BIOMETRIC RECOGNITION OF COWS THROUGH MUZZLE IMAGES APPLIED TO ANIMAL MANAGEMENT

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Abstract. Individual cattle identification plays an important role in animal traceability, health management, productivity monitoring, and precision livestock farming. Conventional identification methods, such as ear tags and electronic devices, present limitations related to identifier loss and operational failures. In this context, bovine muzzle biometrics emerges as a promising alternative by exploring potentially unique anatomical patterns for each animal. This work investigates the feasibility of recognizing cows through biometric analysis of muzzle images using a computer vision and deep learning pipeline. The methodology includes image preprocessing, feature extraction with a convolutional neural network, generation of normalized embeddings, and similarity comparison using cosine distance. A preliminary experimental evaluation was conducted using a dataset of 150 images from 30 cows, with five images per individual. The proposed approach achieved a global accuracy of 92.7% using a 1-nearest neighbor leave-one-out validation strategy. Dimensionality reduction analyses with PCA, t-SNE, and UMAP demonstrated clustering tendencies by individual, indicating the potential of bovine muzzle biometrics for automatic cattle identification and future applications in livestock management and animal traceability.

1. Introduction

Individual cattle identification is a fundamental requirement for animal traceability, sanitary control, reproductive management, productivity monitoring, and precision livestock farming. As livestock production systems become increasingly data-driven, reliable animal identification is essential to support decisions related to feeding, health, reproduction, and herd management. In this context, precision farming depends on identification methods that are accurate, scalable, and compatible with real-world field conditions [Awad 2016, Lee et al. 2023].

Traditional cattle identification techniques, such as ear tags, tattoos, branding, and electronic devices, have contributed significantly to livestock traceability. Nevertheless, these methods still present limitations, including identifier loss, operational failures, maintenance costs, and the need for physical contact or animal restraint [Awad 2016]. Such challenges motivate the investigation of alternative approaches based on intrinsic biological characteristics of the animals.

Animal biometrics has emerged as a promising solution for automatic identification. Similar to human biometric systems, animal biometrics explores anatomical traits that are unique and relatively stable over time. Among the biometric traits investigated in cattle, muzzle patterns have attracted particular attention due to the presence of grooves, wrinkles, and texture structures that may function as a natural fingerprint for each individual [Awad 2016]. Because of its non-invasive nature, muzzle biometrics has strong potential for integration into automated livestock monitoring systems.

Recent advances in computer vision and deep learning have significantly improved the ability to extract discriminative representations from complex images. Deep convolutional neural networks have been widely employed in biometric applications as feature extractors capable of transforming images into compact numerical representations, commonly referred to as embeddings. These representations enable similarity-based comparisons between samples and provide robustness against moderate variations in illumination, viewpoint, and image acquisition conditions [Li et al. 2022, Lee et al. 2023, Kimani et al. 2023].

In the context of cattle identification, recent studies have demonstrated encouraging results using muzzle biometrics combined with deep learning techniques [Li et al. 2022, Lee et al. 2023, Kimani et al. 2023]. Earlier approaches based on handcrafted texture descriptors and conventional classifiers had already indicated the discriminative potential of muzzle patterns [Tharwat et al. 2014, Awad et al. 2013]. With the introduction of deep neural architectures, the performance and robustness of such systems have improved substantially.

Motivated by this scenario, the present work proposes a biometric recognition pipeline for cattle identification using muzzle images. The proposed methodology includes image acquisition and organization, preprocessing procedures, feature extraction through a convolutional neural network, embedding normalization, and similarity comparison using cosine similarity. The system is structured into two main stages: biometric enrollment and posterior identification from new input images. This architecture is compatible with applications involving animal traceability, herd monitoring, sanitary management, and precision livestock systems.

As a preliminary validation, an experimental dataset composed of 150 images from 30 cows, with five images per animal, was organized and evaluated. A convolutional backbone network was employed to generate 1280-dimensional embeddings, followed by nearest-neighbor classification and dimensionality reduction analyses. The proposed pipeline achieved an accuracy of 92.7% using a 1-nearest neighbor leave-one-out validation strategy with cosine similarity. Visualization methods such as PCA, t-SNE, and UMAP revealed grouping tendencies according to individual animals, although partial overlap between some classes was still observed, indicating the need for dataset expansion and methodological refinements.

