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Computer vision-based approaches to cattle identification: A comparative evaluation of body texture, QR code, and numerical labelling

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Abstract: Cattle identification systems are advancing to meet the growing demands of precision livestock management, traceability, and ethical animal treatment. This study investigates three methods: body texture recognition, QR code collars, and numerical labelling, implemented using the YOLOv8 convolutional neural network. Each method was evaluated in terms of accuracy, scalability, adaptability to dynamic herd changes, and operational efficiency under various environmental conditions. Body texture recognition, while leveraging unique natural patterns and achieving a mean Average Precision (mAP50–95) of 0.78 proved limited by its reliance on frequent dataset retraining to accommodate changes in herd composition and susceptibility to misidentification in larger herds. QR code collars demonstrated adaptability in dynamic herds by enabling pre-trained convolutional neural networks to assign reserved codes to new animals without retraining, while removing animals involves simply deleting their codes from the system. This approach also achieved an mAP50–95 of 0.71, which was lower than the body texture-based approach, but offered greater flexibility in herd management. Despite this adaptability, this method demonstrated significant challenges in real-world environments. Occlusion caused by feeders, barriers, or animal movements, along with low-resolution imaging and poor lighting conditions, can compromise detection accuracy, particularly in larger herds with obstructive barn layouts. The numerical labelling method emerged as the most effective solution to dynamic cattle identification, achieving the highest mAP50–95 of 0.84. It provided a scalable and highly accurate approach that integrates seamlessly with automated systems. Unlike traditional body marking techniques such as ear notching and branding, numerical labelling is less invasive, painless, and highly scalable, aligning with ethical livestock management practices while maintaining consistent accuracy across diverse environmental conditions.

Keywords: animal welfare; convolutional neural networks; herd monitoring; livestock biometrics; object detection; precision livestock farming

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Since the early 1970s, cattle identification has become a global concern, prompting research institutes across various countries to engage in developing different identification methods. This marked the beginning of efforts to address the need for efficient and reliable methods of tracking and identifying livestock (Rossing 1999). In the early 1970s, John Bridle at the National Institute of Agricultural Engineering in Silsoe, UK, developed a cattle identification system that was tested on an experimental farm (Bridle 1973). Around the same time, the Technical and Physical Engineering Research Institute and the Institute of Agricultural Engineering in Wageningen, Netherlands, developed an automatic identification system based on Pulse Code Modulation (PCM) technology, which was also tested on a practical farm (Rossing 1999). Later on, a variety of other animal identification methods have been developed.

Accurate animal identification is crucial for reliable experimentation in various research fields. When selecting an identification method, several factors must be considered: the uniqueness and permanence of the individual label, the suitability of the method for the specific animal species, the expertise required for applying and interpreting the identification mark, and the overall cost of implementation. These factors ensure that the chosen method effectively meets the needs of both research accuracy and practical application. Initially, popular cattle identification methods were limited to classical methods such as body marking and wearable devices such as ear tags and collars. However, with recent advancements in precision livestock farming technologies and increased awareness of animal welfare, research has shifted towards more natural, non-invasive methods of cattle identification based on biometrics, as each cow possesses unique external biometric characteristics that can be used for individual identification (Zhao and He 2015).

This paper investigates three distinct cattle identification methods: body texture recognition, QR code collars, and numerical labelling, evaluating their effectiveness in addressing operational challenges in the livestock industry. Body texture recognition utilises the unique coat patterns of cattle, enabling identification based on their natural physical characteristics. QR code collars provide a standardised approach by encoding animal IDs into visually scannable codes affixed to collars worn around the cattle necks. Numerical labelling, on the other hand, involves assigning and displaying unique numbers directly on the animals for easy identification. Each method was implemented and assessed using the YOLOv8 (You Only Look Once) object recognition model, tailored to address the unique requirements of each approach. By systematically comparing these identification methods, this study seeks to determine the most effective solution for varying farm conditions, group sizes, and environmental factors. The findings aim to guide the development of more efficient and scalable cattle identification systems, enhancing operational efficiency in the livestock industry.

CLASSIFICATION OF CATTLE IDENTIFICATION METHODS: A LITERATURE REVIEW

Cattle identification methods can be classified into two main categories: natural feature-based methods, also referred to as biometric methods, and artificial marker-based methods, subcategorised under mechanical and electronic methods (Awad 2016).

Natural feature-based identification methods

Natural cattle identification methods can be further categorised based on their focus into two subcategories: body part-based identification and texture-based identification (Shen et al. 2020). Body part-based identification involves recognising individual cattle by analysing specific body parts, such as the muzzle, face, back, or trunk. For example, the muzzle may display distinct nostril patterns and pigmentation (Li et al. 2021), while the face may feature unique markers such as eye spacing, ear shapes, and facial markings (Mahato and Neethirajan 2024). Similarly, the back and trunk can be identified through characteristics like contours, spine shapes, or distinctive scars and marks (Zin et al. 2020). On the other hand, texture-based identification examines the entire body or large visible sections of the animal, focusing on overall surface patterns, such as fur colouring or spot arrangements. Both approaches leverage the natural variability in these features, making them theoretically well-suited for precise identification.

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Many researchers have conducted experiments for cattle identification based on specific body parts. For example, Kumar et al. (2018) proposed a cow identification system based on their primary muzzle point. The system employed convolutional neural networks (CNN) and deep confidence networks to extract features from the cow's muzzle for identification, achieving an identification accuracy of 98.99%, regardless of the challenge of capturing the cow's muzzle. Similar works were also investigated by different researchers, including Noviyanto and Arymurthy (2013). Kumar et al. (2016) also presented computer vision approaches to cattle recognition using their facial images, achieving good recognition accuracy. Other researchers, e.g. Kim et al. (2005), also investigated the cattle identification approaches based on their face images. The common challenges highlighted by all researchers included poor illumination and the pose (Kumar et al. 2016). Zin et al. (2020) also explored the effectiveness of image-processing technologies in identifying individual cows along with deep learning techniques. The back images of cows in a milking parlour were captured and used to train a convolutional neural network to identify individual cows, achieving an accuracy of 97.01% for the cow's back pattern identification. Zhao and He (2015) investigated the cattle identification approach based on cows' trunks. Side-view images were collected and later cropped only to remain with cows' trunk images, used to train a convolutional neural network, resulting in a recognition accuracy of over 90%. Even though their study achieved good results, relying solely on the trunk region for identification poses a great challenge. Although the trunk is a more stable region for detection compared to the muzzle or face, this approach overlooks important features from other parts of the cow, such as the head and legs, which also have unique contour and texture characteristics (Shen et al. 2020). To address this challenge, Shen et al. (2020) conducted an experiment to identify individual cows while exploiting all the information of the cow object in side-view images, including head, trunk and leg regions, by means of convolutional neural networks, achieving an accuracy of 96.65%. Similarly, Hu et al. (2020) proposed a cow identification method based on the fusion of deep parts features (see Figure 1) using convolutional neural networks and a support vector machine (SVM) classifier, achieving 98.36% cow identification accuracy.

