BG Pulse Journal USA
ISSN:1947-2536 http://www.bgpulseusa.com/index.php/bg

# ANALYSIS OF BIOMETRIC CATTLE IDENTIFICATION METHODS BASED ON MUZZLE IMAGE ANALYSIS

**Zaripov Fazilbek Maxsetovich**
Senior lecturer at Tashkent University
of Information Technologies
named after Muhammad al-Khwarizmi
fazilbek.zaripov@gmail.com
https://doi.org/10.5281/zenodo.20519738

## INTRODUCTION

In the 21st century, the rapid development of digital technologies and artificial intelligence systems has brought identification and monitoring issues in the livestock sector to a new level. Traditional methods that have been used so far include ear tags, microchips, tattoos, and radio-frequency identification (RFID) devices. However, these methods have a number of limitations, such as the possibility of causing harm to animals, the loss of identification marks, or their falsification. Therefore, in recent years, the global scientific community has paid increasing attention to the development of identification methods based on the biometric characteristics of cattle.

Cattle identification is considered one of the important aspects of effective management and monitoring in the field of digital livestock farming [25, 26]. Cattle identification systems are a key module of precision livestock farming systems. Such systems are used for tasks such as cattle monitoring, detection of diseased animals, and early identification of lameness. Cattle identification is the process of recognizing each individual animal on livestock farms. Currently, several identification methods are being used, as shown in Figure 1. Traditional and biometric feature-based cattle identification methods have also been considered in these studies [15].

Cattle identification methods are mainly divided into contact-based and contactless approaches [3]. Contact-based methods include hot branding, freeze branding, ear tags, tattoos, and other techniques [23]. Identification using these methods always requires human involvement, as well as time and considerable effort. In addition, these methods have their own disadvantages. For example, the identification process may be painful for animals; ear tags may be lost; and tattoos may become unreadable over time. However, these methods are cheaper compared to other identification approaches [22].

Another widely used contact-based method is the radio-frequency identification system (RFID) [17]. In this identification system, RFID transponders are directly attached to animals, for example, in the form of ear tags equipped with RFID devices. The device has a unique identifier, which is read by special RFID readers, thereby enabling the recognition of animals. Although the installation cost of this system on farms is relatively high, it is currently used as one of the most common identification methods in automated livestock farms. Since the devices used in this method must remain permanently attached to animals, the system has several drawbacks, such as causing discomfort to animals and the possibility of device damage or loss during animal movement [9].

Contactless methods eliminate animal discomfort. In this approach, animals are identified based on their unique biometric characteristics. Biometric characteristics include iris images, coat or skin patterns, muzzle-region images, and facial recognition [13].

BG Pulse Journal USA
ISSN:1947-2536 http://www.bgpulseusa.com/index.php/bg
BG PULSE JOURNAL

Among the listed biometric characteristics, identification based on muzzle-region images has recently attracted increasing research interest [19]. The muzzle image of cattle contains unique features similar to human fingerprints [3, 4]. The distinctive biometric features of the muzzle region are mainly of two types: raised ridge-like structures and grooves or channels (Figure 2).

