DOI: 10.47743/ejpar.2023-2-3

# IDENTIFICATION OF ANIMALS OF SIGNIFICANT ZOOTECHNICAL VALUE

**THEODOR SAMSON**
*Faculty of Computer Science, "Alexandru Ioan Cuza" University*
*Iasi, Romania*
*theodor.samson@info.uaic.ro*

**ADRIAN IFTENE**
*Faculty of Computer Science, "Alexandru Ioan Cuza" University*
*Iasi, Romania*
*adiftene@info.uaic.ro*

**Abstract**
*Biometric identification has brought about profound change in a variety of fields, and its enormous potential in zootechnics has attracted considerable interest. The primary purpose of this paper is to explore the practical application of biometric technologies for the purpose of identifying cattle in a unique manner. Utilizing these cutting-edge technologies, the research seeks to develop a comprehensive understanding of how biometrics can be used to establish the unique identity of individual cattle samples.*
**Keywords:** *Biometric, SIFT, SVM.*
**JEL Classification:** C38.

## 1. INTRODUCTION

Individual animal identification is essential for a variety of purposes. *First*, it facilitates animal tracking during epidemics and other emergency situations. By maintaining precise records of each animal's movements, it is simpler to identify potential sources of contamination and swiftly contain an outbreak. *Secondly,* animal identification helps prevent the abduction of zootechnical significant animals. The reproductive history or performance records of some animals make them more valuable than others. By precisely distinguishing each animal, it becomes significantly more challenging for criminals to sell these animals on the illicit market. *Lastly*, animal identification enables optimal livestock management through the recording of animal performance and output. Farmers can make better decisions regarding reproduction, nutrition, and other aspects of livestock management if they keep accurate recordings of each animal's behavior, health, and productivity. The solution from this paper has the potential to significantly advance zootechnics by utilizing biometric technologies to identify and manage cattle in a unique manner. Traceability, animal welfare, genetic improvement, and breeding programs are all enhanced by biometric identification. In addition, it enables precise livestock management by providing real-time data for making informed decisions. Exploring the advances in biometric technologies and their application in this field contributes to the creation of innovative livestock management solutions. This research has the potential to make a significant contribution to the scientific community and advance biometric identification practices for zootechnical animals.

## 2. EXISTING WORK

Research in livestock biometrics (Bello et al., 2020) has demonstrated that cattle can be identified through their *nose* prints. The research has revealed the potential of using *cattle muzzle prints* as a dependable biometric identifier, which presents promising opportunities for progress in livestock management. Studies consistently demonstrate the uniqueness and consistency of cattle muzzle prints over time, confirming their viability for individual identification of cattle. *Cattle muzzle prints* have potential as a unique biometric marker to improve cattle management practices. Researchers have utilized advanced image processing techniques to extract and analyze distinctive characteristics found in the nose prints of cattle, facilitating accurate identification. The comprehension of biometric technology enables livestock managers and researchers to create advanced systems that enhance cattle management in areas such as precise record-keeping, enhanced traceability, efficient disease control, and sophisticated genetic analysis. The incorporation of image processing methods into cattle management practices represents a significant shift towards the utilization of biometrics as a valuable tool. Utilizing the unique characteristics present in bovine muzzle prints, ranch managers can establish reliable identification systems that enable individual animal tracking and optimize operational efficiency. This innovation has the potential to transform conventional livestock management practices, resulting in improved efficiency, precision, and animal welfare. The current research on utilizing cattle nose prints as a distinct biometric marker is a noteworthy achievement in the field of livestock management. Advancements in biometrics have made cattle management using this technology more feasible and promising. The utilization of biometrics in cattle management offers promising opportunities for enhancing traceability, disease control, and livestock welfare through advanced image processing methods that extract and analyze distinctive characteristics. This study presents a methodology for identifying bovines through their unique muzzle characteristics. The objective is to create a precise and reliable method that utilizes the distinctive features present in the muzzles of cattle. The researched methodology investigates the use of sophisticated image processing methods and biometric algorithms to accurately analyze and compare muzzle characteristics.

*Nose printing* is a livestock identification technique that utilizes the distinctive patterns of lines and dots found on the nose of an animal (Priesnitz et al., 2021). This method is based on the premise that each animal has a unique nose print that can be used for identification purposes. Just like humans have unique fingerprints, animals also have distinct patterns that are exclusive to each individual. These patterns can serve as a reliable method of permanent identification. Nose printing is a reliable method of identification for livestock, specifically sheep and cattle, in sale and exhibition settings.

