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Comprehensive Survey on Cattle Identification Approaches: From Traditional to Deep Learning Aspects

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Abstract

Cattle identification is essential for distinguishing individual animals, enabling effective tracking of disease progression, vaccination management, production monitoring, ensuring traceability, and establishing ownership. Recently, there has been a notable shift toward the automation of cattle identification, largely driven by advancements in machine learning (ML) and computer vision technologies. This paper provides a comprehensive review of various aspects of cattle identification techniques in the context of animal husbandry, exploring multiple facets of the field. It examines tag-based approaches that focus on hardware solutions, DNA feature-based methods emphasizing genetic identification, and visual feature-based approaches leveraging biometric data. Additionally, the paper discusses machine learning-based methods, deep learning techniques, and integrated learning approaches that combine both ML and Deep learning (DL) strategies for enhanced identification accuracy. Through this structured analysis, the paper aims to highlight the strengths and applications of each method in the advancement of cattle identification practices. Furthermore, the study investigates the standard image and video based datasets utilized in these models, emphasizing their characteristics, scale, and relevance to real-world applications. A thorough meta-analysis of key performance metrics is conducted to evaluate the effectiveness of different cattle identification approaches. Through this analysis, the paper aims to elucidate the strengths and limitations, offering valuable insights for future research and practical implementations in cattle identification.

Keywords: Cattle identification, Animal husbandry, Machine learning, Artificial intelligence, Deep learning, Support Vector Machine, Computer vision

1. Introduction

The increasing demand for reliable livestock identification and tracking systems stems from growing concerns regarding food safety and supply chain integrity. The need for accurate cattle identification has evolved into a dual issue, impacting both human health and the effective management, conservation, and productivity of cattle. Cattle identification encompasses both detection and recognition, employing various algorithms and models to automatically identify and classify individual cattle based on unique characteristics, such as facial features, body markings, or biometric data, including ear tags or Radio Frequency Identification (RFID) implants. Key components of precision livestock management include disease diagnosis, vaccination, tracking, productivity management, and the monitoring of animal welfare and health [1][2]. Traditional ranching practices rely on methods such as electronic devices [3], ear notching, and ear tagging [1] to identify individual cattle. However, these approaches present challenges, including tag loss, duplication, device malfunction, and tag number fraud, which can complicate livestock management. To overcome these limitations, automatic cattle identification systems have been developed using image processing techniques, particularly deep learning, to replace manual identification methods [4]. Advances in computer vision have made the use of visual traits for cattle identification a compelling alternative [5][6][7][8][9]. Visual feature-based identification systems leverage distinct traits to differentiate between breeds and individual animals [10][11]. In recent years, ML and DL methods have gained widespread adoption for automatically identifying cattle using visual cues [12][13][7][14][15][16]. Furthermore, monitoring cattle behavior and movement in dairy farms can provide valuable insights into their health and well-being. The empirical monitoring of animal welfare has emerged as a critical concern for both livestock producers and consumers [17]. Subsequently, EU law has gradually expanded to improve the welfare of animals raised for farming purposes. Additionally, existing European Union regulations related to organic farming emphasize strict adherence to animal welfare standards, requiring farmers to meet the unique behavioral needs of animals [18].

ML and DL are two significant areas of Artificial intelligence (AI) that address complex problems by making decisions automatically. As fundamental branches of AI, both ML and DL focus on developing computer systems capable of learning from data and independently making predictions or judgments [19]. ML involves creating algorithms designed specifically to identify patterns in data and generate predictions or judgments without the need for explicit programming. These algorithms acquire knowledge using labeled datasets, where input data is matched with corresponding output labels [20]. ML algorithms can be divided into supervised learning, where the algorithm learns from labeled data; unsupervised learning, where it trains on unlabeled data to identify patterns independently; and reinforcement learning, where the algorithm learns to make decisions based on feedback from its environment [21][22]. DL, a specialized branch of ML, leverages Artificial Neural Networks (ANN) to analyze and extract insights from data. DL models consist of multiple layers of interconnected nodes or neurons that process a sequence of transformations on the input data [23][24]. These models are particularly effective for handling large and complex datasets and extracting intricate patterns. DL models are trained using back-propagation, a process where prediction errors are propagated backward through the network to adjust the weights of neuron connections. Deep learning has demonstrated remarkable success in tasks such as audio recognition, image processing, autonomous driving, and natural language processing due to its ability to acquire and represent hierarchical structures from data.

The paper examines the latest literature to identify applications of ML techniques in animal husbandry [25][26]. The study addresses challenges and other key aspects related to the importance of using ML in animal husbandry, focusing on cattle identification, animal husbandry, ML, AI and DL [27][28].

1.1 Motivation

1. The motivation behind Cattle Identification in Animal Husbandry Using ML Techniques stems from the increasing demand for efficient and accurate livestock management. Traditional identification methods, such as ear tagging and RFID implants, often present challenges like tag loss, duplication, and device failure, which can lead to inefficiencies in tracking, health monitoring, and productivity management. As the livestock industry grows, ensuring precise identification and tracking of cattle is essential for improving disease control, optimizing herd management, and enhancing food safety.

2. Machine learning (ML) techniques, particularly in the areas of computer vision and deep learning, offer promising solutions to overcome the limitations of traditional methods. By leveraging advanced algorithms, ML can automate the identification process, using unique visual and biometric traits to recognize individual cattle. This not only improves accuracy and efficiency but also supports the broader goals of precision livestock farming, including better health monitoring, welfare assessment, and increased productivity.

3. The integration of ML techniques into cattle identification addresses the industry's need for scalable, reliable, and non-invasive solutions, paving the way for more sustainable and technologically driven livestock management practices.

1.2 Challenges

Addressing challenges in the field of cattle identification is crucial for advancing and facilitating the development of practical, scalable solutions for farmers worldwide. Following are the classified categories outlined for the challenges in this area [8][29-37] -

- **Manual Annotation and Classification:** Annotating and classifying massive datasets for effective model training requires significant time and financial investment. Accurate annotation of ear tags, coat patterns, and facial traits is essential, but labor-intensive.
- **Consistency in Labeling:** Ensuring consistent labeling across annotators poses a challenge, as interpretations of features may vary among individuals, leading to discrepancies in dataset quality and model performance.
- **Logistical Challenges in Large-Scale Deployment:** Deploying machine-learning models for large-scale cattle identification across diverse farms and ranches presents logistical hurdles. Achieving widespread acceptance requires scalable, efficient, and easy to deploy solutions, particularly in resource-constrained environments.
- **Regulatory Compliance:** Compliance with regulatory standards and guidelines concerning animal welfare, data privacy, and food safety is critical for the adoption of ML-based cattle identification systems. Ensuring adherence to these regulations adds complexity to system development and deployment processes.
- **Data Quality and Availability:** Ensuring the quality and availability of annotated datasets, particularly in regions with limited resources or infrastructure, presents a challenge for training accurate and reliable DL models for cattle identification.
- **Environmental Variability:** Environmental factors such as lighting conditions, weather, and terrain variability can affect the performance of DL models in cattle identification tasks, necessitating robustness and adaptability in model design and training strategies.
- **Transferability and Generalization:** Ensuring the transferability and generalization of trained models across different cattle breeds, ages, and environmental conditions is essential for real-world deployment, but requires careful consideration of model architecture, training data diversity, and domain adaptation techniques.

1.3 Research Contribution

The current study aims to categorize various aspects of cattle identification, from traditional to machine learning (ML) and deep learning (DL) techniques. It investigates the invariant features that are essential for efficient cattle identification, analyses the ML models commonly used in this field, and examines the specific DL models applied for this purpose. Additionally, the study explores the datasets employed in cattle identification research and identifies the challenges encountered in addressing this issue. These focus areas highlight where ML can be effectively utilized to enhance cattle management and improve practices within animal husbandry.

The paper is structured as follows: Section 2 offers a thorough review of the literature, highlighting different aspects of cattle identification. Section 3 details standard datasets, while Section 5 examines standard performance parameters. Finally, Section 6 summarizes the key findings and insights, concluding the paper.

2. Various aspects of Cattle Identification

The literature reveals various trends and categories of techniques effectively employed for cattle identification. Farmers have adopted individualized management strategies, recognizing that accurate cattle identification is essential for genetic improvement, disease control, biosecurity, and efficient supply chain management. Common identification methods include ear tagging, DNA analysis, and visual feature-based approaches. Biometric indicators used for cattle identification include DNA profiling, antibody matching, muzzle pattern recognition, and facial feature analysis [1]. These biometric modalities exhibit phenotypic and genomic traits unique to each animal, are resistant to tampering, remain stable over time, and ensure minimal impact on the animal’s health.