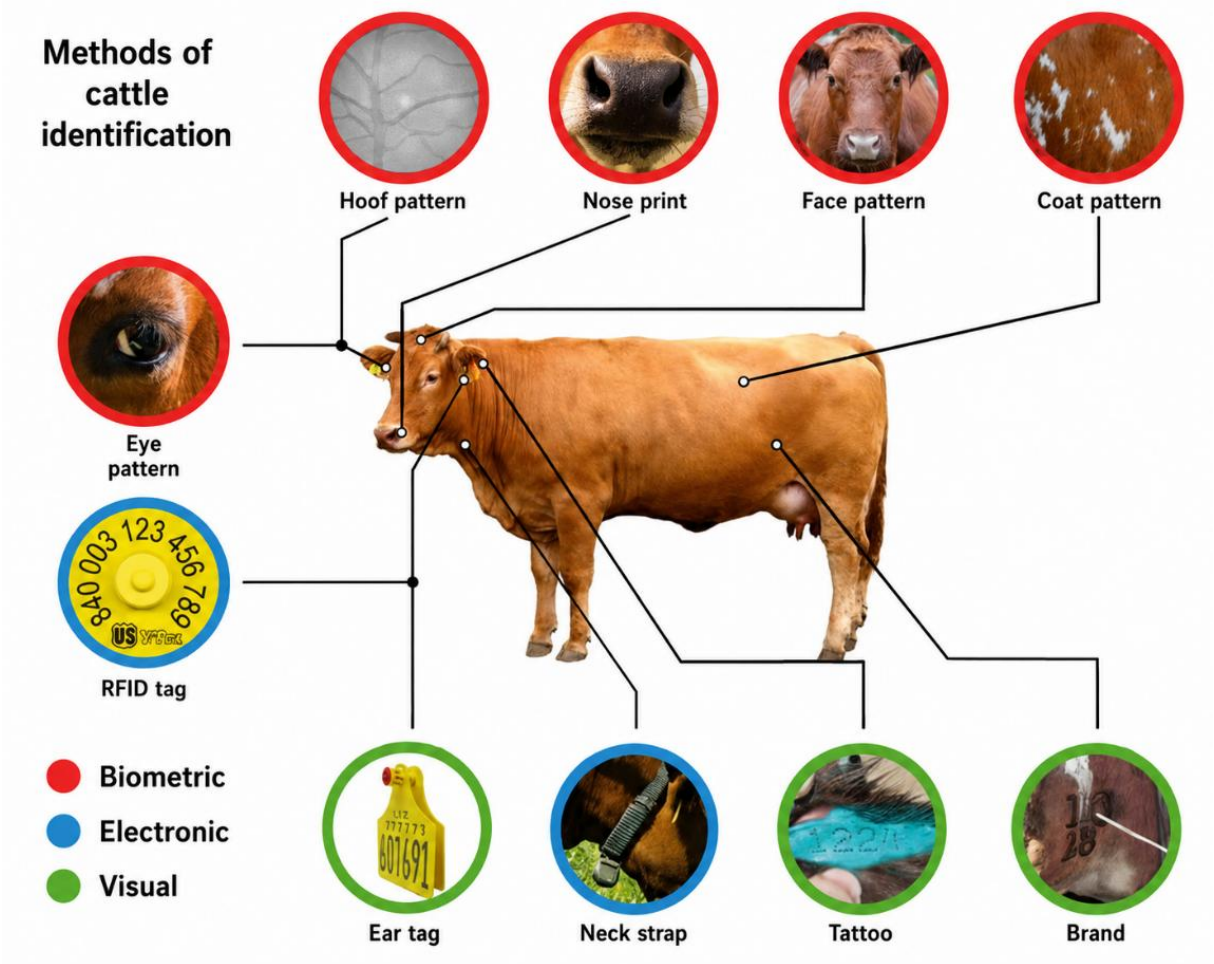



**Figure 1.** Methods of cattle identification. Biometric features, electronic devices, and permanent/classical methods are presented.

The pattern of raised bead-like structures has an irregular formation, and its shape resembles islands, whereas the grooves resemble rivers between these islands. The bead-like structures and grooves serve as unique biometric identifiers for cattle recognition. Based on research findings, the cattle muzzle image has been accepted as an accurate and time-invariant biometric identifier. Studies on this identifier have been conducted since 1921 [12].