This research contributes both scientifically and practically. From a scientific perspective, it advances studies in animal biometrics at the intersection of computer vision, deep learning, and precision agriculture. From an applied perspective, it provides a potentially non-invasive and automatable alternative for cattle identification, reducing the dependence on conventional physical identifiers [Awad 2016, Lee et al. 2023]. Such solutions may improve reliability in livestock records and support faster and more precise management decisions.

1.1. Main contributions

- Development of a biometric recognition pipeline based on cattle muzzle images;
- Application of deep convolutional neural networks for embedding extraction;
- Evaluation of similarity-based cattle identification using cosine similarity and nearest-neighbor classification;
- Analysis of embedding quality using PCA, t-SNE, UMAP, and clustering metrics;
- Discussion of the applicability of muzzle biometrics in precision livestock farming and animal traceability;

2. Methodology

2.1. Problem Formulation

The proposed problem is formulated as an image-based biometric recognition task for cattle identification using muzzle patterns. Given an RGB input image:

$$I \in \mathbb{R}^{H \times W \times 3} \qquad (1)$$

the objective is to map the image into a discriminative latent representation:

$$e = f(I), \quad e \in \mathbb{R}^{d} \qquad (2)$$

where $f(\cdot)$ represents a convolutional feature extraction function and e is the generated embedding vector. The embedding space is expected to preserve biometric similarity, such that samples from the same cow remain close, while samples from different animals become more distant.

This formulation follows the paradigm adopted in modern biometric systems, where recognition is performed through similarity analysis in the latent space rather than direct classification.

2.2. Proposed Biometric Pipeline

The proposed methodology is organized into four main stages:

- acquisition and organization of muzzle images;
- preprocessing and normalization;
- embedding extraction using deep convolutional networks;
- biometric recognition based on similarity comparison.

Initially, the muzzle images are organized according to the identity of each animal, creating a labeled biometric database. Each image is resized and normalized before being processed by the convolutional backbone network.

The generated embeddings are stored together with the animal identity, forming a biometric repository capable of supporting future recognition queries. During inference, a new muzzle image is processed by the same pipeline and compared with the stored embeddings using cosine similarity.

2.3. Image Preprocessing

Image preprocessing is an important step to reduce irrelevant variations and standardize the input space of the network. All images were resized to:

$$224 \times 224\, pixels \quad (3)$$

which corresponds to the input resolution required by MobileNetV2.

After resizing, the images were converted into numerical tensors and normalized according to the preprocessing function associated with the pre-trained backbone. This normalization improves numerical stability and maintains compatibility with transfer learning strategies.

The adopted preprocessing pipeline also helps reduce the influence of illumination variation, acquisition noise, and minor viewpoint changes.

2.4. Feature Extraction

Feature extraction was performed using MobileNetV2 as a convolutional backbone. The final classification layer was removed, allowing the network to operate as a generic visual feature extractor.

The convolutional activations were transformed into compact feature vectors using Global Average Pooling, followed by L_2 normalization:

$$\hat{e} = \frac{e}{\|e\|_2} \quad (4)$$

where $\hat{e}$ represents the normalized embedding vector.

The final embeddings contain 1280 dimensions and represent compact biometric signatures extracted from the cattle muzzle images.

MobileNetV2 was selected due to its reduced computational complexity and strong representation capability, making it suitable for future deployment in embedded or mobile agricultural systems.

2.5. Biometric Recognition Strategy

The recognition stage is based on similarity comparison between embeddings. Cosine similarity was adopted because it is well suited for normalized feature vectors:

$$sim(e_i, e_j) = \frac{e_i \cdot e_j}{\|e_i\| \|e_j\|} \quad (5)$$

Recognition is performed using a 1-nearest neighbor strategy, where the predicted identity corresponds to the embedding with the highest similarity score in the biometric database.

The evaluation protocol follows a leave-one-out strategy, in which each image is temporarily removed from the database and used as a query sample against the remaining images. This approach prevents trivial self-matching and provides a more rigorous evaluation of the discriminative capacity of the embeddings.

