XAI based Cattle Identification with YOLO and SIFT Technique

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Abstract: **In precision livestock farming, accurate cattle identification is essential for enhancing animal welfare, health monitoring, and productivity, while also supporting traceability and minimizing false insurance claims. This paper presents a novel approach for cattle identification using muzzle prints, with a focus on both efficiency and explainability. Taxicab metric, employed for efficient annotation of muzzle patterns significantly reduces the labeling time for training of YOLOv8 model. YOLOv8 is utilized for detecting muzzle prints in images, followed by SIFT (Scale-Invariant Feature Transform) for feature extraction and matching. The incorporation of Explainable AI (XAI) methods, particularly Grad-CAM, further enhances the transparency and interpretability of the SIFT model.**

Keywords— Cattle Identification, SIFT, Yolov8m, XAI, Pattern Matching, Object Detection

I. Introduction

Livestock management plays a vital role in animal care and is a significant contributor to global agricultural production. According to the Food and Agriculture Organization (FAO), livestock constitutes approximately 40% of the total agricultural output in developed regions and around 20% in developing areas, supporting the livelihoods of about 1.3 billion people and accounting for 34% of global food production [3]. A key component of effective livestock management is the accurate identification of animals, which is essential for purposes such as traceability, healthcare management, breed classification, and preventing fraudulent insurance claims [4].

II. Literature Review

Various methods for cattle identification exist [5], which can be broadly categorized into traditional contact-based methods and non-contact methods [6,7]. Contact-based methods, including ear notching, ear tagging, and heat and cold branding, are commonly used. While these methods provide clear identification, they are invasive, often causing pain to the animals and requiring manual effort. The use of plastic tags and metal in these methods can lead to infections and are also time-consuming.

Although RFID (Radio-frequency identification) offers a solution to some of these drawbacks, the chips are expensive and require trained persons for implantation. DNA-based identification is another highly accurate method; however, it is costly and requires veterinary expertise, making it less accessible for farmers [8]. Non-contact methods like iris recognition demand high-quality imaging equipment, which is not only costly but also impractical for field conditions. Additionally, methods based on retinal patterns and coat patterns are unreliable due to changes with the animal's age.

The muzzle, which is the fusion of the nasal entrance and upper lips of cattle, presents unique patterns similar to human fingerprints [9,10,11]. These distinct patterns can be used for identification, where beads and ridges differentiate individual cattle. Several studies have explored muzzle-based identification methods. For instance, Local Binary Pattern (LBP) with classifiers such as SVM, KNN, and Naive Bayes has been employed for cattle identification [12]. Speeded Up Robust Features (SURF) and Linear Discriminant Analysis (LDA) have also been utilized for feature reduction, showing promising results [13]. Another approach using Scale-Invariant Feature Transform (SIFT) for feature extraction has been proposed [14]. Facial descriptors combined with Weber's Local Descriptor (WLD) and various classifiers have been applied to datasets comprising 31 cattle [15,16]. Similarity matching techniques have also been proposed for cattle identification in various studies [17,18,19].

Recently, deep learning methods have gained popularity in livestock identification due to their efficacy in dealing with complex tasks such as classification, object detection, and pattern recognition. A biometric scanner using deep learning and a scheme for automatic cattle recognition based on muzzle prints and face images have been proposed in [20,21]. These methods, including a bag-of-visual-words approach and local invariant feature extraction methods using SURF and Maximally Stable Extremal Regions (MSER), achieved an accuracy of 67% on 75 images. A Convolutional Neural Network (CNN) trained on body patterns demonstrated an 89.95% accuracy when trained for 1000 images [22]. A stacked denoising auto-encoder and deep belief network combined with computer vision achieved high accuracy rate [23]. Furthermore, a deep transfer learning model for mixed breed classification reported a 98% accuracy in muzzle detection [24] but these studies are performed on smaller datasets. Other methods combining Shi-Tomasi corner detection, SURF, and SIFT achieved recognition accuracies of 69.32%, 74.88%, and 79.60% using classifiers like MLP, decision trees, and random forests [25,26].

