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Review Article

Animal Identification in Precise Livestock Farming - A Systematic Review of Current Practices and Perspectives

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Abstract

Precision Livestock Farming (PLF) operates through the implementation of modern technological approaches with regard to monitoring and managing animal health, welfare and productivity of individual animals in real-time. A crucial aspect of PLF is the individual identification of each animal, which contributes to development of personalized decisions, leading to improved health outcomes, optimized feed usage, and greater overall farm efficiency. Currently employed technologies for animal identification include means as ear tags, RFID tags and boluses, neck collars and other devices for identification. Recently, a new promising method for individual identification has emerged, implementing software technologies for animal face recognition. The present paper focuses on the comparison of the currently used methods for identification and animal face recognition on several criteria – accuracy, invasiveness, automation potential, effects on animal welfare and functional challenges. Among the methods analysed, face recognition appeared accurate for over 90%, with high automation potential, non-invasive and excellent outcomes for animal welfare. Although, there are some limitations for the large-scale implementation of this method as hardware costs, light-induced variations and needs for dataset preparation, livestock face identification has the potential to improve the precision and effectiveness of animal husbandry and management. With sustained investment in smart infrastructure for farms and on-field trials, animal face identification could be practically implemented for more efficient and intelligent livestock farming.

Keywords: Animal face recognition, Animal identification, Animal welfare, Precision livestock farming

Introduction

The identification of individual animals plays a vital role in the management of livestock farms, including operations on health monitoring, traceability of live animals and their products, reproduction management, and biosecurity measures. As global agriculture intensifies and shifts toward data-driven decision-making, the demand for accurate, efficient, and ethical identification systems continues to grow. Conventional methods such as ear tags, branding, tattooing, and injectable RFID chips, are widely used, but at the same time some of them present considerable limitations. These include potential for loss or damage [1,2], invasiveness, stress and pain to the animals [3,4], and susceptibility to human error or tampering [5]. Moreover, visual identification tools require physical proximity and often human intervention, which hinders their applicability in automated precision farming environments.

For the purpose of Precision livestock farming (PLF), identification systems must be capable of supporting automated, individualized management of large animal populations. PLF aims to enhance animal health, welfare, and productivity through the integration of real-time monitoring systems and intelligent technologies [6]. To meet these goals, researchers and technologists are exploring novel identification methods that are non-invasive, scalable, and compatible with digital infrastructure.

In the last decade less invasive and digitally applicable approaches have emerged, among which animal face recognition has gained significant attention. This method utilizes computer vision and artificial intelligence (AI) to draw on unique face features to distinguish between individuals, similar to human facial recognition systems. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have enabled high-accuracy identification in various species, including cattle, pigs, and goats [7-9]. These systems have the potential to be integrated with farm management software, surveillance cameras, and Internet of Things (IoT) networks for real-time tracking and decision support.

Furthermore, face recognition technologies promise broader functionalities such as automated monitoring of health and behavior, detection of estrus cycles, and implementation of disease outbreak control measures, all of which are among the essential components of smart farming systems [10,11]. At herd level, their application could mitigate the stress and ethical concerns associated with invasive marking techniques, which could address the growing societal demands for animal welfare and sustainable farming nowadays.

This study provides a structured comparison of different identification technology methods using unified evaluation criteria (accuracy, automation potential, welfare impact, and scalability), complemented by summary performance data and an assessment of methodological quality.

This paper critically evaluates the current state of animal face recognition technologies and their potential role in precision livestock farming. It analyses existing research, compares traditional and modern identification methods, and assesses the technological, practical, and ethical challenges of implementing face biometrics in farm environments. The objective is to determine whether face recognition can serve not only as a supplementary instrument but eventually as a reliable alternative to conventional systems of animal identification.