2.6. Latent Space Analysis

Beyond recognition accuracy, the quality of the latent representations was investigated through dimensionality reduction and clustering analysis.

Three visualization techniques were employed:

- Principal Component Analysis (PCA);
- t-distributed Stochastic Neighbor Embedding (t-SNE);
- Uniform Manifold Approximation and Projection (UMAP).

These techniques allow the projection of high-dimensional embeddings into a twodimensional space, facilitating visual inspection of cluster formation according to animal identity.

Additionally, clustering quality was evaluated using:

- Silhouette Score;
- Davies-Bouldin Index;
- Calinski-Harabasz Index.

These metrics provide complementary information regarding intra-class compactness and inter-class separation in the latent space.

3. Dataset

The experimental dataset consists of 150 muzzle images collected from 30 cows, with five images per individual. Each class corresponds to a unique animal identity.

The images were organized into labeled folders to facilitate supervised processing and embedding association. The dataset contains moderate variability regarding:

- illumination conditions;
- acquisition angle;

- positioning variations;
- muzzle texture and moisture conditions;
- image sharpness and contrast.

Although relatively small compared to large-scale biometric datasets, the database is sufficient to evaluate the feasibility of the proposed methodology as a proof of concept.

4. Results and Discussion

4.1. Embedding Generation and Representation

The experiments carried out in this stage aimed to evaluate the feasibility of the proposed biometric pipeline for cattle identification through muzzle images. The adopted methodology successfully converted all input images into compact biometric representations based on deep feature embeddings.

The experimental dataset consisted of 150 muzzle images distributed among 30 cows, with five images per individual. MobileNetV2 was employed as the convolutional backbone for feature extraction, operating without the final classification layer. After the application of Global Average Pooling and L_2 normalization, each image was represented by a normalized embedding vector with 1280 dimensions.

This result is particularly important because it demonstrates that the proposed pipeline was capable of transforming visual muzzle patterns into numerical biometric signatures suitable for similarity-based recognition. In practical terms, the model learned latent visual representations capable of preserving identity-related information extracted directly from the muzzle texture.

The embedding generation process also confirms the applicability of deep learning techniques in animal biometrics, following principles commonly adopted in modern human recognition systems such as FaceNet-based architectures [Schroff et al. 2015].

4.2. Examples of Embedding Generation

To illustrate the behavior of the feature extraction stage, Figures 1 and 2 present examples of muzzle images and their corresponding normalized embeddings generated by the proposed pipeline.

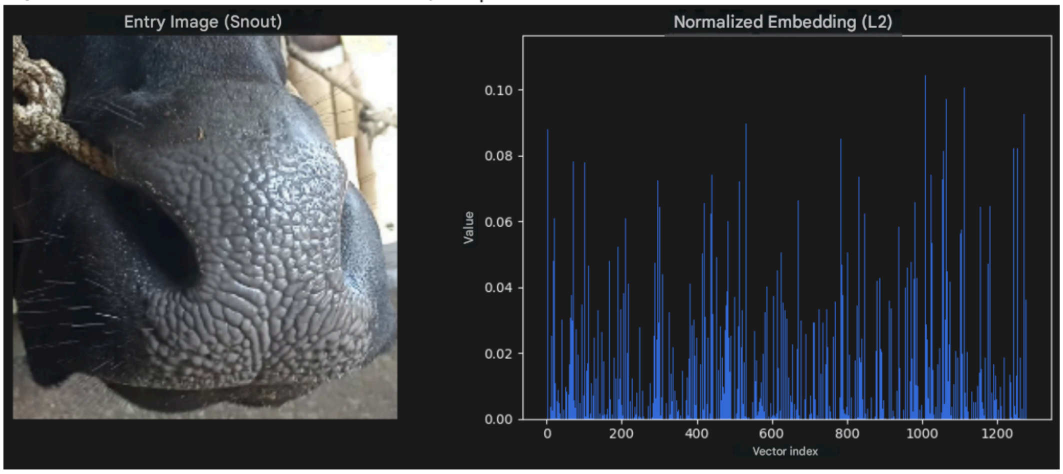

Figure 1. Example of biometric embedding generation from a cattle muzzle image.