A facial recognition method using a sparse Stacked Denoising Autoencoder (SDAE) and group sparse representation techniques demonstrated 96% identification accuracy [27]. Feature descriptor methods and the part-based convolutional network (PCN) have been utilized for yak identification [28,29], while two deep learning models, wide ResNet50 and VGG16_BN, achieved a 99% accuracy rate in the African context using face identification [30]. Additionally, studies using computer vision and deep learning-based scanners have also been conducted [31]. In some cases, muzzle print recognition in dogs has also been explored using spatial and texture-based features, employing two-stage segmentation with UNet and YOLO [32,33]. A tag reading method using YOLO and computer vision has also been proposed for cattle [34].

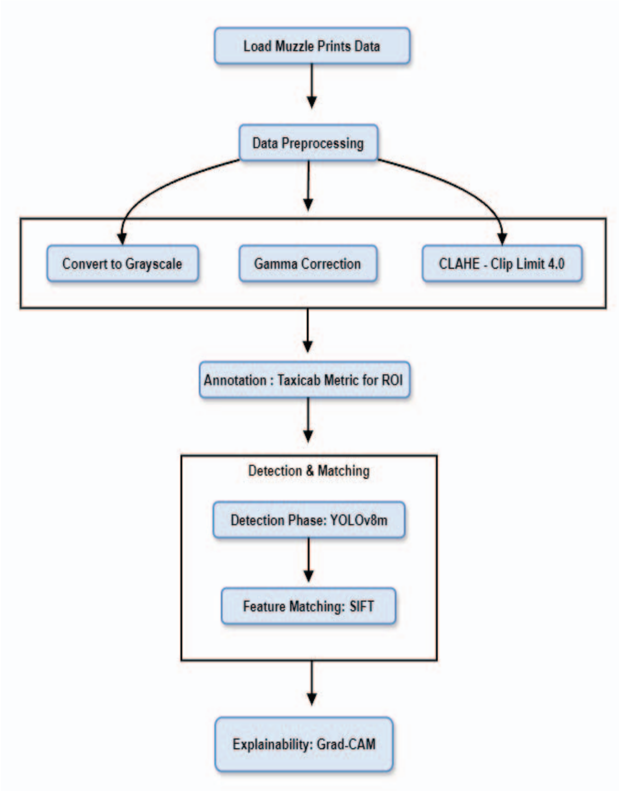
Despite the progress made in livestock identification, there is still scope for improvement, as some methods have been tested on limited datasets or lack time efficiency. We propose an approach for annotating images using the taxicab metric [35], which is both time-efficient and effective. Additionally, we utilize YOLOv8m for muzzle detection. The comparison from related work has been shown in Table 1.

Table 1: Comparison of related work with our proposed method

Reference	Methodology	Results and findings
[9, 10, 11]	Identification using muzzle patterns, which are unique like human fingerprints.	Established the uniqueness of muzzle patterns for cattle identification.
[13]	Speeded Up Robust Features (SURF) and Linear Discriminant Analysis (LDA) for feature reduction.	Showed promising results in feature reduction for identification.
[14]	Scale-Invariant Feature Transform (SIFT) for feature extraction.	Provided high accuracy in feature extraction but performance varies with dataset size.
[15, 16]	Facial descriptors combined with Weber's Local Descriptor (WLD) and various classifiers.	Applied to datasets comprising 31 cattle, with effectiveness shown in identification.
[17, 18, 19]	Similarity matching techniques for cattle identification.	Developed various similarity matching methods for identification purposes.
[20, 21]	Deep learning methods including a biometric scanner and automatic cattle recognition using muzzle prints and face images.	Bag-of-visual-words approach achieved 67% accuracy on 75 images. CNN trained on body patterns demonstrated 89.95% accuracy on 1000 images.
[28, 29]	Feature descriptor methods and part-based convolutional network (PCN) for yak identification.	Utilized for yak identification, showing effective results.
Our work	The proposed work integrates the taxicab metric for efficient annotation, enhancing the identification process.	The paper presents a novel method for cattle identification using muzzle prints, employing the taxicab metric for efficient annotation and YOLOv8 for detection. SIFT achieved 85% accuracy in feature matching, while Grad-CAM provided explainability of the model. This approach reduces manual labeling time and suggests potential for mobile-based identification systems.