The literature analysis is organized around specific themes derived from existing research, including ML and DL techniques for cattle identification based on image processing and computer vision. The various aspects of cattle identification approaches, presenting studies and methods aligned with each category for a comprehensive understanding of the field, are as follows:

1. **Hardware Aspect:** Tag based Approaches
2. **DNA Aspect:** DNA feature based Approaches
3. **Biometric Aspect:** Visual Features based Approaches
4. **Machine Learning Aspect:** Machine Learning based Approaches
5. **Deep Learning Aspect:** Deep Learning based Approaches
6. **Integrated Learning Aspect:** ML and DL based Combined Approaches

Each of these categories contributes to a deeper understanding of how technological advancements can improve cattle identification, ensuring better management, biosecurity, and productivity in animal husbandry.

2.1 Hardware Aspect: Tag based Approaches

Cattle identification techniques based on ear tags have been widely employed in livestock management systems [3][38]. These methods are instrumental in tracking disease patterns and controlling the spread of illnesses [39-40]. Tag-based solutions include a variety of identifiers, such as permanent markers like ear notching, tattooing, and branding, as well as temporary options like ear tags and electronic devices, including RFID technology [1 - 3]. Ear notching involves removing sections of the animal's ear to create a distinctive, recognizable shape, although ear tagging is more commonly used for livestock identification [41]. However, as noted by Wang et. al. [40], ear tags are prone to detachment, raising the risk of losing an animal's individual identification. Additionally, ear tags are vulnerable to damage, duplication, and potential misuse.

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Livestock farmers often utilize passive RFID tags for tracking and identification purposes [3]. These systems comprise a tag, server, reader, communication channel, and RFID back-end, which transmit livestock data as a unique numerical sequence via radio waves. Despite their advantages, the setup and maintenance of RFID systems require specialized expertise and come with security challenges, such as tag data manipulation and system spoofing. Although ear tag-based cattle identification systems are widely accepted and frequently used, they face several limitations, including challenges in monitoring, fraud risks, potential vulnerabilities, disease management shortcomings, and concerns regarding animal welfare. Ear notching, a method of surgically altering sections of the animal's ear or lobes, creates a unique identification marker, but can have welfare implications [42-43]. More economical and welfare-friendly alternatives, such as visible ear tags and RFID devices, are commonly used for cattle identification.

2.2 DNA Aspect: DNA based Approaches

DNA is the fundamental blueprint of life, with no two individuals sharing an identical genetic makeup. Research leveraging DNA-based validation methods has capitalized on the uniqueness of this biological macromolecule. The genome, which resides in an individual's cells, comprises the complete set of genes within the cell [44]. DNA-based techniques for cattle identification have been developed to simplify the identification process for purposes such as disease monitoring, production management, and health surveillance. However, these methods are often constrained by significant time and cost requirements. For example, obtaining unique DNA identifiers for routine identification is both labour-intensive and costly [45].

One prominent application of DNA-based identification technologies is in establishing genetic relationships for genetic improvement programs. Despite its value, the widespread use of DNA for routine identification remains limited due to these cost barriers. Gallinat et.al. [46] proposed a DNA-based identification approach focused on genetic variations in the bovine casein gene, involving the sequencing of four casein genes from a sample of 319 animals. Modern advances in technology now enable the documentation of animal genetics through electrophoretic imaging. Each cattle has a unique genetic profile that can be used for identification by submitting a blood or tissue sample to a laboratory equipped with the appropriate tools. This method remains effective even after slaughter, as DNA fingerprinting can identify meat through skin analysis and differentiate it by brand [47], making it possible to trace stolen cattle even if only the flesh has been taken. Figure 5 shows numbering of livestock using ear notching and whole.

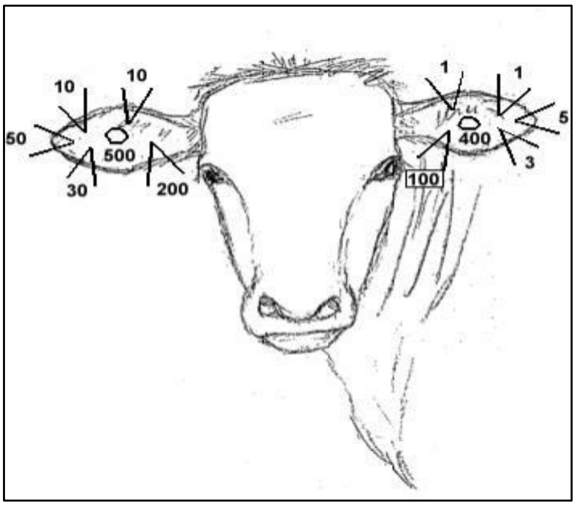

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Figure 5: System for numbering livestock using ear notching and whole.

2.3 Biometric Aspect: Visual Features based Approaches

Pattern recognition enables cattle identification systems to extract biometric and visual features unique to each animal, facilitating accurate individual identification. Distinctive characteristics such as iris patterns, muzzle prints, facial patterns, and body coat markings are commonly employed for this purpose. Traditional techniques including Scale-Invariant Feature Transform (SIFT), pattern matching, and Euclidean distance, Machine Learning methods like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN), as well as Deep Learning models such as Convolutional Neural Networks (CNN), Residual Networks (ResNet), and Inception, have provided accurate and efficient solutions for cattle identification [7-8][48 -51].

Advancements in machine learning and deep learning techniques have shifted focus toward using distinctive body coat and facial patterns for identification [45]. Machine learning models can identify cattle by analyzing these features from photographs of their faces or bodies, while deep learning models excel at automatically extracting features without the need for predefined attributes [7][30]. Recent research efforts have increasingly concentrated on automating cattle identification and addressing the limitations of traditional methods through these advanced techniques. Approaches in Biometric aspect can be categorized into following 3 categories -

2.3.1 Cattle Muzzle patterns-based Approaches

Cattle possess unique muzzle patterns that are distinct from one another. Muzzle print photographs have been extensively utilized for cattle identification [9][31][51-52]. Similar to human fingerprints, cattle muzzle and nose prints exhibit distinct grooves and patterns that serve as unique identifiers. These biometric characteristics have been recognized since 1921 [4]. Digital cameras capture images of cattle muzzle prints, and feature extraction techniques such as SIFT and Speeded Up Robust Features (SURF) are widely used to extract identifying traits [52-53]. Additionally, iris and retinal patterns, which remain stable over time, offer another layer of identification, though capturing these features in livestock poses challenges [54-55]. This concept was first explored in detail by Petersen (1922) through a sophisticated study on this method of authentication [4].

Additionally, Gabor filters and local binary patterns have proven effective for this purpose and in 2018, Kusakunniran and Chaiviroonjaroen [9] has achieved 100% accuracy in identifying 20 cattle, with at least four images per animal in the gallery. Principal Component Analysis (PCA) and Euclidean distance classifiers demonstrated an impressive 98.85% accuracy when identifying 29 calves [51]. Moreover, muzzle print images processed with Gabor filters attained 99.5% accuracy in cattle identification [56].

2.3.2 Retinal and iris-based Approaches

The use of biometric traits, such as retinal and iris patterns, facilitates the identification of cattle [55][57]. Retinal vascular patterns remain stable over time, while iris characteristics are unique and long-lasting [57]. These distinct patterns, extracted from image data, enable differentiation between individual animals [57-58]. By combining iris patterns with the two-dimensional complex wavelet transform, Lu et. al. [55] achieved 98.33% accuracy in identifying beef cattle.

2.3.3 Facial and coat pattern-based Approaches

Machine learning techniques have been applied to extract distinct features from cattle faces and coats for identification purposes. These models analyse local elements in cattle face images, such as pixel intensity, and have successfully identified individual animals in over 85% of 5,000 face images [59]. Additionally, regional coat descriptors and Support Vector Machines are used to further determine each cow's identity [7]. This approach significantly improves the accuracy and efficiency of cattle identification, aiding in the precise management and tracking of livestock. By leveraging advancements in machine learning, livestock managers can optimize operations, increase productivity, and enhance animal welfare, contributing to more sustainable and efficient agricultural practices.

In 2019, Okura et. al. [60] integrated three-dimensional video analysis with RGB-D cameras to observe cows, achieving an 84.2% accuracy rate by incorporating texture and locomotion features into the identification process [89]. However, the success of facial and coat pattern-based cattle identification heavily depends on the proper selection and application of feature extraction and selection methods. Furthermore, the manual extraction of features introduces susceptibility to variations in lighting conditions and camera angles, which can affect the system's accuracy and reliability.

2.4 Machine Learning Aspect: Machine Learning based Approaches

Machine learning (ML) techniques have been extensively applied in cattle identification, analysing and learning from patterns, as elaborated by various authors. Different ML models, tailored for specific identification needs, have been explored in cattle identification technology. Traditional biometric approaches utilize algorithms such as Support Vector Machines (SVM) [61], K-Nearest Neighbours (KNN) [62], and Artificial Neural Networks (ANN) [63-64], alongside techniques like Scale-Invariant Feature Transform (SIFT), pattern matching, and Euclidean distance to effectively distinguish individual animals. Passive RFID systems, which use RFID tags and communication channels, provide reliable livestock management by enabling automatic identification [3].

