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Review

Identification and Recognition of Animals from Biometric Markers Using Computer Vision Approaches: A Review

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ABSTRACT

Although classic methods (such as ear tagging, marking, etc.) are generally used for animal identification and recognition, biometric methods have gained popularity in recent years due to the advantages they offer. Systems utilizing biometric markers have been developed for various purposes in animal management, including more effective and accurate tracking of animals, vaccination, disease management, and prevention of theft and fraud. Animals' irises, retinas, faces, muzzle, and body patterns contain unique biometric markers. The use of these markers in computer vision approaches for animal identification and tracking systems has become a highly effective and promising research area in recent years. This review aims to provide a general overview of the latest developments in image processing approaches for animal identification and recognition applications. In this review, we examined in detail all relevant studies we could access from different electronic databases for each biometric method. Afterward, the opportunities and challenges of classical and biometric methods were compared. We anticipate that this study, which conducts a literature review on animal identification and recognition based on computer vision approaches, will shed light on future research towards developing automated systems with biometric methods.

Keywords: Animal, Biometric markers, Computer vision, Identification, Recognition

Introduction

The worldwide purpose of animal identification is to identify and register animals, ensure effective control of animal diseases and movements, maintain records related to livestock support, health, breeding, and statistics. Tracking, monitoring, and individually identifying farm animals hold significant socio-economic importance. Additionally, the increasing consumer demands for food safety have underscored the necessity of secure traceability systems for the origin and production stages of animals and animal products [1,2]. Many international organizations, such as the World Health Organization (WHO) and Food Safety Authorities, actively support the development of identification and traceability systems, recognizing their importance in ensuring food safety and animal health.

Permanent and reliable identification is the primary goal of animal tracking systems. Traditional identification methods (fleece marks, tattoos, ear notches, plastic or metal ear tags) are inconvenient for sheep-goat-type animals and increase cost, especially in large herds [3]. The reasons for the ineffectiveness of these methods are; losses, deletion, short reading distances, reading errors, adversely affecting the welfare of animals, and being vulnerable to cheating [1]. For this reason, the necessity of reliable methods that can be an alternative to classical identification methods emerges. With epidemics, it was understood that animal identification methods were insufficient in monitoring animals, and new traceability tools were needed [4]. Thus, the process of utilizing biometric technologies as well as electronic identification systems in the traceability of animals and animal products has begun.

The World Organization for Animal Health (WOAH) attaches great importance to the individual identification and tracking of animals, especially farm animals. In addition, consumers all over the world want to have information about the source and production stages of the products they consume, worrying about animal health and the safety of animal products [5]. The transmission of some diseases such as mad cow, anthrax, alum, tuberculosis, brucellosis, and rinderpest to humans by crossing the species barrier in animals brings animal food safety to the fore. From the point of view of the country's economy, the identification and tracking of animals are of great importance. As a matter of fact, in the first mad cow case in England in 1996, meat consumption fell by 40%, resulting in serious economic losses. Beef and beef exports were stopped in 53 countries in 2003 due to the mad cow case in a single cow. This situation caused an economic loss of 3.2-4.7 billion dollars [6]. With an effective animal identification and tracking system, the disease outbreak can be tracked, slowed, and isolated quickly [6]. For these reasons, monitoring livestock has developed rapidly all over the world and continues to evolve. Major exporters such as Australia and Canada have mandatory cattle identification systems. South Korea introduced a comprehensive beef monitoring system in December 2008. In the US, a total expenditure cost of $75.87 million was incurred in 2009 for the identification of cattle alone [6]. In our country (Türkiye), the Ministry of Food, Agriculture, and Livestock started the tagging and registration procedures for bovine animals in 2002.

Animal welfare is an extremely important issue, and some regulations have been made in developed countries, especially in the European Union (EU) countries, with laws and regulations to raise animal welfare standards in animal production and to make animals happier [7]. Animal welfare positively affects the quantity and quality of products obtained from animals. Ear tag application is one of the most used identification methods in our country and all over the world. Ear tagging can not only cause pain and stress in animals but also cause tissue reactions and infections. While ear wounds lead to earring loss, re-identification of the animal will cause pain once again and cause an extra cost. In addition, it is known that pain and stress negatively affect hereditary characteristics such as growth rate, resistance to diseases, milk production, and reproductive ability in farm animals [8]. Also, the ear tag can be easily copied or removed and discarded after the animal is stolen. In this case, there is nothing to be done. Because with other systems other than biometric systems, device tracking is done, not animal tracking. Biometric methods have become one of the popular topics of recent times, as they do not have the above-mentioned disadvantages of classical methods [9-11].