Material and Methods

The study was designed as a comparative systematic review with the objective to classify and compare various animal identification methods within the context of precision livestock farming, evaluating their accuracy, efficiency, impact on animal welfare, and potential for automation, with a particular focus on face recognition and whether it can fully replace or serve as a complementary method to existing practices. A structured literature search was conducted in the period January-April 2025, involving systematic searches in scientific databases such as Web of Science, Scopus, PubMed, and Google Scholar *(Fig. 1)*. The primary search strings included keywords and combination of terms as: "animal identification" AND ("ear tag" OR "RFID" OR "microchip" OR "GPS collar" OR "biometric*" OR "face recognition") "precision livestock farming" AND ("identification" OR "computer vision" OR "deep learning"). All relevant studies were subjected to selection based on predetermined criteria for inclusion - only peer-reviewed articles; published between 1995-2025; being available in English; focused on farm animal species - cattle, pigs, sheep, goats, horses, and poultry; included at least one animal identification method; reported findings on performance, accuracy or applicability. The exclusion criteria were set to removing from the study papers that were not peer-reviewed; papers from editorials, theses, conference abstracts; focus on animal species without farm relevance (like pets and wildlife); related to animal tracking or monitoring without individual identification.

All articles selected as per the criteria were checked for duplication. The compiled set after removing duplicates, was screened through titles and abstracts for relevance to the topic based on the inclusion criteria and potentially relevant articles with full text were assessed for eligibility. From each eligible study information was extracted regarding the identification method used, animal species involved, and performance indicators such as recognition accuracy, reliability, impact on animal welfare, ease of application, cost, potential for automation, integration with farm management systems, and adaptability to different environmental conditions.

The collected data were subjected to qualitative analysis in order to evaluate their methodology, transparency of performance metrics, reproducibility of methods, species diversity and field applicability. Based on this assessment, studies were categorized as of high, moderate and low methodological rigor, with the last group being excluded for further analysis. The remaining studies were used for comparative analysis encompassing traditional physical methods, electronic and biometric identification methods. Data were thematically analyzed and interpreted in light of the goals of precision livestock farming, considering not only the technical performance of each method but also its impact on animals, practical applicability, and potential for future scalability. Particular attention was given to face recognition technology and its ability to meet the requirements of modern identification systems. The results were organized to highlight the strengths and weaknesses of each technology in order to determine whether face recognition can realistically replace or enhance conventional practices in farm environments.

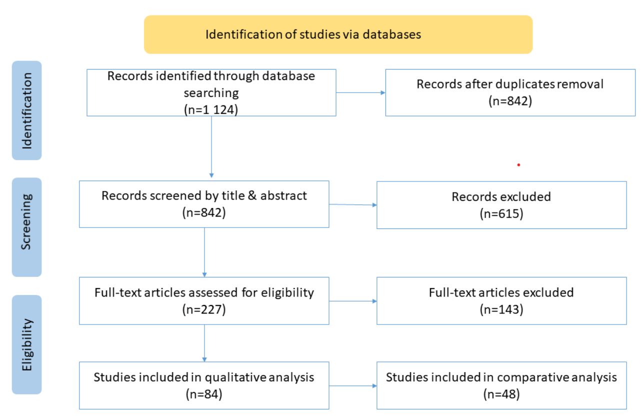

Fig 1. PRISMA flow diagram illustrating the literature search, screening, eligibility assessment, and final inclusion of studies in the systematic review

Results

Traditional Physical Approaches

The comparative review of animal identification methods that are currently available, revealed significant differences in their effectiveness, practicality, and compatibility with the goals of precision livestock farming (PLF) *(Table 1)*. Traditional approaches such as branding, tattooing, and ear tagging, although widely implemented, have several limitations in terms of animal welfare, ease of use, and the possibility of being integrated with animal holdings software. Branding, especially hot-iron branding, causes significant pain and long recovery periods, with healing taking over eight weeks in many cases. Animals subjected to this method often show clear signs of discomfort and avoidance behaviors, raising serious ethical concerns [3,4,12]. Cold branding and tattooing are somewhat less severe, but they are still invasive and not ideal for long-term tracking, especially on farms where digital monitoring is implemented [13,14].