III. METHODOLOGY

The methodology employed in this study is illustrated in Figure 1. Besides preprocessing the raw data, the proposed work is divided into three phases: (1) annotation, (2) detection and matching, and (3) explainability. In the first phase, an annotation method using the taxicab metric is utilized to identify the region of interest (ROI). Second phase involves the detection of muzzle prints using YOLOv8m, followed by matching using the Scale-Invariant Feature Transform (SIFT) technique. Finally, in the third phase, the explainability of the results is analyzed through Grad-CAM, providing insights into the model's decision-making process.



A. Data Preprocessing:

In this work, available data has been used from the source [36]. It consists of 4923 cropped muzzle images which are augmented using the training phase to increase the variability of the data. The data is converted in grayscale and the patterns of images are enhanced through Gamma Correction and CLAHE, which is explained as following:

Gamma Correction:

This gamma correction function adjusts the brightness and contrast of images. It computes a lookup table to modify the pixel intensities, using a gamma value to control the degree of correction. Gamma value of 1.2 has been used for the experiment purpose.

CLAHE (Contrast Limited Adaptive Histogram Equalization):

This technique enhances local contrast by distributing the pixel intensities over a defined region of the image. It modifies the cumulative distribution function (CDF) of pixel intensities, while limiting the contrast amplification in any region by clipping the histogram. The clip limit is set at 4.0 in this case.

B. Phase 1 - Annotation of Muzzle Prints

Taxicab metric has been used to draw a box on muzzle area in images represented in Figure 2. This method is unique to annotate an object in images.

The Taxicab Metric operates on the Euclidean plane by calculating the distance between two points (x, y) and (z, w) as:

$$d_{taxicab}=|x-z|+|y-w|$$

This distance metric ensures the shortest path along grid lines, making it suitable for generating annotation windows in an image-based task. Our annotation process involves the following steps:

i. Image Center Calculation:

The first step in the annotation process is identifying the image's center. The center is crucial as it serves as the anchor point for positioning the annotation box around the muzzle area.
To find the centre of an image the midpoint coordinates from which the rectangle (window) will be calculated. The center of an image is calculated using the integer division of the width and height of the image.

$$center_x = \lfloor width / 2 \rfloor$$
$$center_y = \lfloor height / 2 \rfloor$$

ii. Shift Calculation:

Shifts are introduced to slightly adjust the center of the rectangle. These shifts allow the annotation box to align more accurately with the muzzle's actual position in each image. Here to manage according to our images, we have chosen the below value.

$$shift_x = \lfloor width / 20 \rfloor$$
$$shift_y = \lfloor height / 30 \rfloor$$

iii. Taxicab Distance Constraint:

The taxicab is applied to limit the shifts, ensuring they do not distort the placement of the annotation box. This constraint maintains the balance between the horizontal and vertical shifts.

$$\text{Scale factor} = \text{taxicab limit} / (shift_x + shift_y)$$
$$shift_x = \lfloor shift_x \times \text{scale factor} \rfloor$$
$$shift_y = \lfloor shift_y \times \text{scale factor} \rfloor$$

iv. New Center Calculation:

Once the shifts are adjusted, the new center of the annotation box is calculated, which will serve as the point around which the box is drawn.

$$\text{New } center_x = (center_x + shift_x)$$
$$\text{New } center_y = (center_y + shift_y)$$

v. Rectangle Coordinates Calculation:

The boundaries of the annotation box are determined using the new center. This step ensures that the box is appropriately sized and positioned around the muzzle.