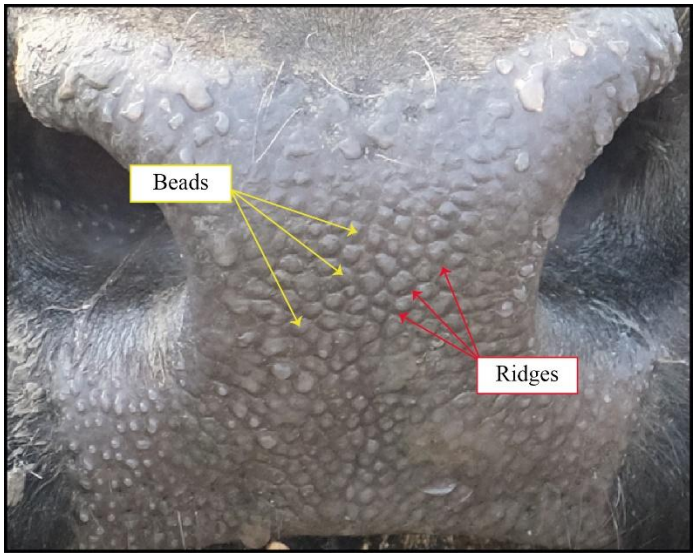



**Figure 2**. Biometric features in the cattle muzzle image.

From the earliest developments in this field to the present day, a number of algorithms have been investigated, ranging from classical feature-based models to deep learning-based automatic systems. In this research work, several scientific studies conducted in recent years were analyzed. These studies cover various stages of automatic identification based on cattle muzzle images, including classical descriptors such as SIFT, LBP, SURF, and Gabor, feature fusion, multimodal approaches involving the muzzle and face or the muzzle and body, as well as deep learning architectures such as VGG, EfficientNet, and YOLO. This analysis helps to clearly demonstrate the stages of scientific development in the field, as well as the existing achievements and limitations.

**STAGES OF DEVELOPMENT IN SCIENTIFIC RESEARCH**

**2002–2010: Formation of the biometric approach**

The idea of identifying cattle through muzzle images was first proposed by Minagawa et al. [4]. The authors printed muzzle patterns on paper using a scanner and evaluated accuracy through a comparative similarity method. However, the obtained result of 66.7% was not satisfactory. Barry et al. [3] analyzed digital images using a pattern recognition approach and achieved an accuracy of more than 98.85%. These results practically demonstrated that the structures in the muzzle region are unique for each animal and can be used as reliable biometric identifiers.

**2011–2016: The period of classical features and classifiers**

Studies conducted between 2011 and 2016 became a turning point in this research field. Noviyanto and Arymurthy used the SIFT descriptor and reduced the error rate sixfold through a matching refinement technique, achieving an accuracy of 99.7% [12]. Tharwat et al. demonstrated an accuracy of 99.5% based on the combination of LBP + LDA + SVM [16]. The MSVM + box-counting fractal feature model developed by Mahmoud and El-Hadad achieved an accuracy of 96.4% on 52 cattle [11]. In a similar period, Tharwat et al. achieved 99.5% accuracy using Gabor filters and a fusion strategy, proving high accuracy even under rotation and occlusion conditions [17]. At this stage, the combination of classical feature extraction methods such as LBP, Gabor, and SURF with classifiers such as SVM, k-NN, and LDA was established as an effective basic architecture for cattle identification.

**2017–2020: Feature fusion and multimodal approaches**

Kumar and Singh combined SURF and LBP features with Gaussian pyramid smoothing and achieved an accuracy of 93.87% on 500 cattle [5]. In the author's subsequent study in 2018, a multimodal model based on Group Sparse Representation Classification (GSRC), which combined muzzle and facial features, was proposed and achieved an accuracy of 96.56% [6]. During the same period, Kusakunniran et al. reported 100% accuracy through the fusion of Gabor and transition LBP features [7]. Awad and Hassaballah proposed a Bag-of-Visual-Words (BoVW) model, in which visual "keyword" vectors were generated from SIFT features and comparative identification was performed based on histograms. In this model, an accuracy of 95.7% was recorded using an SVM classifier, demonstrating that classical methods can provide high performance while maintaining computational efficiency [2]. In 2020, the model proposed by Sian et al. achieved an accuracy of 96.5% through the combination of LBP and improved WLD, improving the model in terms of rotation invariance and noise robustness [15]. In the same year, Kusakunniran et al. proposed, for the first time, a multimodal biometric system by combining muzzle and body patterns. This model achieved an accuracy of 96.32% and FAR = 0.012 [8]. This study laid the scientific foundation for multimodal biometric identification.