While body part-based identification methods have certain advantages, they face significant challenges that limit their reliability in dynamic environments. The practical application of these methods is hindered by several factors. Identification effectiveness heavily depends on the distinctiveness of the selected body part, which can vary considerably among individuals within a herd. Moreover, maintaining the consistent visibility of specific body regions is often challenging in real-world scenarios. For instance, the muzzle may be obscured during feeding, the face may be blocked by movement or other animals, and the trunk may be partially hidden by structural barriers or camera angles. These issues result in inconsistencies in the captured data, reducing the reliability of identification outcomes. Furthermore, body part-based methods may often require specialised imaging techniques to target specific regions, which may complicate the deployment of the system in diverse barn environments.

In contrast, texture-based identification analyses the overall surface details of the animal, such as fur patterns, skin irregularities, and subtle variations in colouration. This approach examines the entire body or its significant portions, capturing comprehensive characteristics that differentiate one animal from another. Texture-based methods are particularly advantageous in situations where the animal's full or partial body is visible, as they

(A) (B) (C) (D) (E)

Figure 1. Some parts of interest for cow identification: (A) muzzle, (B) face, (C) back, (D) trunk, and (E) overall cow object (Hu et al. 2020)

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do not rely on specific anatomical features. This flexibility makes them applicable even when certain body parts are obscured.

Artificial marker-based identification methods

Artificial cattle identification methods have been a critical practice in livestock management for centuries. They can also be classified under mechanical and electronic methods (Bai et al. 2017). Ear tags, collars and body marking are among the examples of mechanical methods, whereas electronic methods use Radio Frequency Identification (RFID) for identification (Achour et al. 2020). Considering the scope of this study, our focus will be limited only to mechanical methods.

Among the earliest techniques, body marking has been used since 1 000 BCE (Before Common Era), when nomadic herders employed branding irons and colour pigments to distinguish livestock and prevent theft (Landais 2000). This practice continues in some regions today, particularly on small-scale farms (Bai et al. 2017). Ear tagging has also been one of the most widely adopted cattle identification methods, known for its cost effectiveness and convenience. Ear tags are generally made from plastic and can include barcodes, alphanumeric codes, or colour patterns for easy differentiation. Properly designed tags must resist tampering, remain legible over time, and securely attach without harming the animal.

Ear tagging continues to be a practical and widely adopted method of cattle identification, even in this century, due to its reliability and cost effectiveness. In many countries, ear tags are integral to dairy farm operations, where they align with international standards for identifying individual cows. From birth, each calf is assigned a unique ID number that is registered in a centralised database. This unique identifier comprises details like the responsible organisation, the country code (e.g. SI for Slovenia), and a specific number, which are both printed as digits and encoded as a barcode (see Figure 2).

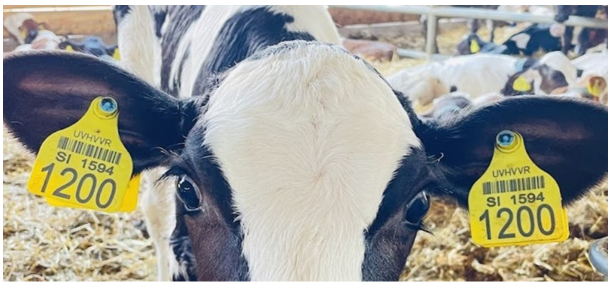

Figure 2. A sample ear tag that is attached to the calf's ear

The practicality of ear tagging has been further enhanced through technological advancements. For example, Zin et al. (2020) have employed pre-trained YOLO models to develop ear tag recognition systems, achieving impressive accuracy rates of 92.5% in identifying individual cows. Similarly, image processing techniques and convolutional neural networks have been used to create systems capable of managing dairy cows with an accuracy of 84% (Zin et al. 2020). These innovations demonstrate that ear tagging remains not only relevant but also adaptable to modern precision farming practices, highlighting its enduring value in the agricultural industry.

Collar tagging also offers another practical solution to cattle identification, particularly in contexts where removability and flexibility are important. One study used plastic plates with digit numbers affixed to collars, achieving an impressive 93.65% accuracy using the Faster R-CNN deep learning model to detect and identify individual cows (Bezen et al. 2020). Collars provide flexibility, as they can be removed or replaced easily, although they may be less durable in harsh environments compared to ear tags. Despite these limitations, collars are particularly useful when integrated with advanced recognition technologies, making them a practical solution to herd management in certain settings.

Together, classical identification methods such as body marking, ear tags, and collars have laid a strong foundation for livestock management, demonstrating reliability and practicality across diverse farming contexts. By integrating these conventional techniques with modern advancements like RFID systems, barcoding, and machine learning-based recognition models, their functionality and efficiency can be significantly enhanced, paving the way to more precise and scalable solutions in animal identification.

EXPERIMENTAL EVALUATION OF INDIVIDUAL METHODS USING CONVOLUTIONAL NEURAL NETWORKS

The experimental part of this study was conducted at the Opařany Agricultural Cooperative

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on a dairy cow farm located in the Czech Republic. The whole experiment was designed to comply with animal welfare principles. The system for image acquisition consisted of a set of several cameras installed in the barn. The camera systems for each method are described in their relevant sections.

The model performance was evaluated using standard object detection metrics: Precision, Recall, and mean Average Precision (mAP). These are defined as follows:

$$Precision = \frac{True\ Positives}{Predicted\ Positives} = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{True\ Positives}{All\ Positives} = \frac{TP}{TP + FN} \quad (2)$$

$$mAP = \left(\frac{1}{N}\right) \times \sum_{i=1}^{N} \left(AP_i\right) \quad (3)$$

where:
TP – number of true positives;
FP – number of false positives;
FN – number of false negatives.

The mAP50–95 represents the average precision calculated at multiple Intersection-over-Union (IoU) thresholds ranging from 0.50 to 0.95 (in increments of 0.05), and it is used to measure the overall detection accuracy of the model across classes. These metrics provide a comprehensive view of the model performance in object detection tasks.

Cattle identification based on body texture

This method was first evaluated in a small herd (6 cows). The camera system was designed to collect data in a 5 × 5 m enclosed pen. The video footage was continuously recorded for 1 month under both daylight and nighttime conditions, which was then used to generate image data. The developed camera system consisted of two types of IP cameras (Hikvision DS-2CD2T46G2-2I RGB). The cameras were placed on the wall in a line, one above the other. The first camera was placed at a height of 4.5 m, and the second one at a height of 5.5 m. The above height positioning of the cameras was chosen so that their field of view would cover the entire area defined for animal movement, and also to take advantage of the possibility of obtaining more variable data by using different angles.