The use of artificial intelligence methods in animal husbandry is becoming increasingly widespread day by day [12-15]. In parallel with this, in recent years, the topic of animal identification and automatic animal recognition through computer vision approaches has also gained popularity [16]. With this system, a database is created from images obtained from animal biometrics. In almost all scientific researches, biometric data collected from animals are not publicly published for researchers to use. To our knowledge, there are several publicly accessible databases that can be used for animal identification and recognition. These databases consist of bovine iris images [17], cattle body patterns [18], and cattle muzzle images [19]. Several biometric features are extracted from the biometric data taken from each living thing, and individual identification and recognition are performed based on this feature set.

The iris patterns, retinal vascular patterns, face, muzzle, and animal body pattern biometric data of animals are analogous to human fingerprints and contain unique biometric features for every living thing. Thanks to these biometric markers, identification, and recognition in animals are successfully performed with the computer vision approach.

This review aims to examine in detail the recognition and identification studies with the computer vision approach and biometric methods in the field of animal husbandry and draw a roadmap for researchers who will work in this field. In addition, the comparative analysis of classical identification methods and biometric identification methods is among the objectives of the study. Considering the contribution of agriculture and animal husbandry to the national economy, the importance of this study can be understood more clearly. In this sense, the importance of this review, which will shed light on the studies to be carried out in the field of agriculture and animal husbandry, becomes more evident.

Animal Identification and Recognition Methods

Classical identification methods leave their place for modern methods due to disadvantages such as animal welfare, losses, deformations, and fraud [20]. Since biometric methods are modern methods and cannot be copied, frauds can be prevented, and there is no such thing as loss or deformation as long as the animal lives. With biometric methods, the animals are not stressed, and animal welfare is protected as an important advantage. Animal welfare is at the center of all these. Animal welfare is a concept related to meeting the needs of the animal in its natural life. In animal breeding, natural lifestyles, shelter conditions suitable for their unique behaviors, feeding the animal without disturbing its physiological, biological, and psychological integrity, and carrying out production activities in a way that does not impair the health of the animal and not restrict its movements are the basic elements of animal welfare [21].

Animal identification systems have been an essential component used in traceability for centuries and are divided into four categories: permanent, temporary,

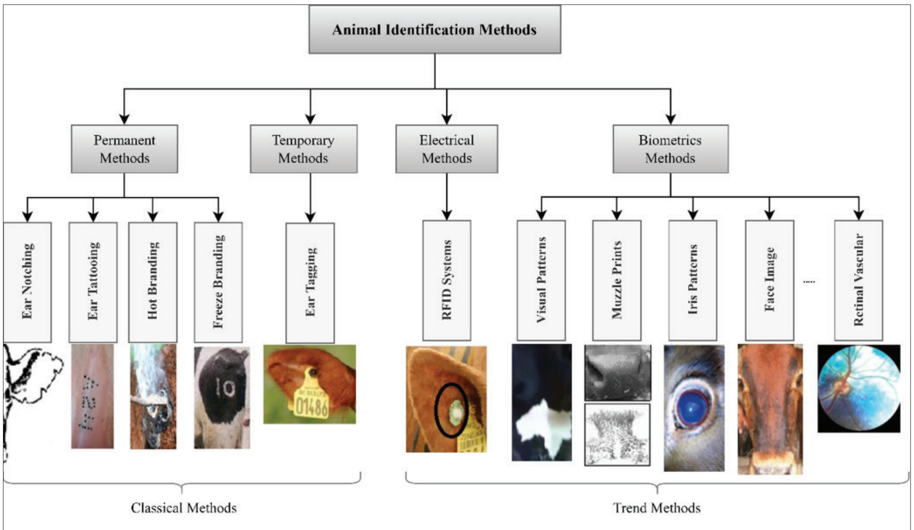

Fig 1. Classical and trend methods in animal identification

electrical, and biometric [20]. These identification methods are presented in *Fig. 1*.

In recent years, identification methods using biometric markers in animals are called trend identification methods. Retinal vessel patterns in animals, muzzle prints, iris, face, and patterns in various parts of their body are biometric markers. Biometric markers are a good alternative to classical methods as they are unique, cannot be changed by others, do not require additional costs, and most importantly do not adversely affect animal welfare. Opportunities and challenges of these classical and trend methods used for identification are presented in *Table 1*.