**2021–2024: Automation and the deep learning stage**

In recent years, deep learning architectures have become the main scientific direction in the field of cattle identification. The YOLOv3–ResNet50 workflow developed by Shojaeipour et al. combined automatic muzzle detection and individual identification, achieving an accuracy of 99.11% on 2,900 images. The model was trained using few-shot transfer learning with only five images per animal. The accuracy of muzzle detection was 99.13%, while the accuracy of the SoftMax classifier was 99.11% [14]. Li and Erickson created the largest open dataset based on 4,923 muzzle images collected in a farm environment in the United States. Using a deep learning model based on the VGG16_BN architecture, they achieved a training accuracy of 98.75%, a validation accuracy of 98.7%, and a loss value of 0.0478 [10]. Sanjel et al. adapted the VGGFace architecture and analyzed 4,923 muzzle images from 268 cattle. The model achieved a training accuracy of 98.88% and a test accuracy of 100%. Through retraining adaptability, when new animals were added, the method reduced training time by 80% by retraining only the final layer. This approach demonstrated non-invasive identification accuracy while applying the principle of incremental learning for the first time [13]. In the same year, Lee et al. developed a comprehensive workflow based on YOLOv8 and EfficientNetV2-S for Hanwoo cattle in South Korea. In this model, the Lion optimizer was used, and accuracies of 0.981 on the validation set and 0.970 on the test set were recorded. The model achieved an F1-score of 0.95, proving its suitability for real-time farm monitoring [9]. Anithaa et al. proposed a hybrid YOLOv5 and VGG16 model and ensured its practical applicability by integrating it with a mobile application. In this system, YOLOv5 achieved an mAP of 58.1%, the VGG16 classifier achieved an accuracy of 95%, and the inference speed was 30.3 ms per image. The model was tested by farmers, and the reliability and usability of the application were rated 4.3 out of 5 [1].

At this stage, deep learning models such as YOLO, VGG, EfficientNet, and VGGFace made it possible to identify cattle from muzzle images in a real-time, non-invasive, and highly accurate manner. At the same time, the adaptation of these models to multimodal systems and mobile applications significantly expanded their practical usability.

Table 1.

**Comparative analysis of cattle identification methods based on muzzle images**

| Year | Author(s) | Applied method / architecture | Number of cattle (classes) | Accuracy rate (%) (%) |
|---|---|---|---|---|
| 2002 | Minagawa et al. | Joint pixel comparison | 10 | 66.7 |
| 2007 | Barry et al. | Ridge pattern recognition | 15 | 58.0 |
| 2013 | Noviyanto va Arymurthy | SIFT + refinement | 20 | 99.7 |
| 2013 | Awad va Zawbaa | SIFT + RANSAC | 15 | 93.3 |
| 2014 | Tharwat et al. | LBP + LDA + SVM | 31 | 99.5 |
| 2015 | Mahmoud et al. | MSVM + fractal feature | 52 | 96.4 |
| 2015 | Tharwat va Gaber | Gabor + Feature/Classifiers Fusion | 31 | 99.5 |
| 2015 | Ahmed va Gaber | SURF descriptor | 20 | 98.0 |
| 2017 | Kumar va Singh | SURF + LBP + Gaussian smoothing | 120 | 93.8 |
| 2018 | Kumar et al. | Group Sparse Representation (GSRC) | 120 | 96.5 |
| 2018 | Kusakunniran et al. | Gabor + tLBP | 31 | 100.0 |
| 2019 | Awad va Hassaballah | Bag-of-Visual-Words (BoVW) | 150 | 95.7 |
| 2020 | Sian et al. | LBP + Improved WLD | 45 | 96.5 |
| 2020 | Kusakunniran et al. | Muzzle + body feature fusion | 31 | 96.3 |
| 2021 | Shojaeipour et al. | YOLOv3 + ResNet50 | 300 | 99.1 |
| 2022 | Li et al. | VGG16_BN | 268 | 98.7 |
| 2023 | Sanjel et al. | VGGFace (VGG16-based) | 268 | 100.0 |
| 2023 | Lee et al. | YOLOv8 + EfficientNetV2-S | 336 | 97.0 |
| 2024 | Anithaa et al. | YOLOv5 + VGG16 + CLAHE | 200 + | 95.0 |

As can be seen from the data presented in Table 1, scientific research in the field of cattle identification based on muzzle images has gradually improved over the last two decades. The development of this research direction shows a clear transition from simple comparative and handcrafted feature-based methods to fully automated deep learning-based identification systems.