Modern approaches integrate ML and deep learning (DL) to analyse more complex biometric features such as facial and body coat patterns, as well as iris and retinal features, thus enhancing identification accuracy [65]. Techniques like SIFT and pattern matching are also used to analyse muzzle-print images, which serve as unique identifiers for cattle [66]. ML models have been utilized to extract distinctive features from cattle faces and coats, identifying individual animals in over 85% of 5,000 images based on features such as pixel intensity. Regional coat descriptors and vector machines further assist in determining the identity of each cow, improving identification accuracy and operational efficiency on livestock farms [67].

By leveraging advancements in ML, livestock managers can optimize their operations, increase productivity, and ensure animal welfare, ultimately contributing to more sustainable and efficient agricultural practices. A variety of works dedicated to cattle identification via ML algorithms are summarized in Table 1. For instance, in a dataset of 377 images, the training set consisted of 83 images, while the testing set comprised 294, yielding a performance accuracy of 97% [7]. The FLANN model, applied to a database of 528 Videos, achieved a performance accuracy of 96.72% by using the FAST algorithm to extract body features of cattle, splitting the dataset into 198 training and 330 testing instances [68]. Another study using the Brute Force model and SIFT method for body feature detection on 1,500 images, with 900 used for training and 600 for testing, achieved a performance accuracy of 98.33% [53]. Table 1 summarizes the

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outcomes of various machine learning (ML) models used in cattle identification, focusing on the patterns and features employed in the identification process. It specifically highlights works that consider the body as the primary feature for identifying cattle. This approach emphasizes how different models and feature extraction techniques perform in recognizing individual cattle based on body characteristics, contributing to more accurate and efficient livestock management systems. The findings in the table showcase the performance metrics, such as accuracy, across different datasets, providing a comprehensive comparison of methods that prioritize body features in cattle identification.

Table 1: Machine Learning based Cattle Identification using body features

Ref.	Model Used	Dataset			Feature extraction method	Used feature	Accuracy (%)	Remarks
		Size	Breed	Split (Train, Val, Test)				
[7]	SVM	377 images	H	83, –, 294	ASIFT	Body	97% Identification Accuracy 69(A): feature-importance prediction accuracy	Disabling the individuality model was found to result in a decrease in identification accuracy
[68]	FLANN	528 videos	H	198, –, 330	FAST)	Body	96.72%	This method depends on High Quality images and highly sensitive to the noise. It has a Low matching Accuracy.
[53]	Brute Force	1500 images	H	900, –, 600	SIFT	Body	98.33%	The method didn't detect features which are defined by color contrast rather than intensity contrast. It is an Expensive approach to convert into Lαβ color space.

Table 2 provides a summary of the outcomes of various machine learning (ML) models applied in cattle identification, focusing on the patterns and features related to the muzzle as the primary characteristic for the identification process. It presents different studies that have utilized muzzle patterns for distinguishing individual cattle and evaluates the performance of these models in terms of accuracy, efficiency, and dataset size. The table highlights the unique advantages of using muzzle prints, which, much like human fingerprints, are highly individualized and remain unchanged over time. By comparing the results of various ML techniques, Table 2 offers insights into the effectiveness of muzzle-based cattle identification methods, contributing to improved accuracy and precision in livestock management practices.

Table 2: Machine Learning based Cattle Identification using Muzzle features

Ref.	Model Used	Dataset			Feature extraction method	Used feature	Accuracy (%)	Remarks
		Size	Breed	Split (Train, Val, Test)				
[52]	SVM	105 Images	NC	75, 15, 15	SURF	Muzzle	93	• Dataset is too small, and is collected from a private farm in North Carolina. • Larger Datasets can increase the Computational Complexity. • The feature descriptor (SURF) not always captures the discriminative features.
[69]	GSRC	5000 Images	M	3000, –, 2000	LBP	Muzzle	93.87	LBP is not inherently scale-invariant also sensitive to rotation.
[59]	ANN	5000	M	3000, –,	LBP	Muzzle	96.74	LBP is not inherently scale-invariant also sensitive to rotation.
[70]	SVM	5000 Images	M	3000, –, 2000	FLPP	Muzzle	96.87	• The difficulty of using FLP techniques might increase exponentially with the size of the cow herd, creating difficulties for managing and interpreting massive amounts of data. • To prepare data for FLP analysis, extensive preprocessing is frequently needed, which can be resource- and time-intensive.
[31]	KNN	5000 Images	M	3000, –, 2000	SURF	Muzzle	93.87	• Private Dataset of 500 Cattle. • The Size of muzzle point patterns needs to be expanded, and various factors can be taken into account when taking a cow's muzzle picture for every subject.
[71]	SVM	322 Images	NC	–, –, –	SVD	Muzzle	75	• Dataset is very small. • Accuracy achieved is low. SVD helps for

								dimensionality reduction, it might lose important features. Cattle unique features are not detailed enough.
[72]	Ada-Boost	31 Head Images	NC	186, –, 31	WLD	Muzzle	98.9	• WLD involves computationally extensive applications if applied to high resolution datasets it may take more processing time. • WLD may find it challenging to extract distinguishing characteristics from cattle with less recognizable muzzle patterns or homogeneous textures, making it impossible to distinguish between individuals.
[73]	ANN	1060 Images	NC	636, 212, 212	Box-counting	Muzzle	99.18 (A)	• The fractal dimension determined by box counting may not always have enough discriminative power, particularly if the differences are small. • There's a chance that the fractal dimension will leave out important details from the muzzle pattern, which could result in inaccurate or partial data representations.
[56]	SVM	217 Images	NC	186, –, 31	Gabor filter	Muzzle	99.5 (A)	Dataset is too small, and is collected from a private farm in North Carolina
[12]	SVM	217 Images	NC	186, –, 31	LBP	Muzzle	99.5 (A)	• This feature descriptor fails to work where texture variation is there. • LBP is not inherently scale-invariant also sensitive to rotation. Dataset collected is very small
[74]	SVM	217 Images	NC	186, –, 31	SURF	Muzzle	100 (A)	• Dataset is too small, and is collected from a private farm in North Carolina. Larger Datasets can increase the

								Computational Complexity. • The feature descriptor (SURF) not always captures the discriminative features.

SVM, a Machine Learning model work on a dataset of 217 images from North Carolina (NC), achieving a perfect 100% accuracy by focusing on muzzle features using SURF feature extraction model [74]. In 2019, Awad et. al. [52] uses SVM on a smaller dataset of 105 images from NC, achieving 93% accuracy with SURF (Speeded-Up Robust Features) for muzzle features. Wagner et. al. [69] uses GSRC approach on larger datasets of 5000 images, achieving 93.87% accuracy with LBP for muzzle features. An Artificial Neural Network (ANN) on the same dataset achieves 96.74% accuracy using LBP for muzzle features [59]. In 2017, Kumar et.al. [70] achieved 96.87% accuracy with SVM on 5000 images using FLPP (Fisher Linear Projection Profile) for muzzle features. Kumar et. al [31] used KNN on the same dataset and achieved 93.87% accuracy with SURF for muzzle features. However, using SVM on 322 images from NC results in a lower accuracy of 75%, likely due to unspecified details regarding the dataset split and feature extraction using SVD (Singular Value Decomposition) for muzzle features [71]. Approaches in table 2 reports high accuracies, ranging from 98.9% to 100%, using various SVM and ANN models on datasets primarily from NC, with a consistent emphasis on muzzle features using methods like WLD (Weighted Local Directional Pattern), Gabor filters, LBP, and SURF.

Using Support Vector Machines (SVM) for identifying cattle based on mammary gland features has demonstrated a 60% accuracy on a dataset of 302 images from North Carolina. This approach employed Local Binary Patterns (LBP) for feature extraction from the mammary glands [75]. Li et. al. [76] utilized Quadratic Discriminant Analysis (QDA) on a larger dataset comprising 1,965 images, achieving a notable 99.7% accuracy. They used Zernike moments to extract features from the tail head region.

Table 3: Machine Learning based Cattle Identification using unique features.

Ref.	**Model Used**	**Dataset**			**Feature extraction method**	**Used feature**	**Performance Accuracy (%)**	**Remarks**
		Size	**Breed**	**Split (Train, Val, Test)**				
[38]	SVM	302 images	NC	150, –, 152)	LBP	Mammary glands	60	The dataset is very small and not annotated. NIR imaging does not capture enough distinct features. Dirt, Hair on mammary glands can affect the NIR Imaging Process.

[42]	QDA	1965 images	H	1667, 298	Zernike moments	Tail head	99.7	Inaccuracies can occur due to image boundary conditions. Zernike moments can be changed with image size and resolution. Local patterns textures on a cow's body that is critical for accurate identification gets missed.