Ear tags, particularly the visual plastic ones, are common due to being inexpensive and easy to apply. They typically display alphanumeric or barcoded information that helps track animals in a herd and are officially recognized in many countries as a main means of identification. However, these tags are easily lost, can be damaged, and often become unreadable due to dirt or wear [15,16]. If they aren't integrated with electronic components as RFID transponders, they also can't support automated tracking systems and data collection.

Electronic Identification

Electronic methods like RFID tags have addressed some of these issues. These tags allow for quicker and more accurate data collection and reduce the need for manual checking. They can be scanned automatically and synchronized with farm management systems, which reduce labour and manual error [5,17]. Even so, they are not perfect as RFID tags can be lost or damaged, and their limited reading range poses problems in crowded or complex farm environments [18]. Other tools like injectable microchips offer more security and minimal invasiveness but have their own set of challenges. They require scanners to be close to the animal, and the transponders could migrate under the skin, which may compromise identification reliability [19,20]. GPS collars are another option, providing additional data on movement and behaviour, but high costs, battery life issues, and signal interference limit their usefulness for continuous identification [21,22].

Biometric Animal Identification

More recently, biometric technologies have emerged as a promising alternative. Among them, face recognition stands out due to its non-invasive nature, high accuracy, and strong potential for full automation. Deep learning models, particularly convolutional neural networks, have shown excellent results across different animal species [30]. One study achieved over 90% accuracy in identifying individual pigs even under variable lighting and different head angles [9]. Similar outcomes were seen in cattle and goats using muzzle and facial images, often with AI-

Table 1. *Comparison of common animal identification methods with their relevance to precision livestock farming*

Identification Method	Accuracy	Invasiveness	Automation Potential	Scalability	Animal Welfare	Challenges	Reference
Hot-iron branding	High	High	Low	High	Poor	Pain, healing time, welfare concerns	Tucker et al. [4]; Schwartzkopf-Genswein et al. [3]; Hernández et al.[12]
Tattooing	High	Moderate	Low	Moderate	Moderate	Poor visibility, labor-intensive	Luetkemeier et al.[13]; Cambiaso-Daniel et al.[14]
Ear tag (visual)	Moderate	Moderate	Low (unless electronic)	High	Good	Loss, tampering, dirt interference	Caja et al.[15]; Awad [16]
RFID tags	Moderate	Low	Medium	High	Good	Read range limitations, tag loss	Rizvi et al.[5]; Harmon et al.[17]; Gao et al.[18]
Injectable microchip	High	Low to moderate	Medium	Moderate	Good	Migration, requires proximity scan	Azoulay et al.[19]; Mergl et al.[20]
Gps collars	High (location-based)	Low	High	Moderate	Good	High cost, battery/signal limitations	Hofmann et al.[21]; Waller et al.[22]
Nasal pattern recognition	High	None	Medium	Low to moderate	Excellent	Image quality sensitive, hard to capture	Choi et al.[23]
Face recognition	High(>90%)	None	High	High	Excellent	Lighting variation, dataset needs, hardware cost	Bae et al.[9]; Bello et al.[8]; Zhang et al.[24]; Choi et al. [23]; Sun et al.[25]; Ma et al.[26]; Ahmad et al., [27]; Neethirajan [28]; Li et al.[29]

enhanced detection methods like YOLO-based algorithms [8,24]. Moreover, studies on dogs have also shown that facial and nasal features remain stable over time, which is crucial for long-term identification applications [23].

Further developments in artificial intelligence have increased the extent of reliability. Advanced models such as LAD-RCNN and ViT-DL-IN21K help systems distinguish individuals with greater precision, regardless of background noise or subtle differences [25,26]. Furthermore, systems integrating face recognition with PLF technologies have already been tested in real-world farm settings, including integration into feeding and milking stations with non-contact animal monitoring. These applications allow for continuous tracking and can also provide health and behaviour data in real time, that are key components of modern, welfare-focused and data-driven farm management [27-29].

