
4. Apply confidence threshold (≥0.4)
5. Obtain normalized bounding boxes [x, y, width, height]

Step 2: Target Elephant Selection

For Multi-Elephant Scenes (Arrow Present):

1. Detect red arrow via HSV segmentation
2. Find arrow tip coordinates
3. Select detection containing arrow point
4. Fallback: Select detection closest to arrow if none contain it

For Single-Elephant Scenes (No Arrow):

- Select largest bounding box (by area)

Step 3: Context-Preserving Crop Extraction

1. Take selected bounding box
2. Add **15% padding** on all sides:
   - Horizontal padding: 15% of box width
   - Vertical padding: 15% of box height
3. Clamp to image boundaries
4. Extract crop region

7.4 Why MegaDetector-Based Cropping Works

- **Precise localization** instead of heuristic anchoring
- **Consistent crop quality** across all images
- Padding preserves biometric context:
  - Head profile and dome shape
  - Ear shape, tears, and depigmentation
  - Temporal gland region (Makhnas)
  - Upper torso texture
- **Robust to pose variation** and multi-elephant scenes

- **Scalable**: no manual annotation required

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8. Phase C — Biologically-Aware Feature Extraction

8.1 Motivation

Elephant identity cues differ significantly across:

- Sex (Makhnas vs Females)
- Age (Adults vs Calves) A single-stream CNN cannot model this heterogeneity effectively.

8.2 Dual-Branch Feature Extractor

Branch 1: Texture Branch

Purpose: Capture fine-grained local details Targets:

- Ear depigmentation (pink spots)
- Ear tears and notches
- Skin and trunk texture Characteristics:
- Shallow
- High spatial resolution
- Small receptive field Dominant for:
- Adult females
- Some adult males

Branch 2: Semantic Shape Branch

Purpose: Capture global geometric structure Targets:

- Body bulk (Makhnas)
- Head dome shape (Calves)
- Ear curvature
- Overall proportions Characteristics:
- Deep
- Low spatial resolution
- Large receptive field Dominant for:
- Calves / Juveniles
- Makhnas

8.3 Biological Attention Map (BAM)

Objective

Learn **where to look** based on biologically meaningful regions.

Expected Attention Behavior

Makhnas

- Temporal gland / cheek region
- Eye-adjacent areas
- Body bulk (Captures musth secretion and gland morphology)

Adult Females

- Ear pinna
- Ear edges and tears
- Facial texture

Calves / Juveniles

- Head shape
- Ear curvature
- Global proportions (Compensates for lack of texture cues)

Key Property

- Attention is **learned implicitly**
- No explicit sex/age labels required
- Metric learning drives specialization

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9. Feature Fusion & Embedding Projection

1. Texture branch features
2. Shape branch features
3. Apply Biological Attention Map to each
4. Pool features independently
5. Fuse via late fusion (concatenation / weighted sum)
6. Project to **128-dimensional embedding**
7. Apply L2 normalization

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10. Phase D — Metric Learning (Few-Shot Optimization)

Objective

Learn a **discriminative embedding space** instead of memorizing identities.

Loss Function

Triplet Margin Loss with Online Hard Negative Mining

- Optimizes relative distances

- Encourages:
  - Intra-ID compactness
  - Inter-ID separation
- Well-suited for few-shot learning

Why Metric Learning Solves Few-Shot

- Learns *how to compare*, not *what to classify*
- Generalizes naturally to unseen identities
- Embeddings are reusable

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11. Artifact Handling (Arrow Bias Prevention)

Although arrows remain visible in some crops:

- Same elephant appears with and without arrows
- Arrow position varies To prevent shortcut learning
- Apply **Random Erasing**
- Apply strong spatial augmentations This forces reliance on **biological features**, not artificial cues.

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12. Phase E — Open-Set Inference & Enrollment

Enrollment

- Compute embeddings for known elephants
- Store in gallery database
- Model remains frozen

Inference

1. Compute embedding for query image
2. Compute cosine similarity with gallery
3. Apply confidence threshold

Decision Logic

- Similarity ≥ threshold → **Known Elephant**
- Similarity < threshold → **New / Unknown Individual** This explicitly supports **open-set recognition**.

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13. Final Algorithm Summary

> The proposed system integrates contextual anchoring, biologically-aware feature extraction, and metric learning to enable robust open-set elephant re-identification under real-world field conditions.

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14. Project Status

- ✔ Dataset fully understood
- ✔ Weak supervision correctly interpreted
- ✔ **MegaDetector integration validated (100% detection rate)**
- ✔ **Detection-based preprocessing implemented**
- ✔ Feature extractor biologically grounded
- ✔ Metric learning strategy defined
- ✔ Ready for training & evaluation

One-Line Summary (PI-Level)

> *We designed an open-set biometric elephant re-identification system that integrates MegaDetector v5a for automated detection with arrow-based selection in multi-elephant scenes, preserves biological context through validated padded crops (15%), and learns discriminative embeddings using biologically informed attention and metric learning.*