2.5 Deep Learning Aspect: Deep Learning based Approaches

Advanced deep learning methods have significantly advanced image segmentation, autonomous visual feature extraction [77], and visual identification, generating substantial interest in these areas [78][79]. Deep learning (DL) has proven effective in animal farm management in recent years, addressing various needs such as animal verification, surveillance, and medical monitoring [19]. The categorization of studies in this domain is based on their objectives. In the recognition category, the focus is on initially detecting calves using DL detection models and then classifying individual cattle using DL classification models [13]. Convolutional Neural Networks (CNNs) have been employed to categorize cattle images, introducing methods for identifying bovine trunks. For instance, a deep neural network demonstrated the ability to distinguish cattle based on their coat patterns, achieving a video processing accuracy of 98.1% for 23 cows, compared to 86.1% for 89 cows using frame-based methods [80].

The classification of Holstein Friesian cattle exemplifies the effective application of these DL techniques. CNN-based approaches, using primary muzzle point images, achieved an accuracy of 98.99% in identifying individual cattle [32]. Similarly, CNN models trained on rear photos of cows attained a recognition accuracy of 97.01% [81]. Further studies reported that 93.33% of tested videos and 90.55% of tested frames were correctly identified [82]. YOLO (You Only Look Once) was used to identify bovine subjects in side-view images, achieving 96.65% accuracy with an enhanced CNN model. A recent study introduced a Bidirectional Long Short-Term Memory (BiLSTM) model that classified 50 calves with 91% accuracy, contributing to the field of cattle identification [83]. Recent advancements include the development of a Long-term Recurrent Convolutional Network (LRCN) incorporating InceptionV3, achieving a 99% success rate for identifying the Pantaneira cattle breed.

CNNs are widely utilized for livestock identification due to their simplicity and effectiveness [34]. These networks consist of pooling, convolutional, and fully connected layers, with convolutional layers playing a crucial role in generating feature maps from input data [84][85]. Region-based CNN (R-CNN) models, including Fast, Faster, and Mask R-CNN, have proven to be powerful object detection tools. Faster R-CNN, which uses a fully convolutional network to propose regions and is then processed by the Fast R-CNN detector, is particularly effective for cattle detection [86][87][88]. The findings suggest that Faster R-CNN and YOLO are among the most popular algorithms for cattle detection. YOLO, known

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for its efficiency and effectiveness, employs regression-based techniques to predict classes and bounding boxes in a single pass. Variants like YOLO-V2 and YOLO-V3 have enhanced localization accuracy and object detection performance [89][90]. Table 4 summarizes the outcomes of DL models in cattle identification.

Table 4: Deep Learning based Cattle Identification using body features.

Ref.	Used feature	Dataset			Accuracy (%)	Feature extraction Method	Remarks
		Size	Breed	Split (Train, Val, Test)			
[91]	Body	13,603 frames	NC	9064, –, 4539	96.3	Skew histogram	Cattles have variations in their skin spots, hair, and coat pattern so the skewness-based statistical measures do not apply properly on the dataset. Skewness cannot capture much of complex patterns in cattles.
[15]	Body	32 videos	H	14, –, 18	93.6	Inception v3, LSTM	Dataset is very small to measure the accuracy.
[92]	Body	150 images	NC	–	–	SIFT	-
[37]	Body	4736 images	H	1895, 473, 2368	93.7	Res-Net	Unique markings or physical characteristics may not be easily captured or visible from aerial images. Drones' limited onboard processing power can impede real-time data analysis and decision-making, particularly for difficult biometric identification.
[93]	Body	21,600 images	NC	19,440, –, 2160	98	CNN	Incepetion v3 Model
[94]	Body	17,258 images	C	13,806, –, 3452	99.2 (Detection Accuracy)	CNN	NasNet large Model is used for best Detection
[78]	Body	750 images	NC	500, –, 250	94 (Detection Accuracy	CNN	Mask R-CNN Model is used for best Detection

The Skew Histogram method is employed to extract features focusing on body characteristics [91]. Advanced techniques such as Inception v3 and Long Short-Term Memory (LSTM) networks are used for feature extraction based on body features [15]. Traditional methods like Scale-Invariant Feature Transform (SIFT) are also applied for extracting features from body characteristics [92]. Additionally, ResNet, a deep learning architecture renowned for its effectiveness in image recognition, is utilized to extract body features [37]. Convolutional Neural Networks (CNNs), known for their powerful feature extraction capabilities, are employed by [5], [93], [94], and [78] for analysing body features. Table 5 summarizes the outcomes of deep learning models in cattle identification, detailing various patterns and features used, including face, head, and muzzle, among others, in the identification process.

Table 5: Deep Learning based cattle Identification using Muzzle, Head and Uniquefeatures.

Ref.	**Used feature**	**Dataset**			**Accuracy (%)**	**Feature extraction method**
		Size	**Breed**	**Split (Train, Val, Test)**		
[8]	Dorsal coat	940 images 1064 videos	H	–, –, – 957, –, 107	98.13 96.03 (mAP)	VGG-M 2024, LSTM
[32]	Muzzle	5000 images	NC	4000, –, 1000	98.99	CNN
[95]	Head	6000 images	NC	–, –, –	84	–
[30]	Face	85,200 images	H	82,010, –, 3190	94.92 (F)	CNN
[96]	Face	1323 images	NC	926, –, 397	95 (P) For Detection Only	–

The VGG-M 2024 architecture combined with Long Short-Term Memory (LSTM) networks achieved an impressive accuracy of 98.13% for analyzing the dorsal coat of cattle [8]. For muzzle features, Kumar et. al [32] used Convolutional Neural Networks (CNNs) and attained a notable accuracy of 98.99%, demonstrating the effectiveness of CNN-based feature extraction in distinguishing detailed muzzle characteristics. Accuracy of 84% was achieved by Zin et. al. [95] in identifying cattle based on head features, although the specific feature extraction method was not detailed. Yang et. al. [30] used CNN and ResNet 50 to provide a commendable accuracy of 94.92% for analyzing face features of cattle [30].

2.6 Integrated Learning Aspect: ML and DL based Combined Approaches

Advancements in ML and DL techniques have increasingly facilitated the use of body coat and face patterns for identification [45][55][7][30]. ML models leverage features from photographs of cattle faces or bodies for identification, while DL models excel at feature extraction without predefined attributes [30[97][8]. Recent research has focused on automating cattle identification and addressing the limitations of traditional methods [45].

In cattle identification, Machine Learning (ML) is widely used to analyse patterns for accurate livestock identification, leveraging features specifically designed for identification needs. However, research shows that ML models may suffer from reduced accuracy when using non-standard muzzle print images. The demand for large and complex image or video

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datasets has led many studies to incorporate data augmentation techniques to improve training data and labels. While ML methods have historically been predominant in cattle identification for livestock management, Deep Learning (DL) models are gaining traction due to their superior accuracy, especially when dealing with large datasets. Recent studies show an increasing preference for DL models in cattle identification and detection tasks. DL-based approaches often rely on features such as cattle head, muzzle print, and body coat patterns, which have proven effective in feature extraction and image representation. Among DL models, Convolutional Neural Networks (CNNs)**,** ResNet**,** and Inception have consistently outperformed others in identification tasks. Notably, DL classification models began to be applied to livestock identification in 2015, with detection models emerging later in 2019. Early architectures like CNN and LeNet have been successfully employed since their introduction, solidifying DL's growing role in improving the accuracy and efficiency of cattle identification systems.

3. Standard Datasets

The dataset used for machine learning (ML) models includes various characteristics and their corresponding results or labels. Deep learning (DL) algorithms are capable of autonomously extracting complex and abstract features from a dataset and learning from these features. While the implementation of DL and ML models might appear straightforward, challenges arise in selecting appropriate algorithms, fine-tuning parameters, and choosing features to enhance prediction accuracy [19].

The effectiveness of these approaches is closely linked to the quality and diversity of the dataset. Table 6 offers a detailed overview of cattle datasets from rigorously reviewed studies, highlighting key parameters such as breed, cattle count, dataset size, data type, capture location, image resolution, and acquisition methods. Notably, the Holstein cattle dataset has been a cornerstone in numerous studies due to its distinctive coat patterns and patches. Utilizing these unique features, ML and DL methods have demonstrated high efficacy.

This review found that image-based datasets were the most prevalent, appearing approximately 40 times across studies and including various image types such as RGB, grayscale, and Near-Infrared (NIR), captured from different angles including side, top, back, and front views of the cattle. Additionally, video datasets were utilized in 15 investigations. Digital cameras were the primary tool for data acquisition in most studies, though some researchers employed Unmanned Aerial Vehicles (UAVs) or drones. Photographs or videos of cattle from farms were extensively analysed to develop decision-making systems for identification using ML or DL techniques. Despite variations in image resolutions, higher resolutions did not always result in superior accuracy. In fact, many studies found that low-resolution images worked effectively for ML/DL models [98][99].