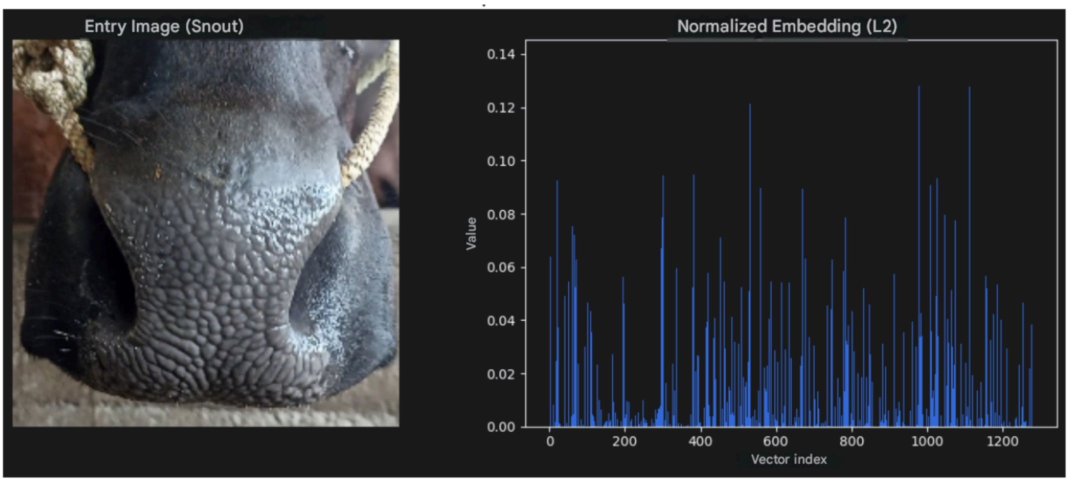

Figure 2. Second example of embedding generation using a different muzzle sample.

Although cattle muzzles share similar anatomical characteristics, the generated embeddings exhibit distinct numerical activation patterns for each image. This behavior indicates that the convolutional backbone was able to encode discriminative structural and textural information into compact latent representations.

Additionally, the use of L_2 normalization improved embedding comparability and stabilized similarity measurements during the recognition stage.

4.3. Quantitative Results

Table 1 summarizes the main results obtained during the preliminary validation stage.

Table 1. Main results obtained by the proposed biometric pipeline

Parameter / Metric	Result
Number of images	150
Number of cows	30
Images per individual	5

Parameter / Metric	Result
Embedding dimension	1280
Backbone	MobileNetV2
Validation strategy	1-NN + cosine similarity
Validation protocol	Leave-one-out
Global accuracy	92.7%
Silhouette Score	0.2178
Davies-Bouldin Index	1.8231
Calinski-Harabasz Index	4.64
Explained variance in PCA	16.9%

The proposed methodology achieved a global recognition accuracy of 92.7%, demonstrating that muzzle biometrics can support reliable cattle identification even under a preliminary experimental configuration.

The obtained performance is particularly expressive considering that the model was not fine-tuned specifically for cattle muzzle recognition and that the dataset contains 30 distinct classes with natural acquisition variability.

4.4. Latent Space Visualization

To investigate the organization of the embedding space, dimensionality reduction techniques including PCA, t-SNE, and UMAP were applied to the generated embeddings.

Figure 3 presents low-dimensional visualization of the generated embeddings using PCA, t-SNE, and UMAP projections. The PCA projection explained approximately 16.9% of the total variance and provided a global linear visualization of the latent space. Although partial overlap between classes was still observed, some grouping tendencies according to animal identity became visible.

The non-linear techniques produced more expressive results. The t-SNE visualization revealed compact local clusters, indicating that samples belonging to the same animal tend to remain close in the latent space. Similarly, UMAP demonstrated improved structural organization and more distinguishable cluster separation for several individuals.