$$\text{top } left_x = \text{new } center_x - \lfloor \text{rectangle width} / 2 \rfloor$$
$$\text{bottom } right_x = \text{new } center_x + \lfloor \text{rectangle width} / 2 \rfloor$$

$$\text{top left}_y = \text{new center}_y - \lfloor \text{rectangle height} / 2 \rfloor$$
$$\text{bottom right}_y = \text{new center}_y + \lfloor \text{rectangle height} / 2 \rfloor$$

vi. Bounds Checking:

Finally, the coordinates of the box are checked to ensure that they remain within the image boundaries. This prevents any part of the annotation box from extending outside the image, which could cause errors during training or feature extraction. In the following Figure 2, three different images are labelled with the taxi method. The image dimensions have been taken the same for all rectangle, width is 120, rectangle height is 200 and taxicab limit is 200.

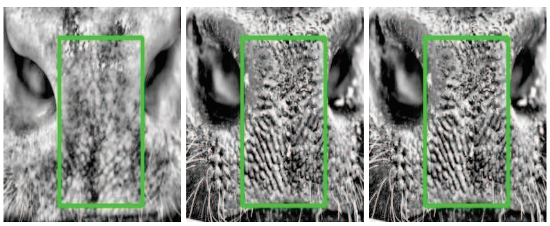


Figure 2: Three different images with taxicab window

C. Phase 2: Detection and Matching

YOLOv8m**,** proposed in 2023 by the Ultralytics team [38, 39, 40], is a state-of-the-art model for object detection, offering a balance between detection speed and accuracy. It is part of the YOLO (You Only Look Once) family, known for its real-time object detection capabilities. YOLOv8m, with its medium-sized architecture, leverages convolutional layers and anchor-based detection to precisely identify objects. In this study, YOLOv8m was utilized for detecting cattle muzzles demonstrated in Figure 2, benefiting from its ability to handle high-resolution images efficiently. Its use streamlined the detection of muzzle regions, crucial for cattle identification tasks based on unique muzzle patterns. In Figure 3 (a) and 3 (b), YOLO has labelled some images with name muzzle and in second images it has labelled as class 0.

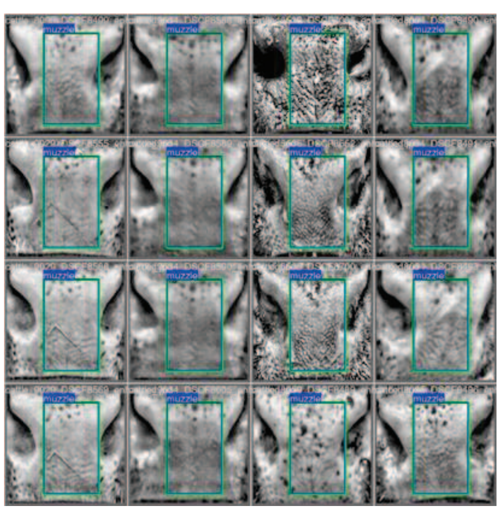


Figure 3 (a)

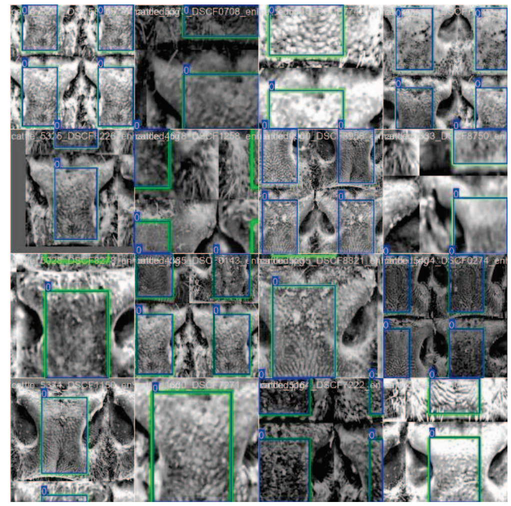


Figure 3 (a), (b) : YOLO Outputs

Scale Invariant Feature Transform (SIFT) [41, 42] has been proven as a good technique to do object recognition. From an image, it can be extracted features which are invariant from scale and rotation. These features can be matched with their corresponding features in the database with high probability. SIFT detects the key points in an image, which are the distinctive points of a muzzle pattern image. The key points will be used to match one another, and the number of matched key points will be used as a measure of pattern similarity. In this work, SIFT has been used for muzzle patterns matching shown in Figure 4 (a), (b), (c).