**RESULTS**

According to the analysis, identification accuracy has increased from approximately 60–70% in early studies to nearly 99% in modern deep learning-based models. Early approaches mainly relied on visual comparison, ridge pattern analysis, and classical feature descriptors. Although models based on classical methods such as SIFT, SURF, LBP, and Gabor features achieved relatively high accuracy, they usually required manual preprocessing, careful feature engineering, and additional matching or classification procedures. As a result, their computational cost was relatively high, and their applicability in real-time farm environments was limited.

In contrast, recent deep learning architectures, including VGG, ResNet, EfficientNet, and YOLO-based models, have made it possible to automate the main stages of the identification pipeline, including muzzle region detection, feature extraction, and individual classification. These models can be trained on larger datasets and are more suitable for real-time image processing and deployment in practical livestock monitoring systems. In particular, the integration of object detection models with convolutional neural networks has improved the robustness of cattle identification under varying image acquisition conditions.

However, the analysis also shows that existing models are not yet sufficiently optimized from an architectural point of view. Although some deep learning models demonstrate high identification accuracy, they often contain redundant layers and a large number of parameters during the feature extraction and classification stages. This increases computational complexity, requires more hardware resources, and may reduce inference speed. Therefore, there remains a need to develop improved architectures that can preserve high recognition accuracy while reducing computational cost and increasing practical efficiency.

**CONCLUSION**

From this perspective, this dissertation proposes an improved model architecture for cattle identification based on muzzle images. The proposed approach is aimed at enhancing the discriminative capability of the neural network while reducing unnecessary computational operations. In the proposed model, the original output layer is removed and the classification head is redesigned using the following structure: FC–512–ReLU–Dropout–FC–LogSoftmax. This modification allows the network to extract more informative and discriminative features from cattle muzzle images and improves the separability of individual cattle classes.

The redesigned fully connected block helps to reduce overfitting through the use of Dropout and strengthens nonlinear feature representation through the ReLU activation function. At the same time, the final LogSoftmax layer provides a stable probabilistic output for multi-class cattle identification. By preserving the semantic relationships between extracted features and improving the classification stage, the proposed model increases the accuracy and reliability of identification.

Thus, the proposed architecture can be considered a promising solution for non-invasive, automated, and reliable cattle identification. It is especially relevant for digital livestock farming systems, where accurate recognition, reduced computational cost, and fast inference are important requirements for practical implementation.