Traditional methods are still used for identification in many countries. As seen in *Table 1*, traditional identification methods have several disadvantages. RFID microchip technology, one of the trending methods, has been widely employed in recent years, especially in pet identification. However, this method also has a series of disadvantages similar to traditional identification methods. For instance, microchip implantation requires a medical procedure, must be administered by a specialist, carries a risk of infection, microchips can migrate within the body, they can malfunction, and can only be read with specialized scanners. While RFID is considered a trending approach, it structurally differs from other trending identification methods, such as biometric-based identification, as shown in *Table 1*. As observed, biometric-based identification methods offer numerous advantages, making them a popular research topic in recent years [22].

Biometric Methods in Animal Identification a Recognition

Biometrics is an automated system that measures an individual's physical or behavioral uniqueness and performs identification by comparing it to existing records. Biometric identification methods do not cause pain and do not change the appearance of the animal. Biometric features are unique, non-replicable, reusable, measurable, robust, and have distinctive physical features. There is no confusion in biometric systems compared to traditional methods [23].

Biometric identifiers include retinal vascular patterns,

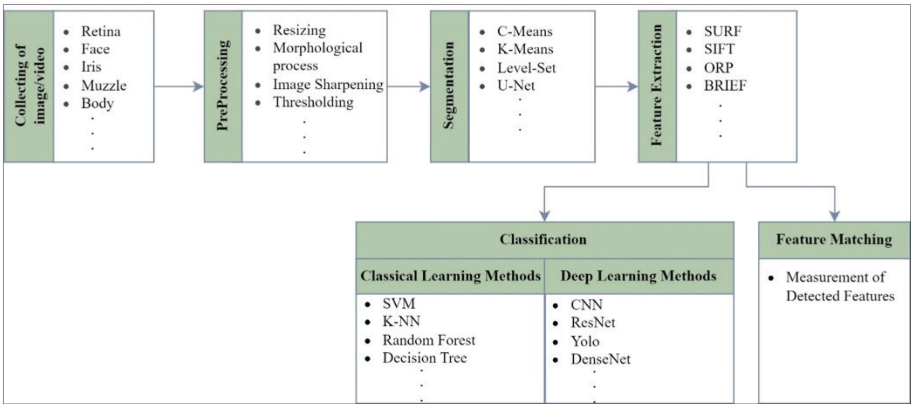

Fig 2. Flow diagram of the image processing for animal identification

Table 1. *Opportunities and challenges of identification methods*

Parameters	Method	Opportunities	Challenges
Trend Identification Methods	RFID	● wide range of applications ● can store information (i.e., owner, the farm, diseases, and the animal›s vaccination status) ● integrated with mobile computing ● easily managed remotely	● painful ● costly ● needs a professional person ● low reliability ● minimum recognition rate ● object tracking, not animal
	Retinal Vascular Pattern	● non-painful ● time-immutable ● applied across a wide variety of animals ● less prone to error and fraud ● useful in monitoring and tracking ● injury to the cornea does not interfere with the retina image ● considerable identification accuracy	● processing time ● the difficulty of capturing a retinal image due to eye diseases
	Muzzle Print	● non-painful ● time-immutable ● less prone to error and fraud ● cannot be forged or altered ● useful in monitoring and tracking	● capturing accurate images ● difficult image processing
	Face	● non-painful ● time-immutable ● less prone to error and fraud ● cannot be forged or altered ● useful in monitoring and tracking	● capturing accurate images ● pose, expression, illumination, aging, and disguise
	Iris Pattern	● non-painful ● less prone to error and fraud ● cannot be forged or altered ● useful in monitoring and tracking	● time-mutable iris texture (with age, disease, and medication) ● difficult to capture iris images (blurred images and images occluded by eyelids or eyelashes)
	Body Pattern	● non-painful ● time-immutable ● less prone to error and fraud ● cannot be forged or altered ● useful in monitoring and tracking	● applicable to animals with the pattern ● capturing accurate images
Traditional Identification Methods	Ear notching	● Permanent ● relatively quick and simple ● highly visible ● low cost	● painful ● laborious operation /An exhausting ● time-consuming ● limited scalability (not suitable for large-sized farms) ● unbounded cost ● susceptible to theft, fraud, and duplication ● not useful in monitoring and tracking
	Ear tattooing	● less painful ● permanent ● low cost ● equipment portable	● limited scalability ● time-consuming ● laborious operation ● time-mutable ● less useful dark animals ● susceptible to theft, fraud, and duplication ● not useful in monitoring and tracking
	Hot iron branding	● easy and simple	● painful ● manually identified ● time-mutable ● susceptible to theft, fraud, and duplication ● not useful in monitoring and tracking ● causes inflammation
	Freeze branding	● faster application time	● painful ● manually identified ● susceptible to theft, fraud, and duplication ● not useful in monitoring and tracking
	Ear tagging	● low cost ● most widely used ● relatively atraumatic ● quick and easy to perform	● painful ● time-mutable ● susceptible to damages, duplications, losses, unreadability, and fraud ● do not perform well as a long-term identification ● can cause infection ● unbounded cost (tags can fall out) ● not useful in monitoring and tracking