One study applied convolutional neural networks and deep metric learning to automate biometric identification of Holstein-Friesian cattle based on their distinctive black-and-white coat patterns, akin to Turing's reaction-diffusion systems. This method achieved 93.8% accuracy in recognizing and identifying individual calves from aerial images in open herd scenarios, with essential portions of the source code, network weights, and supporting datasets (OpenCows2020) made publicly available. The approach is well-suited for disease tracking, precision farming, health monitoring, and veterinary research, as it does not require wearable or physical tags [37].

Another study proposed the use of multi-view images to enhance visual cow identification in real farm environments. It introduced a new loss function, SoftMax-nB, which minimizes bias and integrates distance metrics such as triplet and tight losses, thereby improving feature separation. Evaluations on the MVCAID100 and OpenCows2020 datasets demonstrated superior performance compared to existing models in both face recognition and cow identification tasks, advancing precision livestock farming applications [100].

Additionally, a study demonstrated an automated pipeline using key point matching in distinctive body patterns to detect individual Giant Sunfish. Root SIFT achieved the highest mean average precision (mAP) of 75.91% on the TinyMola+ and OpenCows2020 datasets, evaluating descriptors like ORB, SIFT, Root SIFT, and SuperPoint. The pipeline's adaptability allowed for re-identification of cows and seals without additional instructions, transitioning from a ranking-based to a binary classification method and achieving 98% accuracy and 44% recall on TinyMola+, thus significantly reducing the need for manual verification [101].

Table 6: Summary of Standard Image Datasets for Cattle Identification

Ref.	**Type**	**Breed # of animals**		**Acquisition device**	**Capture location**	**Resolution**	**Data size**
[75]	Image (M.G)	NC	151	Camera	Indoor	3840×2160	302
[7]	Image (B)	H	50	Kinect 2	Indoor	–	377
[52]	Image (M)	NC	15	Camera	–	–	105
[66]	Image (T)	H	10	DS-2CD2T32 (D)-I3	Indoor	1920×1080	1,965
[32] [69]	Image (M)	M	500	Camera	Indoor	500×500	5,000
[73]	Image (M)	NC	53	Camera		–	1,060
[71]	Image (M)	NC	46	Camera	–	300×400	322
[33]	Image (F& B)	An	216	Camera	Outdoor	–	5,042
[92]	Image (B)	NC	26	Camera	Outdoor	640×480	150
[8]	Image (B)	H	112	Kinect 2	Indoor	–	940
[102]	Image (B)	M	5	Camera	Outdoor	–	775

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[37]	Top-viewimage (B)	H	46	DJI Inspire MkI, Kinect 2	Indoor& Outdoor	–	4,736
[98]	Activity(B)	H	5	–	Outdoor	–	14,400

Table 7: Summary of Standard Video Datasets for Cattle Identification

Ref.	Type	Breed	# of Animals	Acquisition on device	Capture location	Resolution	Data Size	Country
[68]	Video (B)	H	66	Nikon D5200	Outdoor	1280×720	528	US
[53]	Video (B)	H	60	Camera	Outdoor	1280×720	1,500 images	China
[95]	video (He)	NC		AXIS P1448-LE	Indoor	–	6,000 images	Japan
[15]	Video (B)	H	17	DJI Matrice drone	Outdoor	720×720	32	UK
[36]	Video (B)	NC	50	ZED camera	Indoor	401×506	36	
[78]	Video (B)	NC		MAVIC Pro drone	Outdoor	512×512	750 images	Australia
[14]	Rear-view video (B)	NC	41	ZED camera	Indoor	401×506	516	Australia
[103]	Video (B)	H	4	HDR-CX115E	Indoor	–	11,745 frames	Italy
[5]	Video (B)	P	51	Video Recorder	Outdoor	–	212	Brazil

4. Standard Performance Parameters [104-106]

Cattle identification is crucial for livestock management, traceability, disease control, and ensuring food safety. Technological advancements have introduced automated methods for cattle identification, which rely on various performance parameters to ensure efficiency and accuracy. The standard performance parameters used in assessing cattle identification systems are Accuracy, identification rate, Durability and reliability, Scalability, User-friendliness, security and privacy etc.

Accuracy is a key parameter in cattle identification systems, measuring how effectively the system can correctly identify individual cattle. This is essential for accurate tracking, particularly for health monitoring, breeding, and regulatory compliance. The identification rate reflects the percentage of correct identifications, while the error rate indicates the proportion of incorrect or missed identifications, which should be minimized for reliability. Speed is also critical, especially for large herds, as faster systems enable efficient real-time tracking. The time per identification and the system's ability to process large batches of cattle are important for high-volume operations. Durability and reliability are equally vital, as hardware like RFID tags or sensors must endure harsh conditions without malfunctioning, and system uptime must be consistent over time. Scalability ensures the system can handle varying herd sizes without sacrificing performance, with capacity and flexibility allowing it to grow as the farm expands. Integration with other systems is essential for modern cattle management, ensuring seamless interoperability with health, feeding, and breeding systems, and facilitating easy data sharing with external platforms. User-friendliness is another important factor, as the system should be easy to set up, with a simple interface that requires minimal training. Cost-effectiveness balances the system's performance and affordability, taking into account initial setup costs, ongoing maintenance, and operational expenses. Finally, security and privacy are paramount to protect sensitive cattle data, with features like data encryption and user authentication safeguarding against unauthorized access.

An effective cattle identification system must excel in accuracy, speed, scalability, and ease of use. These performance parameters ensure that farms, whether small or large, can efficiently manage their cattle populations while maintaining high standards of traceability and compliance with regulatory requirements. Systems that integrate well with other farm management tools and are cost-effective will be increasingly essential as livestock farming continues to modernize. Measuring accuracy in cattle identification is critical to ensure the system performs effectively and reliably. Below are the common steps and methods to measure the accuracy in cattle identification systems:

a. **True Positive Rate or Sensitivity (Correct Identifications):** The proportion of cattle that are correctly identified by the system out of the total cattle presented.

$$\text{True Positive Rate} = \frac{\text{Correct Identifications}}{\text{Total Identifications}} * 100$$

For example, if 90 out of 100 cattle are correctly identified, the system's accuracy would be 90%. High sensitivity indicates that the system is highly effective at identifying the majority of cattle in the target group, ensuring reliable performance in accurately recognizing the intended animals.

b. **False Positive Rate (Incorrect Identifications):** The proportion of times the system incorrectly identifies an animal as belonging to another group or identity. It represents false identifications.

$$\text{False Positive Rate} = \frac{\text{False Identifications}}{\text{Total Identifications}} * 100$$

Suppose a cattle identification system is designed to recognize a specific breed, and out of 100 non-target cattle (those not belonging to the breed), it incorrectly identifies 20 as part of the target group. The False Positive Rate (FPR) is 20%. This means that 20% of the non-

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target cattle were incorrectly classified as belonging to the target group. A higher False Positive Rate reduces the overall accuracy of the system. Minimizing the False Positive Rate is essential for ensuring the system's reliability and effectiveness in large-scale cattle management.

c. True Negative Rate or Specificity **(Correctly rejected Identifications):** The proportion of non-target cattle correctly excluded by the system. In other words, it measures how often the system correctly excludes cattle from a specific class when they do not belong to that class.

$$\text{True Negative Rate} = \frac{\text{Correct Exclusions (True Negatives)}}{\text{Total Non} - \text{Target Cattle}} * 100$$

For example, if 50 cattle do not belong to a specific breed or group, and the system correctly identifies 45 of them as not belonging, the True Negative Rate would be 90%. A high True Negative Rate indicates that the system is effective at accurately excluding cattle that do not belong to the target group, which helps prevent errors in herd management, such as incorrect breed classifications or improper disease monitoring. Conversely, a low True Negative Rate could lead to mismanagement, as cattle may be wrongly classified or grouped, causing issues in tracking and care.

d. False Negative Rate (Missed Identifications): The proportion of times the system fails to identify a cattle correctly, meaning the system misses the identification altogether.

$$\text{False Negative Rate} = \frac{\text{Missed Identifications}}{\text{Total Identifications}} * 100$$

For example, if 20 out of 100 cattle from the target group are missed, the False Negative Rate would be 20%. A high False Negative Rate indicates that the system is failing to correctly identify a significant number of cattle, which can lead to serious management issues. These include missed health checks, incorrect tracking, and potential gaps in monitoring, all of which can negatively impact the overall efficiency and health of the herd.

e. Confusion Matrix Analysis: A confusion matrix is a tool used to evaluate the performance of a cattle identification system by showing the true positives, false positives, true negatives, and false negatives. This matrix helps visualize the system's overall performance.

i. **True Positive (TP)**: Correctly identified cattle.
ii. **False Positive (FP)**: Incorrectly identified cattle.
iii. **True Negative (TN)**: Correctly rejected cattle (not identified as belonging to the system).
iv. **False Negative (FN)**: Missed identifications.