These observations are consistent with the obtained clustering metrics. The relatively low Silhouette Score suggests that the global separation between clusters is still

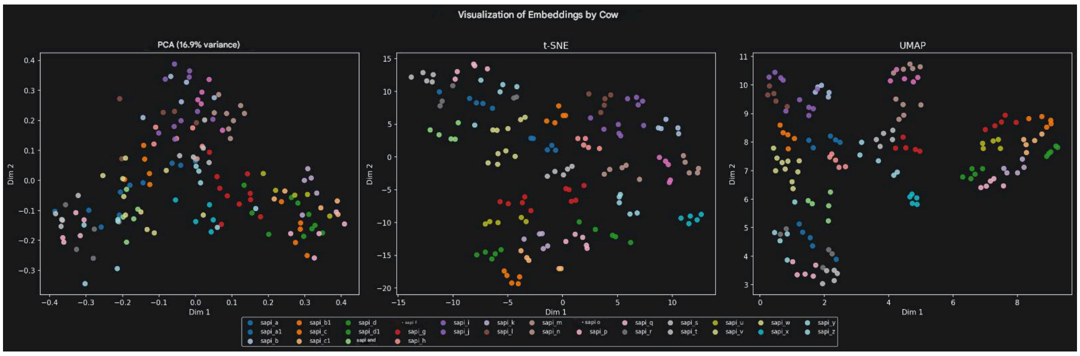

Figure 3. Low-dimensional visualization of the generated embeddings using PCA, t-SNE, and UMAP projections.

limited, although local neighborhood relationships already support high recognition performance.

4.5. Clustering Quality Analysis

Beyond classification accuracy, the structure of the latent space was evaluated through clustering quality metrics.

The obtained Silhouette Score of 0.2178 indicates low-to-moderate global separation between clusters. This suggests that embeddings from some cows remain relatively close to neighboring classes, which is coherent with the overlap observed in PCA projections.

Similarly, the Davies-Bouldin Index of 1.8231 indicates that the generated clusters are not yet ideally compact and separated. The Calinski-Harabasz Index of 4.64 also suggests that the ratio between inter-cluster and intra-cluster dispersion can still be improved.

Although these metrics reveal limitations in the global organization of the latent space, they also demonstrate that the embeddings already contain meaningful biometric information capable of supporting recognition tasks.

4.6. Recognition Analysis

Recognition performance was evaluated using cosine similarity combined with a 1-nearest neighbor classification strategy under a leave-one-out validation protocol.

The confusion matrix in Figure 4 demonstrates a strong concentration of predictions along the main diagonal, confirming that most query samples were correctly associated with their corresponding identities.

Several classes achieved perfect or near-perfect recognition performance, indicating that certain cows present highly discriminative muzzle patterns. On the other hand, a smaller number of classes exhibited partial overlap and occasional misclassification.

This variability suggests that factors such as illumination conditions, acquisition angle, image sharpness, and intrinsic similarity between muzzle patterns may directly influence embedding separability.