An input dataset was created for training a convolutional neural network model applicable to the identification of individual animals in a small herd, with its properties illustrated in Figure 3. In the top left part of the figure, the data shows the frequency of representation for each class (cow 1–6) in the dataset, revealing that the objects cow 1 and cow 2 were the most frequent, while cow 5 and cow 6 were the least frequent. The top right part presents the shapes of the individual bounding boxes. In the bottom left, the occurrence of observed objects is visualised, and in the bottom right, the relative size of the bounding boxes compared to the image is shown. Most bounding boxes had heights ranging from 20% to 50% of the image height, and the bounding box widths rarely exceeded the range of 10–40% of the image width.

To further enhance dataset variability and support robust model generalisation, an integrated augmentation pipeline was developed. It consisted of various geometric transformations such as cutouts, resizing, rotation, and flipping. Further photometric transformations to simulate image variability were also performed. These include blurring, brightness and contrast variation, etc. The total number of objects in the input dataset after augmentation was 20 900.

YOLOv8 model with a batch size of 4, learning rate of 0.01 and SGD optimiser was trained for 100 epochs on a computer setup with an Intel(R) Core(TM) i9-10940X processor, an NVIDIA GeForce RTX 3090 graphics card, and the Windows 10 Pro operating system. The progression of the observed metric values throughout the training is shown in Figure 4.

The results demonstrate a sharp improvement in the metrics Precision, mAP50, Recall, and mAP50–95 during the first 10 epochs. Afterwards, the rate of improvement slowed significantly, but all metrics continued to show positive trends. Throughout all 100 epochs, the loss metrics for bounding boxes, objects, and classes continued to decrease, while the mAP50–95 value, considered the most critical metric for assessing the accuracy of the trained model predictions, kept increasing. From epoch 50 onward, the precision, recall, and mAP50 values remained almost constant, indicating an appropriate training duration (number of epochs).

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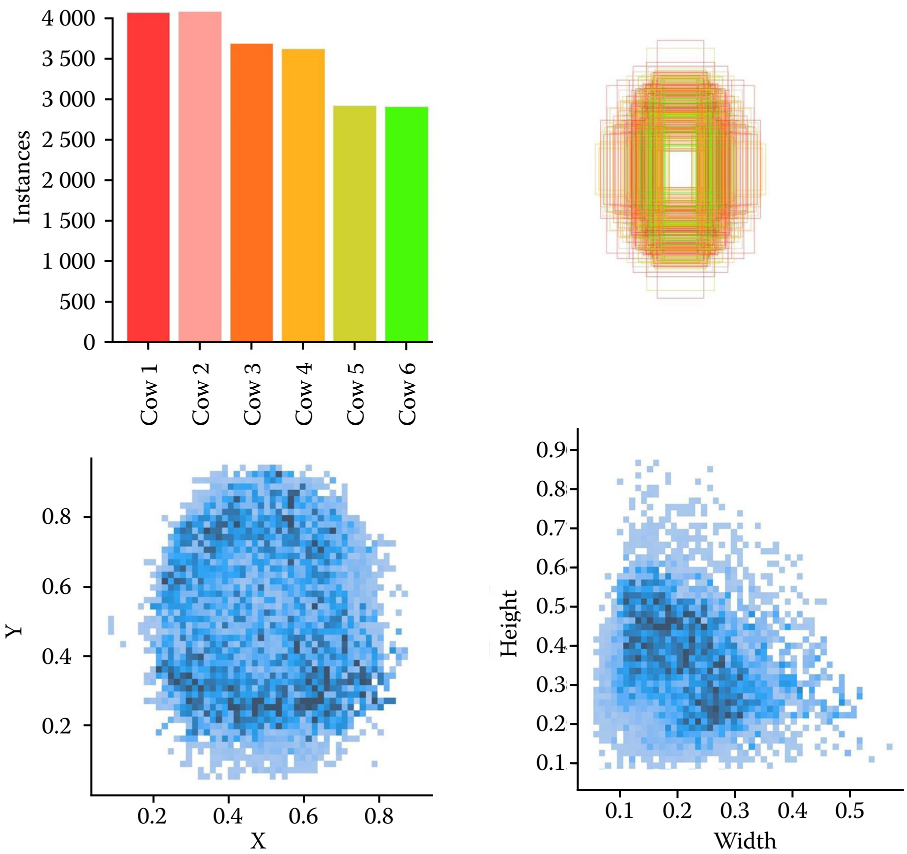

Figure 3. Visualisation of training dataset properties for the body texture recognition method, based on a herd of 6 dairy cows

Top left – frequency of each class in the dataset (cows 1–6); top right – dimensions of bounding boxes; bottom left – occurrences of observed objects; bottom right – relative sizes of bounding boxes compared to the image size

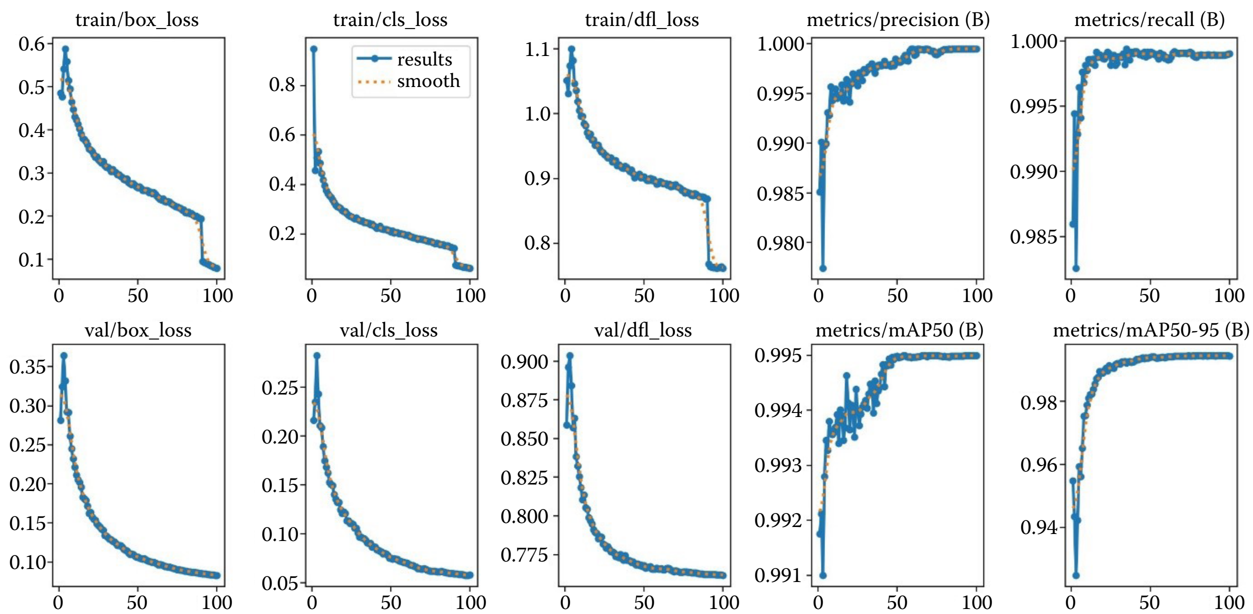

Figure 4. Training progression of the YOLOv8 model applied to body texture recognition in a 6-cow dataset