*Touchless technique in cattle identification* is similar to the touchless 2D fingerprint recognition technology (Bazen et al., 2020). The notion of touchless fingerprint recognition refers to the process of extracting fingerprint characteristics without the need for physical contact with a finger scanner. Thus, a non-invasive method could be employed to obtain distinctive characteristics from a cow's body, such as nose prints, without the need for physical contact or ink application. *Cattle muzzle print identification*, also referred to as muzzle pattern recognition or nose print identification, is a biometric technique that is utilized to distinguish individual cattle by analyzing the unique patterns present on their muzzles. Cattle muzzle prints have distinct characteristics that are comparable to those found in human fingerprints, rendering them useful for identification objectives. This method involves a series of essential steps, which include image acquisition, pre-processing, feature extraction, matching, and classification. These steps play a key role in accurately identifying cattle based on their unique muzzle prints. In order to improve the quality and clarity of muzzle print images, a range of image processing algorithms can be utilized, including but not limited to edge detection, segmentation, and normalization. Various feature extraction methods are commonly used. These methods include local binary patterns (Pietikäinen, 2010), Gabor filters (Mehrotra, Namuduri and Ranganathan, 1992), texture analysis techniques (Tuceryan and Jain, 1993) and various operators for edge detection (Ziou and Tabbone, 1998). The objective of these techniques is to identify and extract the distinctive characteristics of the muzzle patterns and present them as feature vectors for an easier comparison. In addition to applying feature extraction methods, researchers have employed various models to establish the correlation between cattle muzzle prints. Support Vector Machine (SVM) (Noble, 2006) models have been widely used in various applications. The models required training using broad datasets of muzzle prints, which helped in accurately correlating the animals.

## 3. PROPOSED SOLUTION

The objective of this study is to make use of image processing techniques to accurately identify cattle by analyzing their unique muzzle prints. The main goal is to create a precise and effective technique that can consistently identify individual cattle by examining their distinct muzzle features. The purpose of this research is exploring and implementing highly accurate image processing techniques that are tailored to identify key features from printed images, particularly those of cattle. The previously mentioned traits will be applied to develop a matching algorithm capable of differentiating between individual cattle based on their distinct muzzle features.

### 3.1 Methodology

Our approach integrates experimental data collection, image enhancement methods, image processing techniques, feature detection and estimation algorithms to effectively accomplish the research objectives. In the **data collection phase**, a diverse dataset of cattle muzzle images was acquired, trying to collect a broad range of different breeds and distinct patterns displayed in their muzzles. Because only a small portion of this data set was feasible, a new step was needed to gather some extra samples. In order to accomplish this, 2 farms were approached by us and we managed to take pictures of 50 more bovines. In order to improve the quality of the images, we relied on different preprocessing techniques. The **image pre-processing techniques** employed in this study involved resizing, noise reduction, and normalization. These techniques were found to be effective in enhancing the consistency and clarity of the images, thereby facilitating their analysis. The images then were subjected to **image processing techniques** in order to extract relevant information from them. To accomplish this task, several operators for edge detection were tried as well as trying algorithms such as principal component analysis (Mudrova and Procházka, 2005), contour drawing, top-hat filtering (Zeng and Peng, 2006) etc. in order to isolate and examine the muzzle region in particular. The process of correlation between the reference image from the database and the input image is done by applying Scale Invariant Feature Transform (Lindeberg, 2012) (SIFT) feature detection with Lowe's ratio (Lowe, 2004) and filtering the results with the help of Random Sample Consensus (Fischler and Bolles, 1981) (RANSAC). The methodology seeks to achieve precise and dependable identification of cattle by incorporating various components and utilizing their distinctive muzzle prints. In the upcoming chapters, we will thoroughly examine each component of the methodology (Figure 1), present the results that were obtained, and conduct a comprehensive analysis of the findings.


Source: Computed by authors

**Figure 1. Methodology**

### 3.2 Alignment

In order to establish a system based on muzzle print correlation, it is mandatory to have a corresponding reference image for each animal. To achieve this objective, a QR code can be attached or can replace the ear tag. This code should contain all the pertinent details, including the farm identification code, breed, date of birth, ear tag or microchip number, and the database index for the corresponding reference image (Figure 2).