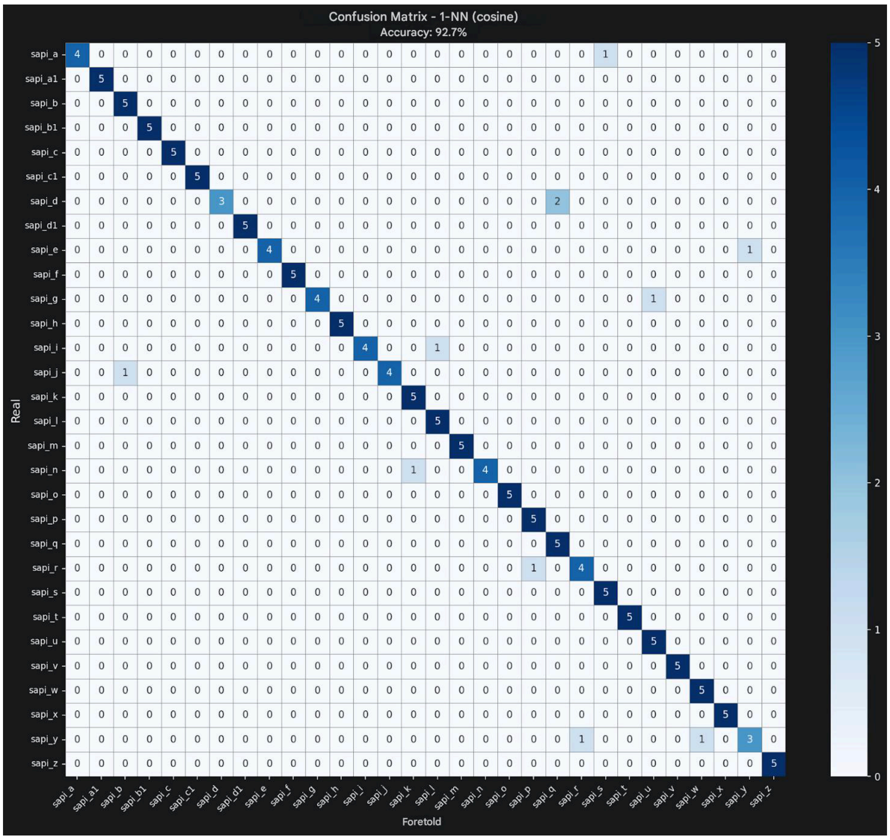

Figure 4. Confusion matrix obtained with cosine similarity and 1-nearest neighbor classification.

An important observation is that high recognition accuracy was achieved even though the latent space organization is not yet fully optimized. This indicates that local neighborhood relationships already preserve sufficient identity-related information for similarity-based recognition.

4.7. Discussion

The obtained results demonstrate that cattle muzzle biometrics represents a promising alternative for automatic livestock identification. Even under a preliminary proof-ofconcept configuration, the proposed pipeline achieved expressive recognition performance and generated discriminative biometric embeddings.

The experiments also reveal an important characteristic of embedding-based biometric systems: high recognition accuracy does not necessarily imply perfect global cluster separation. Although the clustering metrics indicate partial overlap between some classes, the local organization of the latent space already supports reliable nearestneighbor identification.

From a methodological perspective, the results suggest several opportunities for future improvement. The adoption of fine-tuning strategies, metric-learning approaches such as contrastive loss or triplet loss, and larger datasets could significantly improve embedding compactness and inter-class separation.

Increasing the number of images per individual would also improve robustness against illumination changes, acquisition noise, positioning variability, and moisture differences in the muzzle texture.

Another important aspect is the lightweight nature of MobileNetV2. Its reduced computational complexity makes the proposed methodology potentially suitable for deployment in embedded systems, mobile devices, and edge-computing agricultural platforms.

From an applied perspective, the proposed system may contribute to several precision livestock farming applications, including:

- automatic animal traceability;
- herd monitoring;
- sanitary management;
- reproductive control;
- digital livestock management systems;
- non-invasive biometric registration.

Overall, the experimental results support the feasibility of biometric cattle identification through muzzle images and reinforce the relevance of deep learning techniques for animal recognition problems. The obtained findings also establish a consistent foundation for future research involving larger datasets, fine-tuned architectures, and real-world deployment scenarios.

5. Conclusion

This work investigated the feasibility of individual cattle identification through muzzle biometrics using a computer vision and deep learning pipeline. The proposed methodology was capable of processing muzzle images, generating normalized embeddings with 1280 dimensions, and performing similarity-based recognition using cosine similarity and a 1-nearest neighbor strategy.

The experimental results demonstrated that cattle muzzle patterns contain discriminative biometric information suitable for automatic identification. The proposed pipeline achieved a global accuracy of 92.7% in a leave-one-out validation protocol using 150 images from 30 cows. Additionally, PCA, t-SNE, and UMAP analyses showed grouping tendencies according to animal identity, confirming the relevance of the generated embeddings.

Although the clustering metrics indicated partial overlap between some classes, the local organization of the latent space was sufficient to support high recognition performance. These findings reinforce the potential of cattle muzzle biometrics as a noninvasive alternative for traceability, herd monitoring, and precision livestock farming applications.

Future work includes expanding the dataset, applying fine-tuning strategies, incorporating metric-learning approaches such as triplet loss and contrastive loss, and evaluating the system under real-world field conditions. The integration of automatic muzzle detection and mobile deployment scenarios also represents an important direction for future development.

Acknowledgment

The authors acknowledge the financial support provided by the National Council for Scientific and Technological Development (CNPq), Brazil, and Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES). This study was financed in part by the Araucária Foundation for Scientific and Technological Development of the State of Paraná. (FA).

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