Hyperparameters: batch size = 4, learning rate = 0.01, SGD optimiser. The plot shows the evolution of key metrics (precision, recall, mAP50, mAP50–95) and loss values over 100 epochs

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Based on the results obtained from training the convolutional neural network model, we can create two supporting graphs, the F1 curve (Figure 5) and the PR (Precision-Recall) curve (Figure 6), which help to better illustrate the properties of the trained model. The F1 curve allows us to determine the optimal confidence threshold setting that can be applied to inference in the real-world use. In this case, the optimal threshold is 0.879, which is considered a value indicating very good recognition capabilities of the trained model. The PR curve illustrates the balance between Precision and Recall values. This enables a graphical evaluation of the proportion of True Positive results to Positive Predictions. For our YOLOv8 model with hyperparameters of the batch size 4 and learning rate of 0.01, the curve is nearly optimal, showing that no particular class stands out as notably challenging for the trained model to identify.

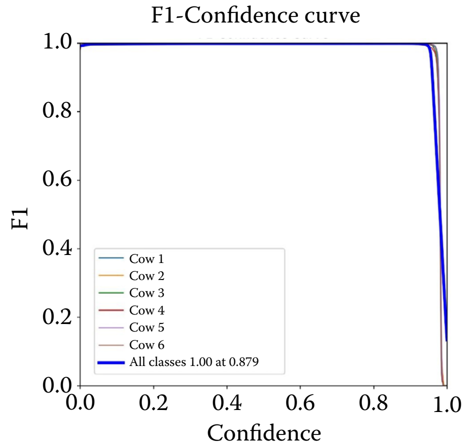

Figure 5. F1-score curve of the YOLOv8 model trained for body texture recognition

The optimal confidence threshold was determined to be 0.879, indicating a strong model performance across all classes

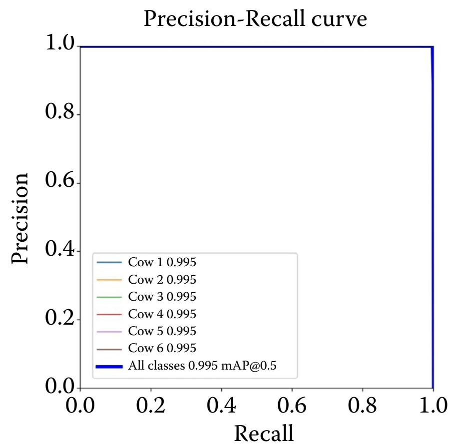

Figure 6. Precision–Recall (PR) curve of the YOLOv8 model trained for body texture-based identification

The curve illustrates a strong balance between precision and recall across all six cow classes

The functionality and accuracy of the trained model designed to identify individual animals in a herd of 6 animals are presented in Figure 7. It is evident that the trained model can easily identify individual objects in the image and reliably determine which specific object it is (cow 1–6). For better clarity, the segmentation of each object is represented in a different colour. Within such a small group of animals, it was possible to select objects that significantly differ in their texture and colouring, which is why the trained model was able to identify individual objects with high accuracy (almost 100%).

Cattle identification using QR code collars

This method was evaluated under a medium-sized herd of up to 30 cows, each one wearing a QR code collar. The system consisted of eight HIKVISION DS-2CD2T46G2-2I RGB cameras strategically deployed to ensure the full visual coverage of the observation area. Similarly, the continuous video footage was recorded over 1 month under varying lighting and activities. Extracted images were also augmented up to 91 694 images.

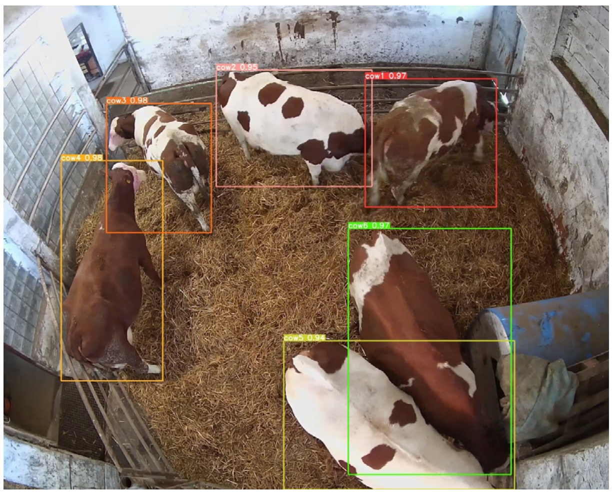

Figure 7. Output of the trained YOLOv8 model applied to a closed herd of 6 dairy cows under daylight conditions, recognising each detected individual (cow 1–6) based on its body texture

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YOLOv8 with similar hyperparameter values as the ones used for the previous method was chosen for training: a batch size of 4, a learning rate of 0.01 and an SGD optimiser. With the above settings, it was trained for 120 epochs on a computer setup with an Intel(R) Core(TM) i9-10940X processor, NVIDIA GeForce RTX 3090 graphics card, and the Windows 10 Pro operating system. The progression of the observed metrics during training is shown in Figure 8. This figure demonstrates a sharp improvement in learning outcomes during the first 30 epochs. Subsequently, the learning rate slowed considerably, though the metrics continued to show improvement. Throughout all 120 epochs, the loss values for bounding boxes, objects, and classes decreased, while the mAP50–95 metric, considered the most important metric for the model prediction accuracy, continued to rise. Precision, recall, and mAP50 remained nearly constant from epoch 30 onward.

The results obtained from training the convolutional neural network model allow us to create two auxiliary graphs, the F1 curve and the PR curve (see Figure 9), which help to better map the characteristics of the trained model. The F1 curve can determine the optimal confidence threshold for inference with the trained model for real-world applications. In this case, the optimal threshold was 0.452. The PR curve shows the balance between Precision and Recall, enabling a graphical evaluation of the True Positive rate and Positive Predictions. For our trained model with hyperparameters of the batch size 4 and learning rate 0.01, the PR curve is nearly optimal, indicating that none of the identified classes possesses particular challenges for detection.

When evaluating the model reliability, problematic zones were identified where the QR code detection was challenging. These problematic areas are the edges of the camera footage: on the left edge, where the feeding aisle is located, the animals lean toward the feed, often moving the QR code out of the camera range or making it difficult for the camera to read, which can lead to misidentification. A similar issue occurred on the right edge of the footage, where similar situations arose. In the middle of the footage, model reliability is very high, except in cases where QR codes are obscured by structures separating individual resting areas in the barn.