The **alignment** of the input image with the reference image is a critical step in the proposed methodology, as even a slight rotation can result in the extraction of a completely different muzzle print. This is particularly important due to the wide range of color variations observed in cattle muzzles, making it challenging to extract accurate prints without proper alignment. Ensuring precise alignment helps maintain the consistency and reliability of the subsequent analysis and processing steps. To achieve alignment, a series of steps must be chained.

- *Grayscale conversion*: The process of grayscale conversion is necessary to reduce the complexity of the image. By doing this, subsequent processing steps are simplified.
- *SIFT feature detection*: Detecting distinctive key points in grayscale images involves using the SIFT algorithm. The SIFT algorithm is capable of detecting key locations that remain constant despite changes in scale, rotation, and other affine transformations. This property makes them highly appropriate for tasks that require image alignment.
- *Brute-force matching* (Jakubović and Velagić, 2018): The brute-force matching technique is applied to identify correspondences between the key points that have been detected in both images. The process involves a comparison of the characteristics of every key point in one image with those of all the key points in the other image. This is done to establish similarities and differences between the two images.
- *Filtering by Lowe's ratio test*: In order to ensure precise matches, the Lowe's ratio test has been used to eliminate any ambiguous matches. The purpose of this test is to evaluate the distances between the best and the second-most ideal matches for every key point. If the ratio of matches exceeds a certain threshold, they are eliminated.
- *Transformation Matrix using RANSAC*: For aligning key points between two images, an estimation of the transformation matrix is required. This is achieved by using the Random Sample Consensus (RANSAC) algorithm. The RANSAC algorithm follows an iterative approach to identify a subset of matches and estimate a transformation matrix based on these matches. This process involves the removal of anomalies to ensure the accuracy of the transformation matrix. By applying RANSAC, the precision of the alignment is guaranteed.

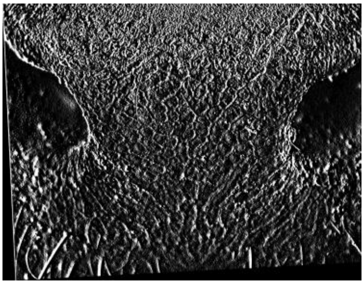
- *Crop*: After achieving alignment, the next step is to crop the aligned images to eliminate any unwanted noise regions. This process results in the desired alignment outcome.

Source: Computed by authors

**Figure 2. Reference image (left), input image (middle), aligned after reference image (right)**

### 3.3 Edge detection

Edge detection plays a vital role in the proposed methodology for identifying cattle based on their muzzle prints. By detecting and highlighting the edges of the muzzle region, it becomes easier to extract the distinct features and patterns that characterize the prints. The Sobel operators (Kanopoulos, Vasanthavada and Baker, 1988) are frequently employed in this context for edge detection. To calculate the gradients in the image, the Sobel X operator was extensively used due to the ridges of the muzzle having a tendency to align more horizontally rather than vertically. While the Sobel Y operator places more emphasis on vertical intensity variations, the Sobel X operator concentrates on recording changes in intensity in the horizontal direction. This is another vital phase in the process of extracting the main features of the muzzle, because this allows to accentuate all the main important features of the muzzle and emphasizes the overall muzzle print (Figure 3).



Source: Computed by authors

**Figure 3. Aligned image after applying edge detection**

## 3.4 Image enhancement

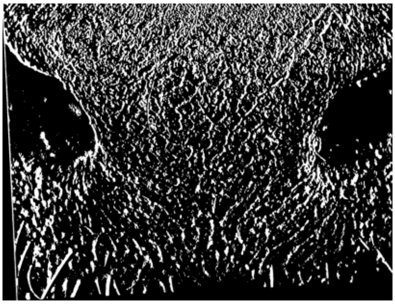
In order to precisely identify the distinct features of the muzzle print, we will use noise removal techniques. The main aim is to clearly create a delimitation between the ridges and valleys of the muzzle, removing unwanted variations or distortions caused by noise. Our objective is to enhance the unique characteristics present in the muzzle print by reducing random variations and distortions. To effectively remove noise from the image, we have opted to employ the technique of median filtering (Astola, Haavisto and Neuvo, 1990) due to the characteristics of the output obtained from the edge detection phase. The edge detection result would often include a large number of isolated pixels close to important ridge areas and in these cases, median filtering proves to be the optimal choice for noise removal by effectively eliminating noise while preserving the essential details of the ridge structure (Figure 4).