Face recognition in animals as a means of identification has several advantages, but its widespread use still faces some challenges. Most studies have been conducted in controlled environments that do not take into account many of the obstacles that may arise in real farm settings *(Table 2)*. Differences in lighting, animal movement, dirt on the face, breed diversity, and changes in appearance with age can reduce the accuracy of these systems [31,32]. One of the main disadvantages remains the high cost and initial investment, along with the need for specific technical knowledge by farm staff, which can further complicate implementation, especially for smaller animal holdings.

Alternative Biometric Identification Methods

In addition to the innovative face recognition methods that have attracted significant interest in recent years, other biometric approaches for livestock identification are also being investigated *(Table 3)*. Among them, retinal imaging is considered one of the most scientifically reliable methods for certain types of farm animals. This is due to the unique vascular structure of the retina, which remains stable throughout the animal's life and provides extremely high discrimination ability. This feature was successfully utilized through computerized techniques like U-Net-based deep learning model, as some authors reported recognition accuracy of 95.6% of cattle retinal patterns [33,34]. Confirmation of the reliability of retina as a biometric marker was achieved also by Saygılı et al.[35] through a newly developed image processing system CattNIS with 92.25% performance of matching retinal images. Extraction of retinal patterns with segmentation of retinal vessels through different deep learning algorithms further proved to be a highly precise method of animal identification in controlled farm environment [36].

Even before the introduction of modern machine learning models, the possibilities of retinal scanning as a means of identification in farm animals appeared to be a particular subject of scientific research. The studies of Allen et al.[37] and Barron et al. [38] demonstrated that the applicability of this method in both cattle and sheep, with reported accuracy levels of 98.3% in cows and 93.09% in sheep respectively, performed higher in comparison to the electronic identifiers used at the time. Despite the huge advantage of the uniqueness of retinal blood vessels, the method has a number of limitations such as necessity of a special camera for the images and close range with the animals for image acquisition, which significantly limits its scalability in large industrial farms.

A number of other non-invasive biometric methods, such as nose prints, muzzle patterns and body-shape recognition, have been investigated as reliable means of animal identification. However, these alternatives also suffer from limitations in terms of image quality, environmental factors and animal positioning. Overall,

Table 2. *Summary of reported performance* of face recognition systems in livestock species*

Species	Model/Algorithm	Dataset Size (animals/images)	Performance Metric	Reported Accuracy or F1-Score	Reference
Cattle	CNN-based classifier	400 animals/4000 images	Accuracy	98.99%	Bello et al.[8]
Cattle	DenseNet121 Detectron2-based system	180 animals/2500 images	F1-score	0.92	Mahato et al.[31]
Pigs	Vision Transformer (ViT), YOLOv8	20 animals/1500 images	F1	0.94	Ma et al.[26]
Goats	Improved YOLOv4	30 animals/2522 images	Accuracy	96.7%	Zhang et al.[24]
Sheep	SqueezeNet-based CNN	114 animals/5371 images	Accuracy	82.39%	Min et al.[30]
Horses	Transfer learning CNN YOLOv7	- 1103 images	Accuracy	96.2%	Ahmad et al.[27]

** Summary statistics across studies: Mean reported accuracy 93.6%; Standard deviation ±4.8%; Dataset size range 1103-5371 images* after comprehensive systematic review on the topic, Cihan et al. [39] argued that each biometric technique had its advantages and disadvantages, highlighting the need for comparative evaluations between multiple methods in terms of accuracy, practicality, and welfare considerations.