Cattle identification based on numerical labelling

The image acquisition system and data preprocessing techniques used to evaluate this method were similar to the QR code approach. However,

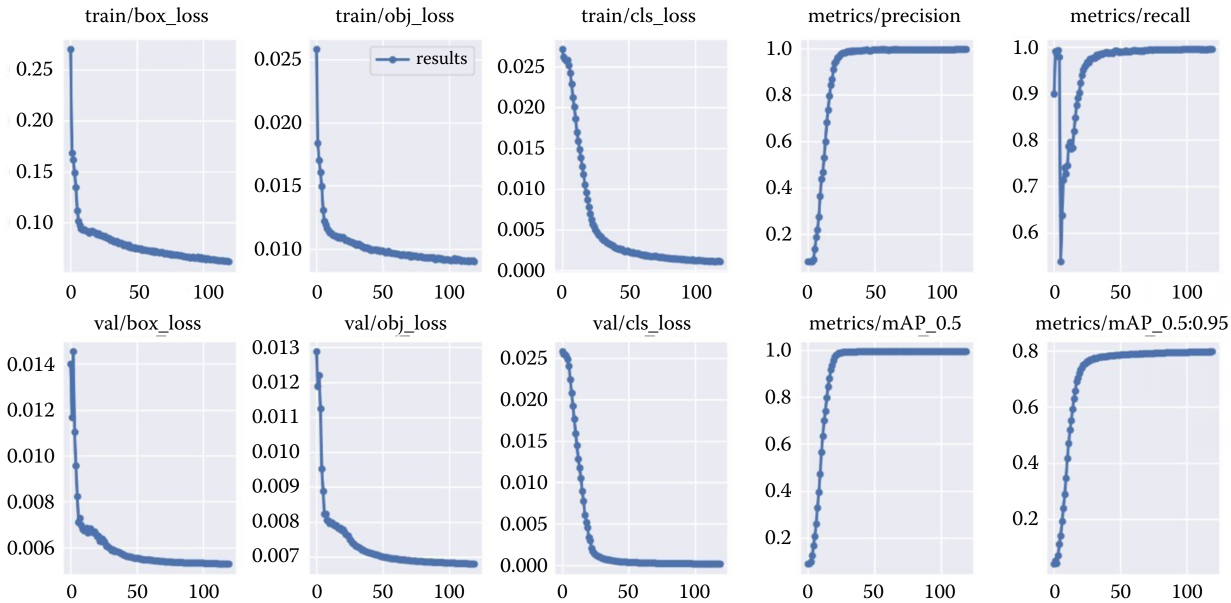

Figure 8. Training progress of the YOLOv8 model for QR code collar recognition in a herd of 30 cows
The network was trained over 120 epochs using a batch size of 4, learning rate of 0.01, and SGD optimiser. Steady improvements in mAP and loss values are observed

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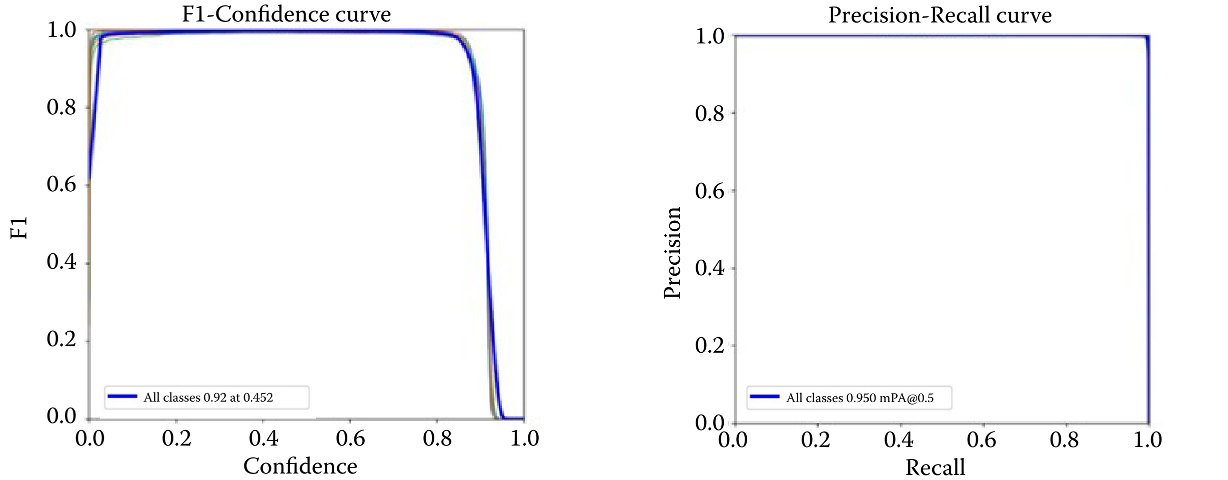

Figure 9. F1-score curve (left) and Precision-Recall (PR) curve (right) of the YOLOv8 model trained on QR code collar data

The model shows a high balance between precision and recall across all classes

the herd size was increased up to 50 dairy cows in the observation. Of these, 30 cows were marked with unique numerical identifiers using special marking animal-safe colours, commonly used to mark animals. An input dataset of 91 694 images was created following similar augmentation techniques mentioned above, with its properties illustrated in Figure 10.