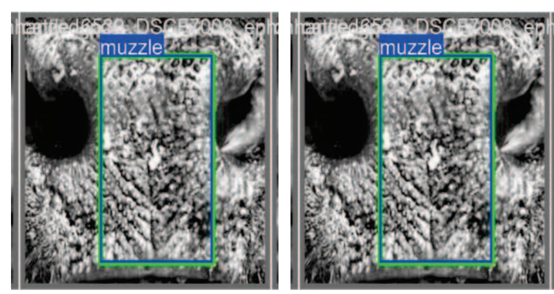


Fig 4 (a) : Muzzle print of same cattle

Fig 4 (b) : Patterns matched with SIFT for same images

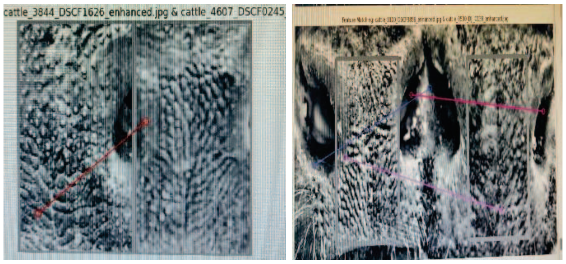


Figure 4 (c) : Patterns not matched with SIFT for different images

D. Phase 3: Explainability

Gradient-weighted Class Activation Mapping, introduced in 2017 by Selvaraju et al. [43], is a widely used technique for visualizing the regions in an image that are most important for a model's decision-making. Grad-CAM uses the gradients of the target class flowing into the final convolutional layer of a neural network to produce a coarse localization map that highlights critical areas of the image. In this work, Grad-CAM was applied to explain the matching process between cattle muzzle patterns using SIFT and shown in Figure 5. By overlaying the Grad-CAM heatmap on the images, we could visualize which muzzle features were most influential in the matching process, providing interpretability for the pattern recognition model.

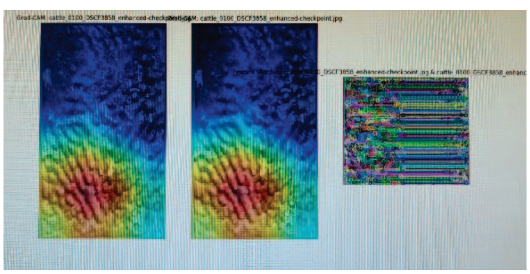


Figure 5: Muzzle patterns matching using SIFT explained with Grad-Cam

In [44], the authors manually annotated the dataset for the YOLOv8 model, training it over 100 epochs to achieve muzzle print identification. This manual annotation process is time-consuming. In contrast, our work utilizes the taxicab method for annotation, which significantly reduces the annotation time. Additionally, we trained our model for only 50 epochs, achieving effective muzzle pattern detection in a more time-efficient manner.

IV. Conclusion

The proposed annotation method significantly reduced the time required to train the YOLOv8m model by eliminating the need for traditional manual labelling. Furthermore, the SIFT technique achieved 85% accuracy in matching the similarities in the images. Grad-CAM also provided a valuable explanation, illustrating how SIFT identifies key patterns for image matching. This insight into the matching process can guide future modifications to the model for better performance on our data. For future work, this method can be adapted into a mobile-based cattle identification system. Additionally, since the current cattle muzzle dataset is limited, expanding the study to include more diverse datasets would enhance the model's generalizability and broaden its applications.

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