Based on the above, accuracy, precision, recall and F1-score definitions are as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100$$

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recal}} * 100$$

f. Real-Time Monitoring of Accuracy

- **Field Testing**: Continuous real-time tracking of cattle can help identify system performance over time. Compare system identifications against human or manual identifications to check the accuracy.
- **Data Logging**: Keep a record of all identifications and compare them against expected outcomes to monitor discrepancies.

g. Long-Term Accuracy (Durability): Evaluate how well the identification system maintains its accuracy over extended periods, especially with hardware like RFID tags or visual recognition systems that may degrade due to environmental factors.

To ensure accurate cattle identification, regular monitoring using metrics like the true positive rate, false positives, recall, precision is essential. Systems should undergo real-time testing to ensure that they are reliable and maintain accuracy over long periods, allowing for efficient herd management and traceability.

5. Conclusion

This paper presents a comprehensive review of cattle identification techniques within the context of animal husbandry, addressing several key aspects. First, it explores hardware-based approaches that utilize tag systems for identification. Next, the DNA aspect focuses on methods that leverage genetic features for cattle identification. The biometric aspect examines visual feature-based approaches that utilize physical characteristics. Additionally, the paper discusses machine learning approaches that apply various algorithms for identification tasks, followed by an analysis of deep learning techniques that enhance accuracy through advanced neural networks. Finally, it considers integrated learning approaches that combine both machine learning and deep learning strategies to optimize identification performance. Through this multifaceted analysis, the paper aims to provide insights into the strengths and applications of each method in improving cattle identification practices. This study highlights the use of diverse datasets focusing on features like ear tags and coat patterns, with ML models like Random Forests and Support Vector Machines achieving varying success, while DL models such as CNNs and Res-Net have shown considerable promise. Challenges remain, including logistical issues with large-scale implementation and the need for high-quality annotated datasets, underscoring the importance of addressing these hurdles to develop effective solutions for the agricultural sector. This study conducts an analysis of standard datasets and performance metrics related to cattle identification. By evaluating these datasets and metrics, the research aims to assess the effectiveness of various identification techniques and identify areas for improvement within the field.

References

1. Awad, Ali Ismail. "From classical methods to animal biometrics: A review on cattle identification and tracking." Computers and Electronics in Agriculture 123 (2016): 423-435.
2. García, Rodrigo, Jose Aguilar, Mauricio Toro, Angel Pinto, and Paul Rodríguez. "A systematic literature review on the use of machine learning in precision livestock farming." Computers and Electronics in Agriculture 179 (2020): 105826.
3. Ruiz-Garcia, Luis, and Loredana Lunadei. "The role of RFID in agriculture: Applications, limitations and challenges." Computers and electronics in agriculture 79, no. 1 (2011): 42-50.
4. Petersen, William Earl. "The identification of the bovine by means of nose-prints." Journal of dairy science 5, no. 3 (1922): 249-258.
5. de Lima Weber, Fabricio, Vanessa Aparecida de Moraes Weber, Geazy Vilharva Menezes, Adair da Silva Oliveira Junior, Daniela Arestides Alves, Marcus Vinicius Morais de Oliveira, Edson Takashi Matsubara, Hemerson Pistori, and Urbano Gomes Pinto de Abreu. "Recognition of Pantaneira cattle breed using computer vision and convolutional neural networks." Computers and Electronics in Agriculture 175 (2020): 105548.
6. Poudel, Padam Bahadur, Mukti Ram Poudel, Aasish Gautam, Samiksha Phuyal, Chiran Krishna Tiwari, Nisha Bashyal, and Shila Bashyal. "COVID-19 and its global impact on food and agriculture." Journal of Biology and Today's World 9, no. 5 (2020): 221-225.
7. Andrew, William, Sion Hannuna, Neill Campbell, and Tilo Burghardt. "Automatic individual holstein friesian cattle identification via selective local coat pattern matching in RGB-D imagery." In 2016 IEEE International Conference on Image Processing (ICIP), pp. 484-488. IEEE, 2016.
8. Andrew, William, Colin Greatwood, and Tilo Burghardt. "Visual localisation and individual identification of holstein friesian cattle via deep learning." In Proceedings of the IEEE international conference on computer vision workshops, pp. 2850-2859. 2017.
9. Kusakunniran, Worapan, and Thanatchon Chaiviroonjaroen. "Automatic cattle identification based on multi-channel lbp on muzzle images." In 2018 International Conference on Sustainable Information Engineering and Technology (SIET), pp. 1-5. IEEE, 2018.
10. Guan, Haike, Naoki Motohashi, Takashi Maki, and Toshifumi Yamaai. "Cattle identification and activity recognition by surveillance camera." Electronic Imaging 32 (2020): 1-6.
11. Mahmoud, Hamdi A., Hagar M. El Hadad, Farid Ali Mousa, and Aboul Ella Hassanien. "Cattle classifications system using fuzzy k-nearest neighbor classifier." In 2015 International Conference on Informatics, Electronics & Vision (ICIEV), pp. 1-5. IEEE, 2015.
12. Tharwat, Alaa, Tarek Gaber, Aboul Ella Hassanien, Hasssan A. Hassanien, and Mohamed F. Tolba. "Cattle identification using muzzle print images based on texture features approach." In Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014, pp. 217-227. Springer

International Publishing, 2014.

13. Li, Shijun, Lili Fu, Yu Sun, Ye Mu, Lin Chen, Ji Li, and He Gong. "Individual dairy cow identification based on lightweight convolutional neural network." Plos one 16, no. 11 (2021): e0260510.
14. Qiao, Yongliang, Daobilige Su, He Kong, Salah Sukkarieh, Sabrina Lomax, and Cameron Clark. "Individual cattle identification using a deep learning based framework." IFAC-PapersOnLine 52, no. 30 (2019): 318-323.
15. Andrew, William, Colin Greatwood, and Tilo Burghardt. "Aerial animal biometrics: Individual friesian cattle recovery and visual identification via an autonomous uav with onboard deep inference." In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 237-243. IEEE, 2019.
16. Beaver, Annabelle, Kathryn L. Proudfoot, and Marina AG von Keyserlingk. "Symposium review: Considerations for the future of dairy cattle housing: An animal welfare perspective." Journal of Dairy Science 103, no. 6 (2020): 5746-5758.
17. Cabezas, Javier, Roberto Yubero, Beatriz Visitación, Jorge Navarro-García, María Jesús Algar, Emilio L. Cano, and Felipe Ortega. "Analysis of accelerometer and GPS data for cattle behaviour identification and anomalous events detection." Entropy 24, no. 3 (2022): 336.
18. Navarro, Jorge, Isaac Martín de Diego, Paula Carballo Pérez, and Felipe Ortega. "Outlier detection in animal multivariate trajectories." Computers and Electronics in Agriculture 190 (2021): 106401.
19. Janiesch, Christian, Patrick Zschech, and Kai Heinrich. "Machine learning and deep learning." Electronic Markets 31, no. 3 (2021): 685-695.
20. Hossain, Md Ekramul, Muhammad Ashad Kabir, Lihong Zheng, Dave L. Swain, Shawn McGrath, and Jonathan Medway. "A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions." Artificial Intelligence in Agriculture 6 (2022): 138-155.
21. Qiao, Yongliang, He Kong, Cameron Clark, Sabrina Lomax, Daobilige Su, Stuart Eiffert, and Salah Sukkarieh. "Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation." Computers and electronics in agriculture 185 (2021): 106143.
22. Tilman, David, Christian Balzer, Jason Hill, and Belinda L. Befort. "Global food demand and the sustainable intensification of agriculture." Proceedings of the national academy of sciences 108, no. 50 (2011): 20260-20264.
23. LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521, no. 7553 (2015): 436-444.
24. Li, Chuyi, Lulu Li, Yifei Geng, Hongliang Jiang, Meng Cheng, Bo Zhang, Zaidan Ke, Xiaoming Xu, and Xiangxiang Chu. "Yolov6 v3. 0: A full-scale reloading." arXiv preprint arXiv:2301.05586 (2023).
25. Low, Chuen Xian, Loh Teng-Hern Tan, Nurul-Syakima Ab Mutalib, Priyia Pusparajah, Bey-Hing Goh, Kok-Gan Chan, Vengadesh Letchumanan, and Learn-Han Lee. "Unveiling the impact of antibiotics and alternative methods for animal husbandry: A review." Antibiotics 10, no. 5 (2021): 578.

26. T. Psota, Eric, Ty Schmidt, Benny Mote, and Lance C. Pérez. "Long-term tracking of group-housed livestock using keypoint detection and map estimation for individual animal identification." Sensors 20, no. 13 (2020): 3670.

27. Andrew, William, Colin Greatwood, and Tilo Burghardt. "Fusing animal biometrics with autonomous robotics: Drone-based search and individual id of friesian cattle." In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision Workshops, pp. 38-43. 2020.

28. He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

29. Yao, Liyao, Zexi Hu, Caixing Liu, Hanxing Liu, Yingjie Kuang, and Yuefang Gao. "Cow face detection and recognition based on automatic feature extraction algorithm." In Proceedings of the ACM turing celebration conference-china, pp. 1-5. 2019.