muzzle print images, face images, animal body patterns, and iris patterns. Thanks to image processing techniques, animal identification is successfully carried out with these biometric identifiers. *Fig. 2.* illustrates the image processing steps commonly employed in past and present studies of animal identification.

The image processing steps provided in the flowchart may vary depending on the requirements of the specific study; therefore, additional steps can be added to these procedures, or certain steps may not be implemented.

This article reviews the evolution of animal recognition and tracking from traditional methods to animal biometrics. It also reports on traditional and trend animal identification methods, their advantages, and their disadvantages. Also, this article explains the use of biometric identifiers to recognize, identify and trace animals effectively. This review presents the latest research findings in animal biometrics with a strong focus on biometric descriptors such as muzzle prints, animal body patterns, iris patterns, and retinal vascular patterns. A discussion of the current challenges in biometric-based identification systems is included in the results that may guide future research directions. In the following titles, the types of biometric methods and the studies carried out in these fields are examined separately.

Recognition and Identification Based on Retinal Vascular Pattern

The retinal vascular pattern at the back of the eye is used as a biometric marker in humans and animals. Although this biometric descriptor has been extensively studied in the literature for humans, limited studies have been conducted on animals. Due to the static nature of retinal vasculature throughout the animals' lifespan, retinal imaging remains impervious to alterations. In stark contrast, items like ear tags are susceptible to replacement, removal, or misplacement [24]. The animal retina has similar features to the human retina, and it is known that it is a biometric feature that does not change throughout its life [25].

Image processing techniques are increasingly being utilized in the analysis of retinal vascular patterns in animals within the field. However, it is evident from the current literature that such studies are limited in number. In these studies, identification is typically carried out using vascular patterns in the retinas of animals such as lambs/sheep, cattle, dogs and goats. Nevertheless, in most of these studies, embedded software-based devices are preferred over image processing methods. These devices provide a matching score that determines whether the data is present in the database when brought close to the animal's eye. However, this approach has several disadvantages. Firstly, the processing capabilities of these software devices are limited and cannot perform complex image processing tasks. Additionally, updating and customizing such software is often challenging and costly. The use of image processing techniques may offer greater flexibility and customization possibilities and has the potential to cover a broader animal population. Details of studies conducted based on retinal vascular patterns in

Table 2. *Overview of studies based on retinal vascular patterns*

Year	Country	Animal	#Animal /Images	Method(s)	Best Method	Comparison Metric(s)	Accuracy	Ref.
2006	Colorado, USA	Dog	18/18	Technology Driven Products GNU Gimp	Technology Driven Products GNU Gimp	Multivariate ANOVA	Age 5 94.00±6.00%	[26]
2008	North Ireland	Cattle	869/1738	Optibrand Software	Optibrand Software	Optibrand Matching Engine	98.30%	[27]
2008	Ireland	Sheep	64/128	Statistical Methods, Image Matching	Statistical Methods, Image Matching	ROC, Matching Score	93.10%	[28]
2008	Ireland	Lamb	19/38	Regression-based Random Effect	Regression-based Random Effect	Matching Score	Age: 1 week 86.00% Age: 8 weeks 96.00%	[25]
2011	Ireland	Sheep	160/320	Optibrand Software	Optibrand Software	Matching Score	Age<2 96.16% Age>2 96.89%	[29]
2012	Barcelona, Spain	Lamb	143/2534	CATMOD ML	CATMOD ML	Accuracy	94.80±0.60%	[30]
2019	Türkiye	Sheep	60/360	Matching Scores, Pearson Correlation Coefficient	Matching Scores, Pearson Correlation Coefficient	Matching Score	Right eyes 75.46% 78.93% 79.97% Left eyes 89.28% 89.10% 89.74%	[31]
2021	West Bengal, India	Goat	12/200	Template Matching, Hamming Distance, CLAHE	Template Matching, Hamming Distance, CLAHEv	Accuracy, Recall, Precision	99.00%	[32]