Source: Computed by authors

**Figure 4. Processed image after removing noise**

## 3.5 Binarization

In order to acquire the best representation of muzzle features and allow our correlation algorithm to distinguish between several muzzle prints, binarization is the essential last stage in image processing (Figure 5). Since the input images have uneven lighting and varying levels of contrast, we have opted to use the Otsu binarization (Otsu, 1979), which automatically determines the threshold. This way, the muzzle prints become recognizable, and it makes it easier for the correlation method to accurately differentiate them by converting the image into a binary form, with pixels designated as either black or white based on a determined threshold. The majority of the characteristics were extracted in this final processing step. Due to the substantial amount of preprocessing needed, it is obvious that this method results in the loss of subtle features, but it also depends on the environment in which the image was taken, such as angle, clarity, brightness, contrast, image obstructions etc.



Source: Computed by authors

**Figure 5. Processed image after applying binarization**

### 3.6 Image correlation

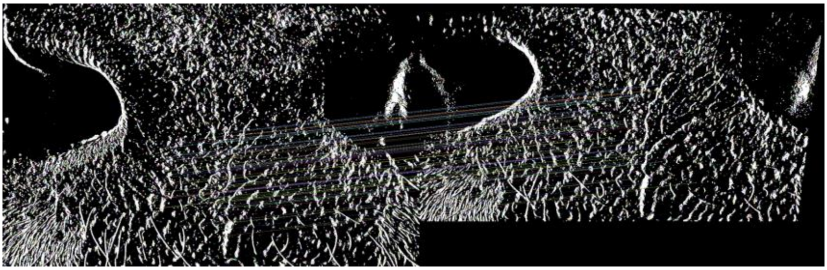
In most of the relevant academic literature, machine learning models, particularly SVM models, have been frequently used for print matching. Nevertheless, due to the major constraint in the dataset at our disposal, we have opted to investigate an alternative methodology that does not rely on a learned or supervised approach. In the context of the discussed approach, several steps are employed in order to reach our objectives. Our methodology involves utilizing the SIFT algorithm in combination with the Random Sample Consensus (RANSAC) algorithm (Figure 6).

These methods are widely recognized for their ability to provide reliable and efficient evaluation of image similarity, without requiring the use of explicit machine learning models. In the beginning, the SIFT algorithm is applied, which means finding unique key points and extracting their corresponding descriptors for every image. This step enables the representation of image regions in a scale-invariant and rotation-invariant manner.

A brute-force matcher is used to find correspondences between the key points in the two photos. Then, Lowe's ratio test is performed to choose the most reliable matches while discarding ambiguous ones. Matches with a sufficiently large ratio are eliminated by taking into account the distance ratios between the best and second-best matches. By using the RANSAC algorithm, the matches are further refined.

By developing a transformation model that best aligns the key points between the two images, RANSAC seeks to filter out misfits. A transformation is computed, and a consensus set of inliers is found by repeatedly choosing a random subset of matches. To select the best matches that meet the stated maximum reprojection error requirement, this process is repeated. The resulting filtered matches are then used to determine the similarity score. The number of RANSAC-filtered matches is evaluated to determine the similarity method.

According to the results, a custom threshold can be chosen since there are enough matches between the input image and the animal corresponding to that muzzle print in the database. If the input image does not meet the predetermined threshold, the cattle are not yet included in the database of muzzle prints. The related animal is indicated by the greatest number of matches. Our proposed method attempts to evaluate the similarity of pictures using the SIFT technique, key point matching, and the RANSAC algorithm in the absence of machine learning models. This approach choice addresses the constraint imposed by the lack of a suitable training dataset and offers a trustworthy approach to assessing image similarity.