30. Yang, Zehao, Hao Xiong, Xiaolang Chen, Hanxing Liu, Yingjie Kuang, and Yuefang Gao. "Dairy cow tiny face recognition based on convolutional neural networks." In Biometric Recognition: 14th Chinese Conference, CCBR 2019, Zhuzhou, China, October 12–13, 2019, Proceedings 14, pp. 216-222. Springer International Publishing, 2019.

31. Kumar, Santosh, Sanjay Kumar Singh, and Amit Kumar Singh. "Muzzle point pattern based techniques for individual cattle identification." IET Image Processing 11, no. 10 (2017): 805-814.

32. Kumar, Santosh, Amit Pandey, K. Sai Ram Satwik, Sunil Kumar, Sanjay Kumar Singh, Amit Kumar Singh, and Anand Mohan. "Deep learning framework for recognition of cattle using muzzle point image pattern." Measurement 116 (2018): 1-17.

33. Chen, Shunnan, Sen Wang, Xinxin Zuo, and Ruigang Yang. "Angus cattle recognition using deep learning." In 2020 25th International Conference on Pattern Recognition (ICPR), pp. 4169-4175. IEEE, 2021.

34. Alzubaidi, Laith, Jinglan Zhang, Amjad J. Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, José Santamaría, Mohammed A. Fadhel, Muthana Al-Amidie, and Laith Farhan. "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions." Journal of big Data 8 (2021): 1-74.

35. Srivastava, Nitish, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. "Dropout: a simple way to prevent neural networks from overfitting." The journal of machine learning research 15, no. 1 (2014): 1929-1958.

36. Qiao, Yongliang, Daobilige Su, He Kong, Salah Sukkarieh, Sabrina Lomax, and Cameron Clark. "BiLSTM-based individual cattle identification for automated precision livestock farming." In 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE), pp. 967-972. IEEE, 2020.

37. Andrew, William, Jing Gao, Siobhan Mullan, Neill Campbell, Andrew W. Dowsey, and Tilo Burghardt. "Visual identification of individual Holstein-Friesian cattle via deep metric learning." Computers and Electronics in Agriculture 185 (2021): 106133.

38. Kumar, Santosh, Sanjay Kumar Singh, Tanima Dutta, and Hari Prabhat Gupta. "A fast cattle recognition system using smart devices." In Proceedings of the 24th ACM international conference on Multimedia, pp. 742-743. 2016.

39. Vlad, M. A. R. I. A., Roxana Andreea Parvulet, and Madalin Stefna Vlad. "A survey of livestock identification systems." In Proceedings of the 13th WSEAS international conference on automation and information,(ICAI12), pp. 165-170. WSEAS Press Iasi, Romania, 2012.

40. Wang, Zaiqiong, Zetian Fu, Wei Chen, and Jinyou Hu. "A RFID-based traceability system for cattle breeding in China." In 2010 international conference on computer application and system modeling (ICCASM 2010), vol. 2, pp. V2-567. IEEE, 2010.

41. Neary, Michael and Yager Ann. "Methods of livestock identification." (2002).

42. Bowling, M. B., D. L. Pendell, D. L. Morris, Y. Yoon, K. Katoh, K. E. Belk, and G. C. Smith. "Identification and traceability of cattle in selected countries outside of North America." The Professional Animal Scientist 24, no. 4 (2008): 287-294.

43. Huhtala, A., K. Suhonen, P. Mäkelä, Mikko Hakojärvi, and Jukka Ahokas. "Evaluation of instrumentation for cow positioning and tracking indoors." Biosystems Engineering 96, no. 3 (2007): 399-405.

44. Adenuga, Bukola M., and Magdalena Montowska. "A systematic review of DNA-based methods in authentication of game and less common meat species." Comprehensive Reviews in Food Science and Food Safety 22, no. 3 (2023): 2112-2160.

45. Kumar, Santosh, and Sanjay Kumar Singh. "Cattle recognition: A new frontier in visual animal biometrics research." Proceedings of the national academy of sciences, india section A: physical sciences 90, no. 4 (2020): 689-708.

46. Gallinat, J. L., Saber Qanbari, Cord Drögemüller, E. C. G. Pimentel, Georg Thaller, and Jens Tetens. "DNA-based identification of novel bovine casein gene variants." Journal of dairy science 96, no. 1 (2013): 699-709.

47. Smith, Gary C., J. Daryl Tatum, Keith E. Belk, John A. Scanga, Temple Grandin, and John N. Sofos. "Traceability from a US perspective." Meat science 71, no. 1 (2005): 174-193.

48. Noviyanto, Ary, and Aniati Murni Arymurthy. "Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method." Computers and electronics in agriculture 99 (2013): 77-84.

49. Kumar, Santosh, Shrikant Tiwari, and Sanjay Kumar Singh. "Face recognition of cattle: can it be done?." Proceedings of the National Academy of Sciences, India Section A: Physical Sciences 86 (2016): 137-148.

50. Jaddoa, Mohammed, Luciano Gonzalez, Holly Cuthbertson, and Adel Al-Jumaily. "Multi view face detection in cattle using infrared thermography." In International Conference on Applied Computing to Support Industry: Innovation and Technology, pp. 223-236. Cham: Springer International Publishing, 2019.

51. Barry, B., U. A. Gonzales-Barron, K. McDonnell, F. Butler, and S. Ward. "Using muzzle pattern recognition as a biometric approach for cattle identification." Transactions of the ASABE 50, no. 3 (2007): 1073-1080.

52. Awad, Ali Ismail, and Mahmoud Hassaballah. "Bag-of-visual-words for cattle identification from muzzle print images." Applied Sciences 9, no. 22 (2019): 4914.

53. Lv, F., Zhang, C., Lv, C., 2018. Image recognition of individual cow based on sift in lαβ colorspace. MATEC Web of Conferences, p. 01023 EDP Sciences volume 176.

54. Allen, A., B. Golden, M. Taylor, D. Patterson, D. Henriksen, and R. Skuce. "Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland." Livestock science 116, no. 1-3 (2008): 42-52.

55. Lu, Yue, Xiaofu He, Ying Wen, and Patrick SP Wang. "A new cow identification system based on iris analysis and recognition." International journal of biometrics 6, no. 1 (2014): 18-32.

56. Tharwat, Alaa, Tarek Gaber, and Aboul Ella Hassanien. "Cattle identification based on muzzle images using gabor features and SVM classifier." In International Conference on Advanced Machine Learning Technologies and Applications, pp. 236-247. Cham: Springer International Publishing, 2014.

57. Allen, A., B. Golden, M. Taylor, D. Patterson, D. Henriksen, and R. Skuce. "Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland." Livestock science 116, no. 1-3 (2008): 42-52.

58. Sun, Shengnan, Shicai Yang, and Lindu Zhao. "Noncooperative bovine iris recognition via SIFT." Neurocomputing 120 (2013): 310-317.

59. Kumar, Santosh, Sanjay Kumar Singh, Rishav Singh, Amit Kumar Singh, Santosh Kumar, Sanjay Kumar Singh, Rishav Singh, and Amit Kumar Singh. "Recognition of cattle using face images." Animal biometrics: techniques and applications (2017): 79-110.

60. Okura, Fumio, Saya Ikuma, Yasushi Makihara, Daigo Muramatsu, Ken Nakada, and Yasushi Yagi. "RGB-D video-based individual identification of dairy cows using gait and texture analyses." Computers and Electronics in Agriculture 165 (2019): 104944.

61. Joachims, Thorsten. Making large-scale SVM learning practical. No. 1998, 28. Technical report, 1998.

62. Cover, Thomas, and Peter Hart. "Nearest neighbor pattern classification." IEEE transactions on information theory 13, no. 1 (1967): 21-27.

63. McCulloch, Warren S., and Walter Pitts. "A logical calculus of the ideas immanent in nervous activity." The bulletin of mathematical biophysics 5 (1943): 115-133.

64. Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors." nature 323, no. 6088 (1986): 533-536.

65. Lee, Taejun, Youngjun Na, Beob Gyun Kim, Sangrak Lee, and Yongjun Choi. "Identification of individual Hanwoo cattle by muzzle pattern images through deep learning." Animals 13, no. 18 (2023): 2856.

66. Wagner, John J., Shawn L. Archibeque, and Dillon M. Feuz. "The modern feedlot for finishing cattle." Annu. Rev. Anim. Biosci. 2, no. 1 (2014): 535-554.

67. Terry, Stephanie A., John A. Basarab, Le Luo Guan, and Tim A. McAllister. "Strategies to improve the efficiency of beef cattle production." Canadian Journal of Animal Science 101, no. 1 (2020): 1-19.

68. Zhao, Kaixuan, Xin Jin, Jiangtao Ji, Jun Wang, Hao Ma, and Xuefeng Zhu. "Individual identification of Holstein dairy cows based on detecting and matching feature points in body images." Biosystems Engineering 181 (2019): 128-139.