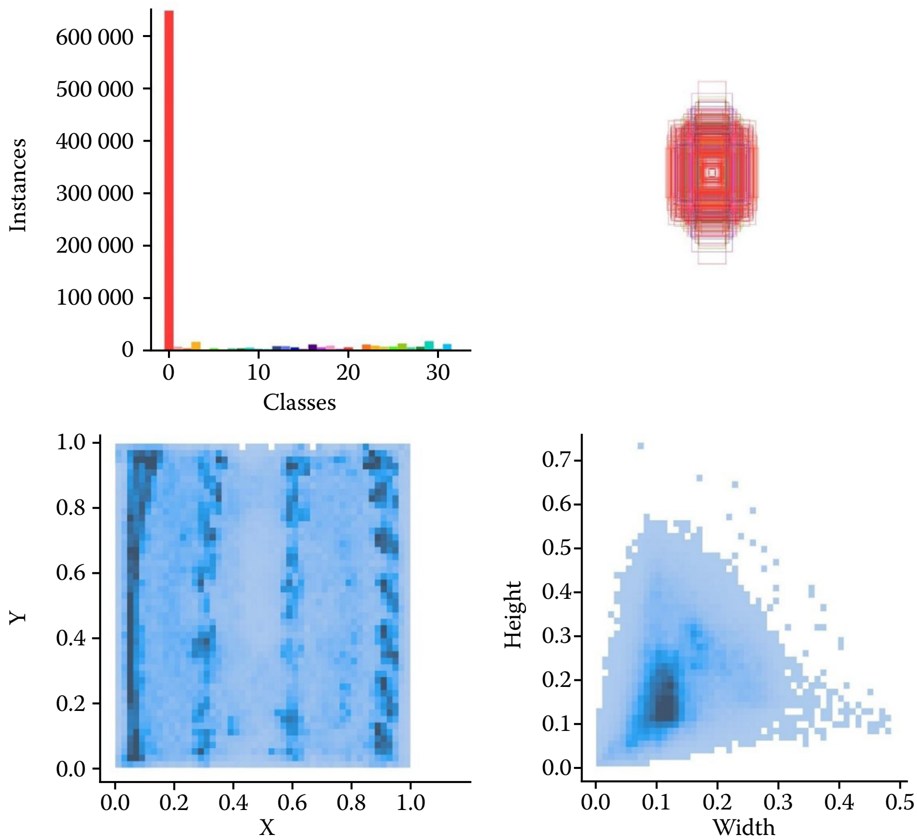

Figure 10. Visualisation of training dataset properties for numerical labelling identification, based on a herd of 50 cows (30 marked)

Top left – class representation; top right – shapes of bounding boxes; bottom left – object occurrence distribution; bottom right – relative bounding box sizes.

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The following hyperparameters were selected for training: a batch size of 4, a learning rate of 0.01 and an SGD optimiser. With the above setup, YOLOv8 was trained for 75 epochs on a computer setup with an Intel(R) Core (TM) i9-10940X processor, NVIDIA GeForce RTX 3090 graphics card, and Windows 10 Pro operating system. The progression of the values of each observed metric during learning is shown in Figure 11.

It shows a sharp improvement in the learning performance over the first 10 epochs. Subsequently, there was a significant slowdown in learning outcomes, but still, the values of each metric showed an improvement. Throughout all 75 epochs, there was a decrease in the values of the loss metrics of bounding boxes, objects and classes. At the same time, there was a steady increase in the value of mAP50–95, which is considered the most important metric in terms of the accuracy of the predictions of the trained model. Precision, recall and mAP50 values have remained virtually constant since epoch number 30. With respect to the remaining improving metrics, the appropriate training time was chosen.

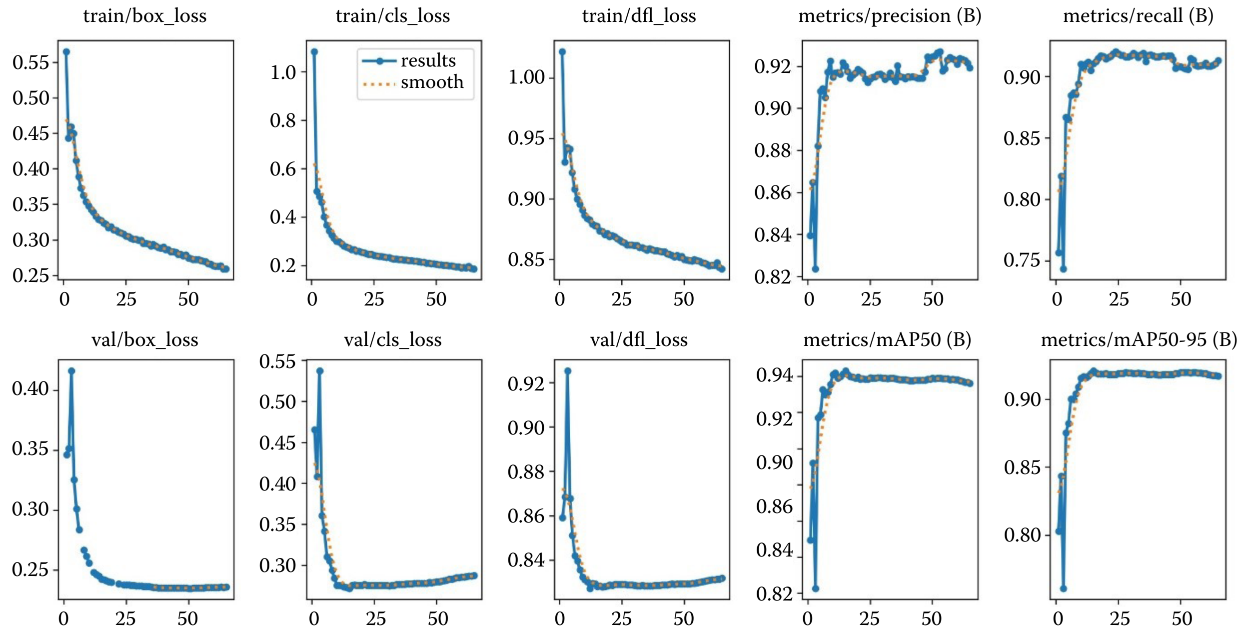

Figure 11. YOLOv8 training progression for numerical labelling method with the hyperparameters of batch size 4, learning rate 0.01 and SGD optimiser

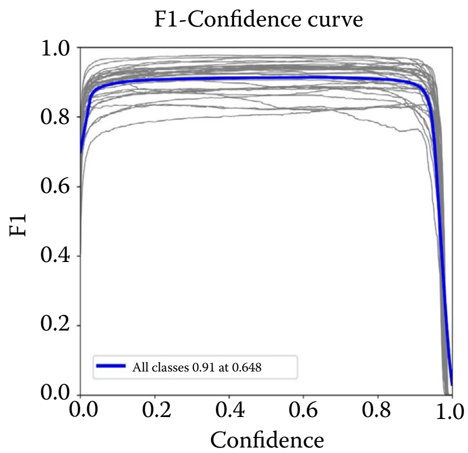

Figure 12. F1-score curve of the YOLOv8 model trained for numerical label identification with a batch size of 4, a learning rate of 0.01, and the SGD optimiser

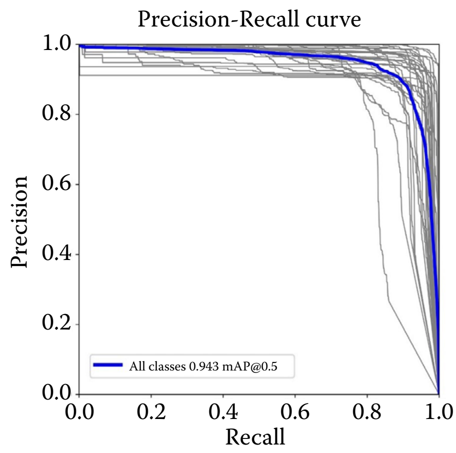

Figure 13. PR curve of the YOLOv8 model for numerical labelling, illustrating class-wise variation in precision and recall performance

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From the results obtained during the training of the convolutional neural network model, we can create two auxiliary graphs: the F1 curve and the PR (Precision-Recall) curve. These graphs help us better map the properties of the trained model. The F1 curve, shown in Figure 12, allows us to determine the optimal reliability threshold that can be applied during the inference of the trained model for the real-world use. In this case, the optimal threshold value is 0.648. The PR curve displayed in Figure 13 illustrates the balance between Precision and Recall values, enabling a graphical assessment of the proportion of true positives to positive predictions. For our trained YOLO model with the hyperparameters of batch size 4 and learning rate 0.01, the curve approaches an optimal shape. However, it is also evident that the model faces greater challenges in identifying certain classes compared to others.