Table 3. *Overview of studies based on muzzle print*

Year	Country	Animal	#Animal /Images	Method(s)	Best Method	Comparison Metric(s)	Accuracy	Ref.
2023	-	Cattle	20/600	SIFT, BRISK, ORB, KAZE, AKAZE	KAZE	Matching score	76.18%	[35]
2022	India	Cattle	186/930	Shi-Tomasi, SURF, SIFT, MLP, DT, RF	Shi-Tomasi, SURF, SIFT +RF	Accuracy, TPR, FPR, AUC	83.35%	[36]
2022	USA	Cattle	268/4923	59 deep learning models	VGG	Accuracy, Processing speed, CI	98.70%	[19]
2021	-	Dog	302/2561	DNNet	DNNet	ROC, FAR	98.99%	[37]
2021	Nigeria	Cow	400/4000	CNN, DBN	DBN	Accuracy	98.99%	[38]
2020	Nigeria	Cow	400/4000	CNN, SDAE, DBN	DBN	Accuracy	98.99%	[39]
2020	-	Arabian horse	50/300	SVM, SVM-GWO	SVM-GWO	Accuracy	99.60%	[40]
2020	Korea	Dog	11/1045	SIFT, SURF, BRISK, ORB	ORB	EER	65.00%	[41]
2020	Indonesia	Cattle	60/460	SIFT- RANSAC	SIFT- RANSAC	Accuracy	93.05%	[42]
2018	India	Cattle	500/5000	SDAE, CNN, DBN	DBN	Accuracy	98.99%	[43]
2016	-	Cattle	31/217	AdaBoost, k-NN, Fk-NN	AdaBoost	Accuracy, Sensitivity, Specificity, AUC, Error	99.50%	[44]
2015	-	Cattle	52/1040	MSVMs	MSVMs	Accuracy	96.20%	[45]
2014	-	Cattle	31/217	NN, NB, SVM, k-NN	SVM	Accuracy	99.50%	[46]
2013	Indonesia	Cattle	48/1440	SIFT	SIFT	EER	99.70%	[33]

the literature are presented in *Table 2*.

The implementation of identification from retinal images has some challenges. For instance, the devices used to obtain retinal images are costly. Obtaining retinal images from animals can be challenging, and external conditions (such as lighting, flash, etc.) can affect the quality of retinal images. Additionally, since obtaining retinal images requires close contact, it can be dangerous to capture images from predatory animals.

Recognition and Identification Based on Muzzle Print

Muzzle prints in animals contain some distinctive features similar to fingerprints in humans. These features are unique to the living thing, do not change over time, and cannot be changed. The use of the muzzle mark as a recognition tool dates back to 1921 [33]. The first image-processing studies were made from the prints of the ink applied to the animal's muzzle and taken on paper. Although the accuracy of this identification method has been proven, it has been accepted as a disadvantage that the printing process takes time, and the ink print images are not of sufficient quality to be used in the computer environment [34].

Collecting muzzle print images has been a subject of extensive research in this field due to its relative ease compared to other biometric features, and ongoing efforts are being made in this regard. In the literature, machine learning methods are commonly employed in studies in this field, and in recent years, identity verification and recognition using deep learning techniques have gained momentum. When examining studies based on muzzle prints, it is generally observed that muzzle prints from various animals such as dogs, cows, horses, and cattle are utilized. Information pertaining to these studies is presented in *Table 3*.

The uniqueness of each animal's muzzle print, as with other biometric identifiers, is advantageous, making muzzle prints a viable authentication tool. Furthermore, the ease and low cost of collecting muzzle print data from animals in a manner that minimizes stress is considered an advantage. However, in implementation, environmental factors such as dirt, humidity, or lighting conditions may affect the quality of muzzle prints, and collecting muzzle prints from certain animals, especially larger and more dangerous species, can be challenging. Additionally, disparities may arise when comparing muzzle print images acquired using different camera types or under different conditions.