69. Kumar, Santosh, Sanjay Kumar Singh, Ali Imam Abidi, Deepanwita Datta, and Arun Kumar Sangaiah. "Group sparse representation approach for recognition of cattle on

muzzle point images." International journal of parallel programming 46 (2018): 812-837.

70. Kumar, Santosh, Sanjay Kumar Singh, Ravi Shankar Singh, Amit Kumar Singh, and Shrikant Tiwari. "Real-time recognition of cattle using animal biometrics." Journal of Real-Time Image Processing 13 (2017): 505-526.

71. Zaorálek, Lukáš, Michal Prilepok, and Václav Snášel. "Cattle identification using muzzle images." In Proceedings of the Second International Afro-European Conference for Industrial Advancement AECIA 2015, pp. 105-115. Springer International Publishing, 2016.

72. Gaber, Tarek, Alaa Tharwat, Aboul Ella Hassanien, and Vaclav Snasel. "Biometric cattle identification approach based on Weber's Local Descriptor and AdaBoost classifier." Computers and Electronics in Agriculture 122 (2016): 55-66.

73. El-Henawy, Ibrahim, Hazem El-bakry, and Hagar El-Hadad. "Muzzle Classification Using Neural Networks." International Arab Journal of Information Technology (IAJIT) 14, no. 4 (2017).

74. Ahmed, Shaimaa, Tarek Gaber, Alaa Tharwat, Aboul Ella Hassanien, and Václav Snáel. "Muzzle-based cattle identification using speed up robust feature approach." In 2015 International Conference on Intelligent Networking and Collaborative Systems, pp. 99-104. IEEE, 2015.

75. Schilling, Benjamin, Keivan Bahmani, Boyang Li, Sean Banerjee, Jessica Scillieri Smith, Tim Moshier, and Stephanie Schuckers. "Validation of biometric identification of dairy cows based on udder NIR images." In 2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS), pp. 1-7. IEEE, 2018.

76. Li, Wenyong, Zengtao Ji, Lin Wang, Chuanheng Sun, and Xinting Yang. "Automatic individual identification of Holstein dairy cows using tailhead images." Computers and electronics in agriculture 142 (2017): 622-631.

77. Tharwat, Alaa, TarekGaber, and Aboul Ella Hassanien. "Two biometric approaches for cattle identification based on features and classifiers fusion." International Journal of Image Mining 1, no. 4 (2015): 342-365.

78. Xu, Beibei, Wensheng Wang, Greg Falzon, Paul Kwan, LeifengGuo, Guipeng Chen, Amy Tait, and Derek Schneider. "Automated cattle counting using Mask R-CNN in quadcopter vision system." Computers and Electronics in Agriculture 171 (2020): 105300.

79. Jiang, Honghua, Chuanyin Zhang, Yongliang Qiao, Zhao Zhang, Wenjing Zhang, and Changqing Song. "CNN feature based graph convolutional network for weed and crop recognition in smart farming." Computers and electronics in agriculture 174 (2020): 105450.

80. O'Shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks. arXiv 2015." arXiv preprint arXiv:1511.08458 (2015).

81. Li, Guoming, Yanbo Huang, Zhiqian Chen, Gary D. ChesserJr, Joseph L. Purswell, John Linhoss, and Yang Zhao. "Practices and applications of convolutional neural network-based computer vision systems in animal farming: A review." Sensors 21, no. 4 (2021): 1492.

82. Roberts, Chris M. "Radio frequency identification (RFID)." Computers & security 25,

no. 1 (2006): 18-26.

83. Qiao, Yongliang, Daobilige Su, He Kong, Salah Sukkarieh, Sabrina Lomax, and Cameron Clark. "Data augmentation for deep learning based cattle segmentation in precision livestock farming." In 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE), pp. 979-984. IEEE, 2020.

84. Weng, Zhi, Longzhen Fan, Yong Zhang, ZhiqiangZheng, Caili Gong, and Zhongyue Wei. "Facial Recognition of Dairy Cattle Based on Improved Convolutional Neural Network." IEICE TRANSACTIONS on Information and Systems 105, no. 6 (2022): 1234-1238.

85. Brownlee, Jason. Deep learning for computer vision: image classification, object detection, and face recognition in python. Machine Learning Mastery, 2019.

86. Shen, Weizheng, Hengqi Hu, Baisheng Dai, Xiaoli Wei, Jian Sun, Li Jiang, and Yukun Sun. "Individual identification of dairy cows based on convolutional neural networks." Multimedia Tools and Applications 79 (2020): 14711-14724.

87. Ren, Shaoqing, Kaiming He, Ross Girshick, and Jian Sun. "Faster R-CNN: Towards real-time object detection with region proposal networks." IEEE transactions on pattern analysis and machine intelligence 39, no. 6 (2016): 1137-1149.

88. Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1-9. 2015.

89. Redmon, J. "You only look once: Unified, real-time object detection." In Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

90. Redmon, Joseph, and Ali Farhadi. "YOLO9000: better, faster, stronger." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7263-7271. 2017.

91. Phyo, Cho Nilar, Thi Thi Zin, Hiromitsu Hama, and Ikuo Kobayashi. "A hybrid rolling skew histogram-neural network approach to dairy cow identification system." In 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ), pp. 1-5. IEEE, 2018.

92. Manoj, Sreenand, S. Rakshith, and V. Kanchana. "Identification of cattle breed using the convolutional neural network." In 2021 3rd International Conference on Signal Processing and Communication (ICPSC), pp. 503-507. IEEE, 2021.

93. Li, Zhangyong, Chao Ge, SiwanShen, and Xinwei Li. "Cow individual identification based on convolutional neural network." In Proceedings of the 2018 International Conference on Algorithms, Computing and Artificial Intelligence, pp. 1-5. 2018.

94. Barbedo, Jayme Garcia Arnal, Luciano Vieira Koenigkan, Thiago Teixeira Santos, and Patrícia Menezes Santos. "A study on the detection of cattle in UAV images using deep learning." Sensors 19, no. 24 (2019): 5436.

95. Zin, Thi Thi, Shuhei Misawa, Moe Zet Pwint, Shin Thant, Pann Thinzar Seint, Kosuke Sumi, and Kyohiro Yoshida. "Cow identification system using ear tag recognition." In 2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech), pp. 65-66. IEEE, 2020.

96. Wang, Ziyan, Fuchuan Ni, and Na Yao. "Mtfcn: multi-task fully convolutional network for cow face detection." In International Conference in Communications, Signal Processing, and Systems, pp. 1116-1127. Singapore: Springer Singapore, 2020.

97. Li, Guoming, Galen E. Erickson, and YijieXiong. "Individual beef cattle identification using muzzle images and deep learning techniques." Animals 12, no. 11 (2022): 1453.

98. Wang, Xi, Xiao DongCheng, ZheFu Chen, and FeiXu. "A method for individual identification of dairy cows based on deep learning." In Proceedings of the 2020 2nd International Conference on Robotics, Intelligent Control and Artificial Intelligence, pp. 186-191. 2020.

99. Bello, R.-W.; Talib, A.Z.H.; Mohamed, A.S.A.B. Deep Belief Network Approach for Recognition of Cow using Cow Nose Image Pattern. Walailak J. Sci. Technol. (WJST) 2021, 18, 8984. https://doi.org/10.48048/wjst.2021.8984

100. Zhao, Jian-Min, and Qiu-Sheng Lian. "Compact loss for visual identification of cattle in the wild." Computers and Electronics in Agriculture 195 (2022): 106784.

101. Pedersen, Malte, Marianne Nyegaard, and Thomas B. Moeslund. "Finding nemo’s giant cousin: Keypoint matching for robust re-identification of giant sunfish." Journal of Marine Science and Engineering 11, no. 5 (2023): 889.

102. Santoni, Mayanda Mega, Dana Indra Sensuse, Aniati Murni Arymurthy, and Mohamad Ivan Fanany. "Cattle race classification using gray level co-occurrence matrix convolutional neural networks." Procedia Computer Science 59 (2015): 493-502.

103. Tassinari, Patrizia, Marco Bovo, Stefano Benni, Simone Franzoni, Matteo Poggi, Ludovica Maria Eugenia Mammi, Stefano Mattoccia et al. "A computer vision approach based on deep learning for the detection of dairy cows in free stall barn." Computers and Electronics in Agriculture 182 (2021): 106030.

104. Qiao, Yongliang, Cindy Cappelle, Yassine Ruichek, and Tao Yang. "ConvNet and LSH-based visual localization using localized sequence matching." Sensors 19, no. 11 (2019): 2439.

105. Qiao, Yongliang, Cameron Clark, Sabrina Lomax, He Kong, Daobilige Su, and Salah Sukkarieh. "Automated individual cattle identification using video data: a unified deep learning architecture approach." Frontiers in Animal Science 2 (2021): 759147.

106. GeeksforGeeks, “Understanding the Confusion Matrix in Machine Learning”, Accessed September 30, 2024. https://www.geeksforgeeks.org/confusion-matrix-machine-learning/.