Figure 14. Identification of individual animals in the barn environment at the feeding and resting areas using the trained convolutional neural network model: unmarked animals – red bounding box, cow 25 – green bounding box, cow 24 – yellow bounding box, cow 31 – blue bounding box, and cow 29 – turquoise bounding box

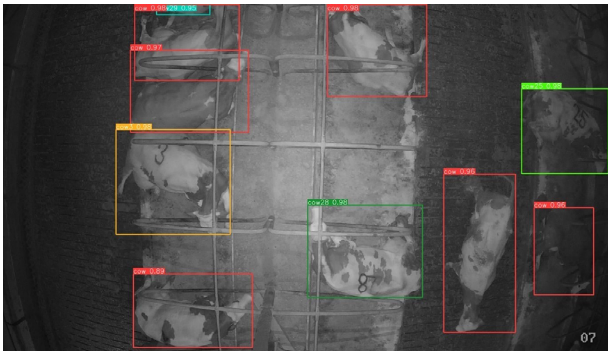

Figure 15. Identification of individual animals in the barn environment at the resting area under difficult lighting conditions using the trained convolutional neural network model: unmarked animals – red bounding box, cow 25 – green bounding box, cow 3 – orange bounding box, cow 28 – dark green bounding box, and cow 29 – turquoise bounding box

The system was able to detect marked animals in an open group, which also contains unmarked animals that are outlined in red bounding boxes in the images. Each marked cow was assigned a different colour for easy distinction in the processed image. For example, in Figure 14, in the left part, from the top, cow 25 is shown in green, cow 24 in yellow, cow 31 in blue, and cow 29 in turquoise. The training dataset for this convolutional neural network model was created from the outset to cover the widest possible range of conditions that may occur in the barn. Consequently, the dataset included images with significantly poor image quality and poor lighting conditions. As a result, the model is capable of detection even at twilight or nighttime, as demonstrated in Figure 15.

PERFORMANCE COMPARISON OF THE INVESTIGATED METHODS: INSIGHTS FROM EXPERIMENTAL EVALUATION IN TERMS OF DYNAMIC CATTLE IDENTIFICATION

Dynamic cattle monitoring presents unique challenges, requiring identification systems to adapt seamlessly to changing group compositions, such as the addition or removal of animals, while maintaining accuracy and efficiency (Montalvan et al. 2024).

Body texture recognition

Our findings highlight that the body texture recognition, which relies on the unique visual features of individual animals such as coat patterns and colouration, eliminates the need for physical markers and leverages natural variability. However, this method faces significant challenges in dynamic group scenarios. Adding a new animal requires collecting additional images, updating the dataset, and retraining the model, similar to when an individual animal is removed from the herd, making the process both time-consuming and computationally intensive. Additionally, in herds with many animals, similar body patterns increase the risk of misidentification, further limiting the scalability of this approach.

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QR code collars

QR code collars demonstrated greater adaptability in dynamic environments. A convolutional neural network can be pre-trained on thousands of unique codes, with additional codes reserved for future use. When a new animal is introduced, the system assigns an unused code, eliminating the need for retraining. Similarly, removing an animal is straightforward and involves deleting its corresponding code. Despite these advantages, the QR code approach faces notable limitations in real-world scenarios. In larger herds, misidentification can occur due to visually similar codes or occlusion caused by feeders, barriers, or animal movement. Low-resolution imaging and poor lighting exacerbate these issues, impacting the reliability of the QR-based identification method in complex barn environments.

Numerical labelling

Numerical labelling emerged as the most practical and effective solution for dynamic cattle identification. By marking animals with numbers using special markers commonly employed in livestock management, this method eliminates the need for retraining or complex visual pattern analysis. Numerical labelling proved to be highly efficient for on-site implementation, offering consistent performance even in challenging environments. Its simplicity and reliability make it a robust alternative to body texture recognition and QR code collars in dynamic monitoring systems.

Overall, the YOLOv8 model, trained across body texture recognition, QR codes, and numerical labels, demonstrated unique strengths and limitations for each method, as summarised in Table 1. Numerical labelling achieved the highest mAP50–95 under diverse environmental conditions, showcasing its robustness and adaptability. In contrast, QR code tagging faced challenges in detection reliability due to occlusion and positional variances within the barn setting.

Numerical labelling in comparison with traditional body marking techniques

Comparing our best method, numerical labelling, with traditional body marking methods such as ear notching, ear tattooing, and branding, highlights its significant advantages in scalability, accuracy, and animal welfare. While these conventional methods served as valuable identification tools in the past, they are increasingly unsuitable for the demands of modern livestock management due to their invasive nature, limited practicality, and ethical concerns.

Ear notching, for example, involves cutting small V-shaped sections into specific locations on the animal's ears to encode unique identifiers. Although simple and cost-effective, this method causes significant pain and distress to the animal, raising serious welfare concerns as the global awareness of animal rights continues to grow. Additionally, ear notching is labour-intensive and lacks scalability, making it impractical for larger herds where efficient and automated systems are essential (Noonan et al. 1994; Leslie et al. 2010).

Ear tattooing, another traditional method, also subjects animals to invasive and painful procedures. A special tattoo piercer is used to punch holes into the inner surface of the ear, after which indelible ink is applied to fill the holes. The ink becomes trapped under the skin, forming visible letters or numbers (Awad 2016). This process, while seemingly less severe than ear notching, involves puncturing the sensitive ear tissue, causing discom-

Table 1. Comparison of the evaluated methods

Identification method	Precision	Recall	mAP50–95	Optimal threshold	Notes
Body texture recognition	0.86	0.84	0.78	0.879	limited accuracy in large herds
QR code collars	0.75	0.77	0.71	0.452	challenges with head movement and occlusion
Numerical labelling	0.91	0.89	0.84	0.648	effective in varied lighting and large groups

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fort and distress. Moreover, tattoos require a close inspection for identification, making them labour-intensive and impractical for managing medium- or large-sized herds.

Branding methods, whether hot or freeze branding, present even greater ethical and practical challenges. Hot branding, which involves burning a mark onto the animal's skin, is a highly painful process that has been prohibited in some countries due to its severe impact on animal welfare. Freeze branding, while less painful than hot branding, relies on destroying pigment cells to create a white mark on the animal's coat. This approach is ineffective for animals with white fur and can be temporarily obscured if the mark blends with the animal's natural colouration (Awad 2016). Both branding techniques are painful, fail to meet modern welfare standards, and lack the flexibility required for scalable herd management.