Table 4. Overview of face image-based image processing studies

Year	Country	Animal	#Animal /Images	Method(s)	Best Method	Comparison Metric(s)	Accuracy	Ref.
2023	-	Horse	-/1103	YOLOv7	YOLOv7	Precision	99.50%, 99.70%	[49]
2022	-	Sheep	81/5265	CNNs	ResNet50V2-ArcFace	Average Precision, Recall, F1-Score	97.00%	[50]
2022	China	Sheep	67/6526	GGFace, AlexNet, ResNet50, YOLOv3, YOLOv4	YOLOv4-CBAM-TL	mAP	91.58%, 90.61%	[51]
2021	-	Sheep	420/1680	Resnet50, VGG16	VGG16	Precision, Recall, F1-score, Support, Accuracy, Macro Average, Weighted average	94.00%	[52]
2020	Brazil	Cattle	51/27849	DenseNet, ResNet50, InceptionResnetV2	DenseNet	Precision, Recall, F1-score, Accuracy	99.85%	[53]
2020	China	Pig	30/1800	CNN	CNN	Accuracy	83.00%	[54]
2019	-	Sheep	52/52000	CNN, Cosine, AlexNet	CNN	Accuracy	98.00%	[48]
2019	West Africa	Chimpanzee	23/10 million	CNN	CNN	Accuracy	92.50%	[55]
2019	Türkiye	Cattle	5/1579	Faster R-CNN	Faster R-CNN	Accuracy	98.44%	[56]
2018	-	Dog	500/5000	SVM, FLPP, PCA, LDA, ICA, LBP, SURF	SVM-FLPP	Accuracy	96.87%	[57]
2018	Scotland	Pig	10/1553	CNN, Fisher face, VGG-Face + SVM	CNN	Accuracy	96.70%	[58]
2015	Varanasi	Cattle	120/1200	PCA, LDA, ICA SURF, LBP	SURF- LBP	Accuracy	92.50%	[59]
2007	-	Sheep	50/200	Cosine distance	Cosine distance	Accuracy	96.00%	[47]

Recognition and Identification Based on Face Images

Another biometric-based method using image processing technology is animal face recognition. Like the face recognition system in humans, animal recognition and identification can be performed using facial images of animals. Animal facial biometrics includes important features that can be used in recognition, such as eyes, muscles, mouth, and many hidden features [47,48].

In the literature, it has been seen those different types of animals, such as cattle, horses, pigs, sheep, dogs, and non-human primates, can be successfully recognized and identified from facial images. Various summary information about the identification, classification, and recognition studies based on facial biometrics are presented in *Table 4*.

Identification from facial images also has some practical challenges. Animals can often be restless, and ensuring they stay still to capture facial images can be difficult. External conditions can affect the quality of facial images. Particularly, lighting conditions can influence image quality. The facial structures of some animals can complicate the recognition process. Obtaining facial images may require close contact with animals, which can be dangerous in some cases. Differences between facial images obtained with different camera types or under different conditions can impact recognition accuracy.

Recognition and Identification Based on Animal Body Pattern

Some animals exhibit patterns or spots on their bodies, representing a biometric approach utilized in animal identification or recognition studies. Research based on such patterns has a limited overall impact in the literature when compared to more common biometric features like facial recognition or retinal scans. This limitation stems from several key factors, including the limited population of animals with these patterns, the highly individualistic nature of these patterns, and the restricted scope of applications. For example, in the literature, studies have been conducted on identification using patterns on the bodies of cattle and cows, speckle patterns on the skin of Atlantic salmon, patterns on the shells of sea turtles, black stripes on the body of Sumatra barbs, and feather patterns of Saimaa Ringed Seals. Detailed information on these studies is provided in *Table 5*.