Source: Computed by authors

**Figure 6. Feature correlations**

### 3.7 Limitations of the study

There is a lack of extensive, diverse datasets that are specifically centered on cattle muzzle prints. We have obtained a dataset from another research (Xiong, Li and Erickson, 2022), which is of moderate size and it includes muzzle prints from more than 250 individual cattle, with approximately six images per animal. Unfortunately, there are several different resolutions, in which numerous images are of such small dimensions that the ridges and valleys of the muzzle cannot be extracted. On top of that, a lot more images, apart from those of low resolution, are not of great quality. Considering that only a small fraction of these images was considered usable, we have taken the initiative to include additional samples that were obtained from two more farms. Nevertheless, it is important to acknowledge that there may be limitations in our study regarding the representation of various cattle breeds and their respective muzzle characteristics.

While conducting this work, we became aware of environmental factors that can lead to lower or greater precision in identifying muzzle prints, such as light and the quality of images. Although suitable techniques for image preprocessing are applied to minimize these effects, it must be understood that uncontrollable environmental factors may still impose certain limitations. In order to achieve the best results, it is preferred that the images sent as input are close enough to the animal, allowing for the distinct characteristics of their muzzle to be perfectly visible. Additionally, it is mandatory that the capture be obtained from a comparable angle to that of the reference image.

## 4. RESULTS AND ANALYSIS

The findings and analysis from our thesis on identifying cattle muzzle prints are presented in this chapter. The suggested methodology shows that it can successfully distinguish between various cattle based on their muzzle features. The important conclusions from our experiments are highlighted in the next points:

- *Distinction between individual cattle*: Using each individual cattle's distinctive muzzle print, our method successfully distinguishes one cattle from another. We found through extensive testing that the system regularly and correctly associates animal muzzle prints with their associated animals.
- *High matching numbers for the same animal muzzles*: We found that the matching numbers between different captures of the same animal can lead to as many as 200 matches during our tests. This result highlights the accuracy and dependability of our algorithms in matching muzzle prints to the appropriate animals.
- *Setting a threshold for database inclusion*: We recommend taking into account at least 40 matches when establishing a threshold for assessing if an animal is in the database. This advice is based on our thorough investigation, which showed that even the lowest matching score for the same animal across many images was 44 matches overall.
- *Matches for different cattle individuals*: Our research revealed a maximum of 37 matches in terms of discerning between distinct cattle individuals. This result shows that the system successfully distinguishes between calves with distinct muzzle prints, ensuring accurate identification even when working with animals with varying features.
- *Experimental setup*: We used a sample size of 30 cattle for our tests. We were able to thoroughly evaluate how well our system worked because every animal had two to four different photographs representing it. Bovines from both the extracted dataset and the ones photographed from nearby farms were included in the testing phase, ensuring its diversity and depth.

### 4.1 Presentation of the dataset

In this section, we present the dataset used in our cattle muzzle print identification study. The dataset consists of both pictures that were taken by our team and pictures that were received from a third-party source. Our goal is to give a summary of the dataset and talk about the image quality. We will highlight noteworthy photos, discuss their relevance, and analyze images that are considered of lower quality. We hope to lay a foundation for the subsequent analysis of our methods through this exploration. As mentioned in the previous chapters, the main images used in our research come from the research paper

(Li, Erickson and Xiong, 2022). The provided images are of high quality, with the muzzle print being clearly visible without any obstructions. These images fit the criteria for an ideal representation for our analysis, making it a good example of an input. The presence of noise as well as the image's low resolution, which makes it challenging to extract the muzzle's specifics correctly, are both obstacles. In particular, there are overlapping items that make it difficult to clearly see the muzzle print. These elements collectively contribute to lowering the image's quality and suitability for precise analysis.

Undertaking the endeavor of building our own collection of muzzle photos proved to be a challenging task. Cattle posed challenges throughout the process due to their tendency to move and reluctance to face the camera. Despite these challenges, we were able to obtain a number of samples, a couple being displayed below. These photos (Figure 7) demonstrate our sincere attempts to collect a varied and thorough collection of cow muzzle prints, highlighting the distinctive traits of the animals included in our study.

Source: Computed by authors

**Figure 7. High quality muzzle example from own dataset**

## 5. CONCLUSIONS

The objective of this paper was to investigate the feasibility of recognizing cattle through their muzzle characteristics. The methodology proposed for this study comprises a set of image processing techniques. These techniques involve aligning the input image to a reference image, applying edge detection, noise removal, blurring, Otsu binarization, and correlating the output to the corresponding image. The findings gathered through this methodology have shown great potential, emphasizing the practicality of making use of muzzle characteristics as a dependable method for identifying cattle.