Comparative Performance Analysis of Identification Methods

Data from the reviewed studies revealed distinct differences among the explored identification technologies, based on performance indicators. Traditional physical means (branding, tattooing, ear tags) demonstrated high reliability when considered for manual identification visually, but they lacked automation capacity and negatively affected animal welfare due to their invasiveness. Reported error rates for visual ear tags in farm animals ranged from 5-20% due to tag loss or damage [40].

The performance of electronic identification systems such as RFID showed moderate to high accuracy (85-98%), which was influenced by various factors as environmental conditions and the distance between the animal and the reading device. Furthermore, when applied in large herds with big density, the reliability of the method was reported to decrease due to signal interference and tag loss [18]. Injectable transponders as microchips, on the other hand, demonstrated high identification accuracy (>95%) but their detection during reading required close proximity with the animal and showed migration events, although rarely reported [19,20].

Modern identification approaches like biometric methods, particularly face recognition, were found reliable for recognition of multiple animal species under controlled or semi-controlled conditions, with reported accuracies exceeding 90%. However, when tested under field conditions, the performance of face recognition models

Table 3. *Comparison of alternative biometric identification methods in livestock*

Biometric Method	Species	Core Technology	Dataset Size	Reported Performance	Advantages	Limitations	Reference
Retinal imaging	Cattle	Machine learning classifiers (SIFT, SURF, BRISK, FAST, HARRIS)	300 animals 2430 images	Accuracy 95.6%	Very high uniqueness and stability	Requires specialized capture device	Cihan et al.[33]
Retinal imaging	Cattle	Feature matching (CattNIS)	300 animals 2430 images	Accuracy 92.25%	High robustness	Difficult field acquisition	Saygılı et al.[35]
Retinal imaging	Cattle	U-Net segmentation	300 animals 540 images	Accuracy 97.4%	Highly accurate vascular mapping	Requires controlled setup	Cihan et al.[34]
Retinal imaging	Cattle	Dedicated retinal scanner	869 animals 1739 images	Accuracy 98.3%	Excellent permanence	High equipment cost	Allen et al.[37]
Retinal imaging	Sheep	Retinal pattern matching	64 animals 128 images	Accuracy 93.09%	Reliable biometric marker	Handling and restraint	Barron et al.[38]
Retinal vessels	Cattle	Image preprocessing and segmentation methods	234 animals 1206 images	Iidentification accuracy is not reported (segmentation performance only)	Robust biometric feature	Requires eye positioning	Cihan et al.[36]
Nose pattern	Dogs (method transferable)	CNN-based recognition	60 dogs/180 images (extended to 70 dogs/278 images)	The authors report a zero error rate in comparisons between real and fake data, which corresponds to 100% identification accuracy under controlled experimental conditions.	Highly distinctive patterns	Image capture sensitivity	Choi et al.[23]
Muzzle pattern	Cattle	SIFT feature extraction and matching	15 animals 105 images	Accuracy 93.3%	Non-invasive	Dirt/occlusion issues	Awad et al.[16]
Face recognition*	Multiple species	Deep CNN/ViT	Variable	Mean accuracy 93.6%	Fully contactless	Lighting/ pose/ sensitivity	Present review

** Summary of dataset size and mean accuracy are presented in Table 2* change due to lighting variations, face occlusion, and age-related morphological changes. These findings highlight that while biometric systems offer superior automation and welfare outcomes, their reliability remains context-dependent.

Despite the challenges mentioned, all studies on the use of face recognition for animal identification highlight a wide range of advantages. The technology is humane, requires no physical contact with the animal, and can be integrated with automated monitoring systems, giving it strong potential for widespread adoption in the future.

Discussion

The findings of this review suggest that animal face recognition technology has a substantial potential for modernizing identification practices in precision livestock farming. While traditional and electronic identification systems have provided a stable basis for traceability and animal tracking, they continue to hold significant disadvantages with regard to animal welfare, automation capability, and long-term reliability. In contrast, face recognition emerges as a non-invasive, accurate, and potentially more scalable alternative, especially when animal husbandry holdings consider orientation toward data-driven and welfare-oriented management systems.