Table 5. *Overview of pattern-based image processing studies*

Year	Country	Animal	#Animal /Images	Method(s)	Best Method	Comparison Metric(s)	Accuracy	Ref.
2022	US	Cattle	268/4923	59 DL models	VGG16_BN	Accuracy CI	98.70%	[19]
2022	-	Cattle	48/12000	SVM	SVM	Precision, Recall, Average precision, F1-score	98.67%	[60]
2021	-	Cattle	46/4736	CNN	CNN	Accuracy	93.80%	[61]
2021		Cattle	18/10402	CNN, GMM	GMM	Accuracy	76.90%	[18]
2021	Norway	Atlantic salmon	328/1312	CNN	CNN	Accuracy	96.70%	[62]
2021	Lundu, Sarawak	Sea turtles	16/70	SIFT, SURF, ORB, HOG	HOG	Accuracy	65.00%	[63]
2021		Sumatra barb	43/215	HOG, LBP, HP and body shape	LBP	Accuracy	93.00%	[64]
2021	-	Cow	4/2500	YOLO	YOLO	Precision, F1-score, Accuracy	90.00%	[65]
2019	-	Cattle	17/147	YOLO v2, LRCN	LRCN	Accuracy	94.40%	[66]
2019	-	Cattle	66/528	FAST, SIFT, FLANN, ORB, Brute Force	FAST + SIFT + FLANN	Accuracy	96.72%	[67]
2017	China	Cattle	10/1965	QDA, SVM	QDA	Precision, F1-score, Accuracy	99.70%	[68]
2015	Varanasi	Ringed seal	46/2000	PAT, ROT, TOP, k-NN	PAT + ROT + TOP +	Accuracy	88.60%	[69]

Pattern-based identification studies face several challenges, including the following: Some animals' body patterns may change over time or differ as the animals grow. This can make it difficult to record animal body patterns in a standardized manner. The visibility and quality of patterns can be influenced by environmental factors. Especially in open areas or natural habitats, environmental conditions (such as seasonal changes or their living environment) can affect the perception of body patterns. Developing suitable technologies to record and recognize body patterns may be necessary. The cost and complexity of these technologies can pose challenges to implementation.

Recognition and Identification Based on Iris Patterns

Animal iris, like human iris, is a unique biometric marker. The use of iris images for biometric identification is common. Recognition systems have been developed using iris images of animals such as tarentola, cattle, Atlantic salmon, goats, cow, horse, owl, and tiger, as given in *Table 6*.

When examining recognition studies conducted using iris images, it is observed that a wide range of animal species, from fish to tigers, have been utilized in these studies. Among biometric markers, iris is considered more reliable compared to other methods such as facial recognition, pattern recognition, and muzzle prints. Additionally, the collection of iris images is easy and cost-effective when compared to retina scans, making it a more practical choice in biometric recognition systems. Iris-based recognition is seen as a potentially valuable tool for the identification and tracking of animals.

Identification from iris images also has challenges in real-world applications, including the following: The mobility of animals can make iris scanning challenging. Ensuring that the animal remains still, as the eye must stay fixed, can be a challenging process. The structure and characteristics of irises can vary among different animal species.

Conclusion and Recommendations

Animal identification is essential to prevent epidemics, administer vaccines, monitor animal health, and prevent theft and fraud. Many methods have been used to identify animals from the past to the present. Traditional methods of identification, which adversely affect animal welfare,

Table 6. Overview of iris-based recognition studies

Year	Country	Animal	#Animal /Images	Method(s)	Best Method	Comparison Metric(s)	Accuracy	Ref.
2023	India	Black Bengal Goats	49/ 5880	Resnet152V2	Resnet152V2	Accuracy	82.49%, 92.68%, 77.17%, 87.76%	[70]
2023	-	Angus	11/80	15 DNN models	U-Net + VGG16	Dice, Accuracy, Precision	99.50%	[71]
2020	Norway	Atlantic Salmon	14/41	VeriEye	VeriEye	Matching Score	98.00%	[72]
2020	India	Black Bengal Goats	5/25	Hamming Distance	Hamming Distance	Matching Score	59.00%	[73]
2019	-	Cattle	11/80	HSV, Watershed Segmentation	HSV + Watershed Segmentation	Precision, Recall, F1-score, Intersection over union	96.25%	[74]
2017	-	Horse	28/2000	DCNN	DCNN	EER	90.50%	[75]
2017	-	Horse	145/1015	Circular Hough Transform, Canny Edge Detection, K-means clustering	Circular Hough Transform + Canny Edge Detection + K-means clustering	Jaccard similarity	95.00%	[76]
2015	-	Owl	Different images of Owl	Hamming Distance	Hamming Distance	Accuracy	94.00%	[77]
2015	-	Cow	8/48	SURF	SURF	Accuracy	91.67%	[17]
2014	-	Cow	6/60	Hamming Distance	Hamming Distance	Matching Score	98.33%	[78]
2013	-	Lizard (Tarentola geckos)	54/924	I^3S	I^3S	Accuracy	95.00%	[79]
2012	-	Tiger	Different images of Tigers	Hamming Distance	Hamming Distance	Matching Score	not specified	[80]

have begun to give way to modern methods with the development of technology. Ear notching, ear tattooing, hot iron branding, and freeze branding, which are among the traditional methods, are almost no longer used, and the ear tagging method is used more widely. While classical identification methods negatively affect animal welfare, problems such as loss, repetition, fraud, and security cannot be avoided.