In contrast to these traditional methods, numerical labelling provides a non-invasive, scalable, and welfare-conscious alternative. By marking animals with temporary numbers using livestock-safe spray markers, this method completely avoids the physical pain, tissue damage, and stress associated with invasive techniques like ear notching, tattooing, or branding. The application process is quick, painless, and requires minimal restraint, aligning with modern animal welfare standards. Additionally, because markings can be reapplied as needed without harming the animal, this method offers flexibility and adaptability in dynamic farm settings. Numerical labelling also eliminates the need for close physical inspection or labour-intensive manual recording, as the identifiers are easily recognised and processed by convolutional neural networks. This makes it especially suitable for use in precision livestock farming systems where animal well-being, traceability, and automation are critical. Overall, digital labelling represents an ethically responsible and operationally efficient approach to individual animal identification.

CONCLUSION

In conclusion, the findings of this study provide valuable insights into the effectiveness of various identification methods for cattle within precision livestock management systems. Each identification method presents unique strengths and limitations, and the choice will depend on the specific operational context and the unique needs of individual farms, varying according to herd size, operational needs, and environmental constraints. Farms with smaller herds may benefit from the simplicity of QR codes or the natural identification potential of body texture recognition, provided their herd composition is stable. Conversely, large-scale operations may find the numbering method to be the most feasible option due to its adaptability, reliability, and consistency across variable environmental conditions.

Despite the promising results, this study acknowledges several limitations. Future research could further optimise these identification methods, focusing on improving robustness in texture recognition for larger herds and minimising occlusion effects in the QR code method through enhanced camera positioning and environmental control. Similarly, for the numerical labelling method, even though it achieved high detection rates overall, their visibility may also be limited in rear-view camera angles, especially during feeding scenarios when cows lean forward. These limitations highlight the importance of camera placement and system calibration in practical deployments.

The dataset used for training was also confined to small and medium herd sizes, which may not capture the complexities present in larger herds. Future research should aim to evaluate these methods in larger and more diverse herds to assess their scalability and robustness. In addition, future work could explore the integration of such identification systems into farm-level automation platforms, enabling real-time monitoring, alert generation, and decision support. Practical deployment may also benefit from developing adaptive models that can accommodate changes in herd composition and lighting conditions without requiring full retraining. These directions would support the practical viability and long-term sustainability of computer vision-based identification in modern livestock systems.

In addition to technical performance, the practical implementation of these methods varies in terms of cost, labour, and maintenance. Body texture recognition is non-invasive and does not require the physical handling of animals but demands high-quality imaging systems and frequent retraining when the herd composition changes, which can increase computational and data an-

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notation costs. QR code collars are relatively low-cost and easy to deploy, but they require a regular inspection to ensure the codes remain visible and properly positioned on the animal. Numerical labelling using livestock-safe markers involves minimal equipment cost and is quick to apply, though reapplication may be needed after some time due to fading. From a labour perspective, all methods require initial setup and occasional maintenance, but numerical labelling offers the most streamlined integration into existing barn routines. These practical factors should be considered alongside the model performance when selecting a method for real-world deployment.

Conflict of interest

The authors declare no conflict of interest.

REFERENCES

Achour B, Belkadi M, Filali I, Laghrouche M, Lahdir M. Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on convolutional neural networks (CNN). Biosyst Eng. 2020 Oct;198:31-49.

Awad AI. From classical methods to animal biometrics: A review on cattle identification and tracking. Comput Electron Agric. 2016 Apr;123:423-35.

Bai H, Zhou G, Hu Y, Sun A, Xu X, Liu X, Lu C. Traceability technologies for farm animals and their products in China. Food Control. 2017 Sep;79:35-43.

Bezen R, Edan Y, Halachmi I. Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms. Comput Electron Agric. 2020 May;172:105345.

Bridle JE. A review of animal identification - from simple manual techniques to automatic transponding systems. Landbauforsch Völkenrode. 1973;18(Sonderheft):127-48.

Hu H, Dai B, Shen W, Wei X, Sun J, Li R, Zhang Y. Cow identification based on fusion of deep parts features. Biosyst Eng. 2020 Apr;192:245-56.

Kim HT, Ikeda Y, Choi HL. The identification of Japanese black cattle by their faces. Asian-Australas J Anim Sci. 2005 Jun;18(6):868-72.

Kumar S, Pandey A, Satwik KSR, Kumar S, Singh SK, Singh AK, Mohan A. Deep learning framework for recognition of cattle using muzzle point image pattern. Measurement. 2018 Feb;116:1-17.

Kumar S, Tiwari S, Singh SK. Face recognition of cattle: Can it be done? Proc Natl Acad Sci India Sect A Phys Sci. 2016 Jun;86(2):137-48.

Landais E. Le marquage du betail dans les systemes pastoraux traditionnels. Rev Elev Med Vet Pays Trop. 2000;53(4):349-63.

Leslie E, Hernandez-Jover M, Newman R, Holyoake P. Assessment of acute pain experienced by piglets from ear tagging, ear notching and intraperitoneal injectable transponders. Appl Anim Behav Sci. 2010 Nov;127(3-4):86-95.

Li S, Fu L, Sun Y, Mu Y, Chen L, Li J, Gong H. Individual dairy cow identification based on lightweight convolutional neural network. PLoS One. 2021 Nov 29;16(11):e0260510.

Mahato S, Neethirajan S. Integrating artificial intelligence in dairy farm management – biometric facial recognition for cows. Inf Process Agric. 2024 Oct 9;Forthcoming.

Montalvan S, Arcos P, Sarzosa P, Rocha RA, Yoo SG, Kim Y. Technologies and solutions for cattle tracking: A review of the state of the art. Sensors (Basel). 2024 Oct 9;24(19):6486.

Noonan GJ, Rand JS, Priest J, Ainscow J, Blackshaw JK. Behavioural observations of piglets undergoing tail docking, teeth clipping and ear notching. Appl Anim Behav Sci. 1994 Mar;39(3-4):203-13.

Noviyanto A, Arymurthy AM. Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method. Comput Electron Agric. 2013 Nov;99:77-84.

Rossing W. Animal identification: introduction and history. Comput Electron Agric. 1999 Nov;24(1-2):1-4.

Shen W, Hu H, Dai B, Wei X, Sun J, Jiang L, Sun Y. Individual identification of dairy cows based on convolutional neural networks. Multimed Tools Appl. 2020 Jun;79(21-22):14711-24.

Zhao K, He D. Recognition of individual dairy cattle based on convolutional neural networks. Trans Chin Soc Agric Eng. 2015 Mar;31(5):181-7.

Zin TT, Pwint MZ, Seint PT, Thant S, Misawa S, Sumi K, Yoshida K. Automatic cow location tracking system using ear tag visual analysis. Sensors (Basel). 2020 Jun 23;20(12):3564.

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