## REFERENCES

1. Anitha J, Avanthika R, Kavipriya B et al. (2024) Cattle identification using muzzle images. In: Applied Data Science and Smart Systems, pp 370–377
2. Awad AI, Hassaballah M (2019) Bag-of-Visual-Words for Cattle Identification from Muzzle Print Images. Applied Sciences 9:1–12. doi: 10.3390/app9224914
3. Awad, Ali, Ismail (2016) From classical methods to animal biometrics: A review on cattle identification and tracking. Computers and Electronics in Agriculture 123:423–435. doi: 10.1016/j.compag.2016.03.014
4. Baranov AS, Graml R, Pirchner F et al. (1993) Breed differences and intra-breed genetic variability of dermatoglyphic pattern of cattle. J Anim Breed Genet 110:385–392. doi: 10.1111/j.1439-0388.1993.tb00751.x
5. Barry B, Gonzales-Barron U, Mcdonnell K et al. (2007) Using Muzzle Pattern Recognition as a Biometric Approach for Cattle Identification. Transactions of the ASABE 50:1073–1080. doi: 10.13031/2013.23121
6. Hideo Minagawa, T. Fujimura, Marika Ichiyanagi et al. (2002) Identification of beef cattle by analyzing images of their muzzle patterns lifted on paper. In:
7. Kumar S, Singh S, Singh A (2017) A Muzzle Point Pattern based Techniques for Individual Cattle Identification. IET Image Processing 11. doi: 10.1049/iet-ipr.2016.0799
8. Kumar S, Singh S, Abidi A et al. (2018) Group Sparse Representation Approach for Recognition of Cattle on Muzzle Point Images. International Journal of Parallel Programming 46:1–26. doi: 10.1007/s10766-017-0550-x
9. Kumar M (2022) Shi-Tomasi corner detector for cattle identification from muzzle print image pattern. Ecological Informatics 68. doi: 10.1016/j.ecoinf.2021.101549
10. Kusakunniran W, Wiratsudakul A, Chuachan U et al. (2018 - 2018) Automatic cattle identification based on fusion of texture features extracted from muzzle images. In: 2018 IEEE International Conference on Industrial Technology (ICIT). IEEE, pp 1484–1489
11. Kusakunniran W, Wiratsudakul A, Chuachan U et al. (2020) Biometric for Cattle Identification using Muzzle Patterns. International Journal of Pattern Recognition and Artificial Intelligence. doi: 10.1142/S0218001420560078
12. Lee T, Na Y, Kim BG et al. (2023) Identification of Individual Hanwoo Cattle by Muzzle Pattern Images through Deep Learning. Animals (Basel) 13. doi: 10.3390/ani13182856
13. Li G, Erickson GE, Xiong Y (2022) Individual Beef Cattle Identification Using Muzzle Images and Deep Learning Techniques. Animals (Basel) 12. doi: 10.3390/ani12111453
14. Mahmoud H, Mohmaed H (2015) Automatic cattle muzzle print classification system using multiclass support vector machine. IJIM 1:126. doi: 10.1504/IJIM.2015.070022
15. Nishanov AX, Zaripov FM (2023) Chorvachilik sohasida qoramollarni vizual identifikatsiya qilish usullari. In: “Fan va ta’limni rivojlantirishda raqamli texnologiyalarning roli” respublika ilmiy-texnik anjumanining ma’ruzalar to‘plami, Nukus, pp 158–161
16. Noviyanto A, Arymurthy AM (2013) Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method. Computers and Electronics in Agriculture 99:77–84. doi: 10.1016/j.compag.2013.09.002
17. Samandarov B, Geldibayev B (2024) Development of a database of the livestock complex monitoring system using RFID devices. AIP Conf Proc 3147:40003. doi: 10.1063/5.0210270
18. Sanjel A, Khanal B, Rivas P et al. (2023 - 2023) Non-Invasive Muzzle Matching for Cattle Identification Using Deep Learning. In: 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE). IEEE, pp 1998–2002

19. Shojaeipour A, Falzon G, Kwan P et al. (2021) Automated Muzzle Detection and Biometric Identification via Few-Shot Deep Transfer Learning of Mixed Breed Cattle. Agronomy 11:2365. doi: 10.3390/agronomy11112365
20. Sian C, Jiye W, Ru Z et al. (2020) Cattle identification using muzzle print images based on feature fusion. IOP Conference Series: Materials Science and Engineering 853:12051. doi: 10.1088/1757-899X/853/1/012051
21. Tharwat A, Gaber T, Hassanien AE et al. (2014) Cattle Identication using Muzzle Print Images based on Texture Features Approach
22. Tharwat A, Gaber T, Hassanien AE (2015) Two biometric approaches for cattle identification based on features and classifiers fusion. IJIM 1:342–365. doi: 10.1504/IJIM.2015.073902
23. Xiong Y, Li G, Erickson G (2022) Individual Beef Cattle Identification Using Muzzle Images and Deep Learning Techniques
24. Зарипов ФМ (2024) Қорамолларни бурун қисми тасвири орқали идентификация қилиш. Мухаммад ал-Хоразмий авлодлари 4:77–81
25. Нишанов АХ, Зарипов ФМ (2023) Чорвачиликда қорамолларни идентификация қилиш муаммолари. In: “Xalq xo‘jaligi sohasida ilg‘or texnologiyalar tatbiqi muammolari” mavzusidagi hududiy ilmiy-texnik konferensiyasi ma’ruzalar to‘plami, Nukus, pp 22–27
26. Нишанов АХ, Зарипов ФМ (2025) Қорамолларни бурун қисми тасвирлари асосида идентификация қилиш соҳасидаги замонавий тадқиқотлар ва ривожланишлар таҳлили. In: Axborot texnologiyalaridan foydalanishni yangi bosqichga ko‘tarishning ilmiy asoslari va avtomatlashtirishning zamonaviy muammolari” mavzusida IV-Xalqaro ilmiy anjumani ma’ruzalar to‘plami, Toshkent, pp 366–371