Electronic identification systems such as RFID and injectable microchips offer significant improvements in traceability and partial automation. RFID tags enable integration with herd management platforms and support real-time data collection [5,17], yet they still require tag placement and may be susceptible to damage or loss. Subcutaneous microchips are less prone to tampering but require proximity-based scanning and have reported issues with migration or incorrect implantation [19,20]. Additionally, GPS collars have proven valuable for environmental and movement tracking but are cost-prohibitive for many operations and remain unsuitable for identification alone [21,22].

Biometric identification, particularly face recognition, addresses several of these limitations by offering a contact-free, animal-friendly, and technologically advanced solution. Modern deep learning algorithms such as convolutional neural networks (CNNs), LAD-RCNN, and ViT-based models have demonstrated high accuracy (often exceeding 90%) across a variety of species, including cattle, pigs, goats, and poultry [26,41,42].

Beyond basic identification, face recognition systems can be integrated with smart sensors and edge devices to support real-time behavioral analysis, health monitoring, and reproductive tracking without human interference [29,43,44]. In addition, novel applications such as emotion recognition through facial expressions may open up new possibilities for welfare assessment and ethical livestock management [45].

However, face recognition techniques still could not be fully implemented due to several technical and practical challenges such as lighting variability, facial obstructions, and unpredictable animal movement, that can significantly reduce the accuracy of image-based systems [24,46]. Most current models also struggle with generalization across breeds or age groups due to morphological differences [31]. In addition, the initial infrastructure costs -including high-resolution cameras, edge processing devices, and reliable data storage- can be serious burden and challenge for small-scale farmers. The comparative review on animal identification techniques [39] comprehensively presents the perspectives of future application of such novel approaches, but simultaneously emphasizes that no single biometric modality could be considered universal across all indicators. Searching for a long-term solution for a feasable, effective, automated and non-invasive method will require probably a combination of hybrid systems with multiple biometric cues.

The successful integration of face recognition technologies into existing PLF systems also requires attention to farmer education, usability, and ethical concerns. Adoption is likely to depend on farmers' perceptions of cost-benefit balance, as well as their comfort with digital tools [47]. Stakeholder involvement, including input from veterinarians, animal welfare experts, and technologists, will be essential to ensure responsible deployment that aligns with both productivity and welfare goals [28,48].

In conclusion, the continued development of artificial intelligence, sensor technologies, and affordable edge computing is likely to reduce the barriers posed by traditional identification methods. With growing public and regulatory focus on ethical and sustainable livestock production, the demand for non-invasive, automated, and animal-friendly identification methods is expected to increase. The present systematic review demonstrates that no single animal identification method currently satisfies all technical, economic, and welfare requirements of PLF. Traditional and electronic systems remain reliable but are constrained by invasiveness, loss, and limited automation. In this context, animal face recognition is poised not only to supplement but potentially to replace conventional systems in the near future. With sustained interdisciplinary collaboration, ongoing field trials, and investment in smart farming infrastructure, face recognition can become a central tool in the transition toward more ethical, efficient, and intelligent livestock farming.

However, existing evidence indicates that face recognition systems are not yet universally robust under real farm conditions. Technical challenges, infrastructure costs, and limited large-scale validation remain significant barriers.

In this regard, future efforts should focus on improving biometric identification performance under variable farm and environmental conditions, reducing hardware and implementation costs, and enhancing user-friendly integration with management systems that are already in operation. The focus should be directed towards development of integrative identification frameworks, possibly combining face recognition with highly reliable, although less practical approaches like retinal imaging, in order to achieve both scalability and accuracy. Using distinct benchmarks across biometric methods for comparison and creation of standardized datasets and evaluation protocols will be essential for determining their real-world suitability with regard to precision livestock farming.

Declarations

Availability of Data and Materials: Data availability is not applicable to this article as no new data were created in this study.

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