For the future, there are several areas for exploration that can lead to the improvement of the methodology. A more precise and accurate representation of the key features of cattle muzzle images can be achieved by selecting or developing an operator that is specifically tailored to cattle muzzle characteristics while efficiently removing supplementary noise. This requires careful consideration and attention to detail. Furthermore, conducting a more in-depth analysis of the alignment process may yield advantageous results. At present, the process of alignment is centered on reducing discrepancies in the placement and direction of images in order to aid in the processing of the images that follow. It is possible to develop a task-specific alignment approach that can handle greater variations in rotations. By utilizing rotational alignment techniques that are customized to the unique features of cattle muzzle images, subsequent image processing steps can be executed with enhanced accuracy.

**References**


1) Astola, J., Haavisto, P., Neuvo, Y. (1990). Vector median filters. *Proceedings of the IEEE*, 78 (4), pp. 678-689.
2) Bazen, A.M., Verwaaijen, G.T., Gerez, S.H., Veelenturf, L.P., Van Der Zwaag, B.J. (2000). A correlation-based fingerprint verification system. In *Proceedings of the ProRISC2000 workshop on circuits, systems and signal processing*, pp. 205-213.
3) Bello, R.W., Olubummo, D.A., Seiyaboh, Z., Enuma, O.C., Talib, A.Z., Mohamed, A.S.A. (2020). Cattle identification: the history of nose prints approach in brief. In *IOP Conference Series: Earth and Environmental Science, IOP Publishing*, 594(1), pp. 12-26.
4) Fischler, M.A., Bolles, R.C. (1981). Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6), pp. 381-395.
5) Jakubović, A., Velagić, J. (2018). Image feature matching and object detection using brute-force matchers. In *2018 International Symposium ELMAR*, *IEEE*, pp. 83-86.
6) Kanopoulos, N., Vasanthavada, N., Baker, R.L. (1988). Design of an image edge detection filter using the Sobel operator. *IEEE Journal of solid-state circuits*, 23 (2), pp. 358-367.
7) Li, G., Erickson, G.E., Xiong, Y. (2022). Individual Beef Cattle Identification Using Muzzle Images and Deep Learning Techniques. *Animals*. 2022; 12(11):1453. https://doi.org/10.3390/ani12111453
8) Lindeberg, T. (2012). Scale invariant feature transform. *Scholarpedia*: Chapter 7(5), 10491. DOI: 10.4249/scholarpedia.10491.
9) Lowe, D.G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60, pp. 91-110.
10) Mehrotra, R., Namuduri, K.R., Ranganathan, N. (1992). Gabor filter-based edge detection. *Pattern recognition*, 25(12), pp. 1479-1494.
11) Mudrova, M., Procházka, A. (2005). Principal component analysis in image processing. In *Proceedings of the MATLAB technical computing conference*, Prague.
12) Noble, W.S. (2006). What is a support vector machine? *Nature biotechnology*, 24 (12), pp. 1565-1567.
13) Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE transactions on systems, man, and cybernetics*, 9 (1), pp. 62-66.
14) Pietikäinen, M. (2010). Local binary patterns. *Scholarpedia*, 5(3), 9775.

15) Priesnitz, J., Rathgeb, C., Buchmann, N., Busch, C., Margraf, M. (2021). An overview of touchless 2D fingerprint recognition. *EURASIP Journal on Image and Video Processing*, 2021(1), pp. 1-28.
16) Tuceryan, M., Jain, A.K. (1993). Texture analysis. *Handbook of pattern recognition and computer vision*, pp. 235-276. https://doi.org/10.1142/9789814343138_0010.
17) Zeng, M., Li, J., Peng, Z. (2006). The design of top-hat morphological filter and application to infrared target detection. *Infrared physics & technology*, 48 (1), pp. 67-76.
18) Ziou, D., Tabbone, S. (1998). Edge detection techniques-an overview. *Pattern Recognition and Image Analysis C/C of Raspoznavaniye Obrazov I Analiz Izobrazhenii*, 8, pp. 537-559.
19) Xiong, Y., Li, G., Erickson, G. (2022). Beef Cattle Muzzle/Noseprint database for individual identification. *Zenodo*. https://doi.org/10.5281/zenodo.6324361