Unlike traditional methods, biometric identification using retinal vascular patterns, iris patterns, muzzle prints, facial features, and body patterns offers numerous advantages over conventional approaches. These applications are painless, ensuring animal welfare, and are highly resistant to fraud or loss. Technological advancements and increased interdisciplinary studies have driven a growing shift towards biometric methods for animal identification. This review aims to provide a comprehensive examination of studies employing biometric techniques for identification and recognition, presenting both their strengths and weaknesses to researchers. In this review, studies that utilized retinal vascular patterns, iris patterns, muzzle prints, facial recognition, and body pattern biomarkers were scrutinized meticulously, and their advantages and disadvantages were assessed individually. Additionally, the challenges that may be encountered in the practical implementation of these biomarkers for identification were presented. As a result of this review, it is evident that using retinal vascular patterns for animal identification stands out as the most advantageous method, ensuring both animal welfare and economic benefits at a national level.

This review article presents the following recommendations as a result:

· The widespread adoption of biometric animal identification methods, especially those based on facial, iris, and retinal vein patterns, is essential.

· The use of biometric methods in international trade transactions should be encouraged as it can support both animal welfare and economic growth.

· To develop successful biometric-based identification systems, attention must be paid to the accuracy and precision of data collection processes, ensuring high-quality images are captured.

· Making animal biometric data accessible to researchers can facilitate advancements in the field of animal science by increasing the quantity and quality of interdisciplinary studies.

The review emphasizes the significance of utilizing biometric markers in the development of animal identification and recognition systems. Considering the undeniable role of animal husbandry in national economies, it is anticipated that the use of the mentioned biometric markers will become a necessity in the near future.

Abbreviations

ANN: Artificial Neural Networks

ARI: Adjusted Rand Index

AUC: Area Under Curve

BRISK: Binary Robust Invariant Scaling Keypoints

CI: Comprehensive Index

CLAHE: Contrast Limited Adaptive Histogram Equalization

CNN: Convolutional Neural Network

CWT: Complex Wavelet Transform

DBN: Deep Belief Network

DCNN: Deep Convolutional Neural Networks

DL: Deep Learning

DNNet: Dog Nose Network

EER: Equal Error Rate

EU: European Union

FAR: False Acceptance Rate

FAST: Features from Accelerated Segment Test

Faster R-CNN: Faster Regional-Convolutional Neural Networks

Fk-NN: Fuzzy K-Nearest Neighbor

FLPP: Fisher Linear Projection and Preservation

FPR: False Positive Rate

GMM: Gaussian Mixture Model

GWO: Gray Wolf Optimization

HOG: Histogram of Directed Gradients

HP: Horizontal Density Profiles

HSV: Hue, Saturation, Value

I^{3}S: Interactive Individual Identification System

ICA: Independent Component Analysis

IoU: Intersection over Union

KLT: Kanade-Lucas-Tomasi

k-NN: k-Nearest Neighbor

LBP: Local Binary Pattern

LDA: Linear Discriminant Analysis

LRCN: Long-term Recurrent Convolutional Network

ML: Maximum Likelihood

MSVMs: Multiclass Support Vector Machines

NB: Naive Bayes

NN: Nearest Neighbor

ORB: Oriented FAST and Rotated BRIEF

PCA: Principal Component Analysis

QDA: Second-order Discriminant Analysis

RANSAC: Random Sample Consensus

RFID: Radio Frequency Identification

ROC: Receiver Operating Characteristic

ROI: Region of Interest

SDAE: Stacked Denoising Auto Encoder

SIFT: Scale Invariant Feature Transform,

SURF: Speeded Up Robust Feature

SVM: Support Vector Machine

TPR: True Positive Rate

WLD: Weber's Local Descriptor

WOAH: The World Organization for Animal Health

YOLO: You Only Look Once

YOLOv4-CBAM-TL: Convolutional Block Attention Module- Transfer Learning

Availability of Data and Materials

Not applicable.

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Competing Interests

The authors declared that there is no conflict of interest

Author Contributions

PC: Conceptualization, designed, planned, methodology, investigation, writing original draft. AS, NEO and MA: Conceptualization, methodology, writing and editing. All authors read and approved the final manuscript.

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