Recognition of Cattle Using Face Images

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REVIEW ARTICLE

Cattle Recognition: A New Frontier in Visual Animal Biometrics Research

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Abstract Visual animal biometrics is an emerging research field of computer vision, pattern recognition, and cognitive science. Recently, cattle recognition has played a significant role in understanding, controlling and the outbreak of critical diseases, vaccination, production management, traceability, and ownership assignment of a livestock animal. The traditional animal recognition methodologies, such as ear-tagging, freeze-branding, ear-tattoos, embedded microchips, ear tips or notches-based, and electrical-based marking approaches, have been applied to recognize individual livestock animal. However, standard animal recognition procedures are invasive. The performance of conventional methods is not good due to their vulnerability to losses, easy duplication, and fraud of embedded tag number. These are major security issues and challenges for the identification of cattle throughout the world. Visual animal biometric systems are gaining more proliferations due to widespread applications to recognize individual cattle based on their primary biometric muzzle point image characteristics. This paper aims to provide a comprehensive review of cattle recognition and tracking from non-biometric recognition approaches (classical animal recognition methods) to visual animal biometric systems using muzzle point image pattern along with measurements and interpretations based on current state-of-the-art methods. Moreover, this paper demonstrates the basic deployment of the animal biometric system to uniquely identify the animals using their biometric characteristics. This study can hopefully encourage new multidisciplinary researchers and scientists to provide excellent efforts for the designing and development of adequate algorithms for solving the classification and recognition problems. The literature review is followed by the presentation of references for more details, incorporating applications and current trends.

Keywords Visual animal biometrics · Muzzle point · Cattle recognition · Cognitive Science · Computer vision · Pattern recognition · Phenotypic · Classification · PCA · LDA · ICA · LBP · SIFT · Feature extraction

1 Introduction

Visual animal biometrics received attention recently [1]. It has gained more proliferation due to a vast plethora of efficient and quantified methodologies for detecting and representing the different visual appearances of species, identification of animal or species based on visual features and phenotypic appearances [1, 2]. Visual animal biometrics also provides the coherent set of methodologies and computer vision-based models for analysis of individual behaviors based on morphological image pattern and biometric characteristics [2].

Visual animal biometrics is operated among computer vision, pattern recognition, image processing, and cognitive sciences. Visual animal-based recognition systems or frameworks are applied at various scales to recognize and classify different species or individual based on

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discriminatory set of features. The recognition systems also detect the occurrence of, and variation in behaviors of different species, as well as perform the computation and measurement of morphological pattern, and calculation of the difference in inter-individual, and intra-individual class changes over time [2–4].

For the recognition and analysis of animal's behavior, visual animal biometric-based recognition systems and models utilize the variety, uniqueness, and immutable biometric characteristics [1–4]. Visual features of animals include joint-stripped code pattern on coat pattern of zebra's body, different spot patterning structures of the body surface (for tiger, whale); a morphological image pattern, vocalizations, and movement of body dynamics are salient biometric characteristics of animal or species [1, 2, 4]. However, in the prestigious visual animal recognition-based systems, species or individual animals are recognized and detected using marking their bodies using classical animal identification methodologies.

The traditional animal method includes ear-tattoos, ear-tagging-based systems, paint- or dying-based sketch patterning-based marking techniques, the embedded microchips, ear tips or notches-based, and RFID-based identification systems [5, 6]. For example, when a unique identification number (code) is scanned, the confirmations of code are transferred by reading devices in a database for final actions. The major limitation of the RFID identification and tracking-based method is that embedded or attached devices can get lost or damaged easily [5–7]. The reading or scanning the attached tags through liquid or metals still exists in the RFID system.

In the available literature, traditional identification systems are done for the prevention of thievery for horses and other animals. However, these traditional identification approaches are unable to prevent the efforts for fraudulent, duplication, and manipulation of embedded tags in the body of animals [8]. Traditional animal identification methodologies are divided into several categories: (1) permanent marking-based identification methodology, (2) semi-permanent marking-based identification method and (3) temporary-marking-based marking method [3–9].

The permanent animal marking-based identification methods include ear-tipping or notches-based marking techniques, ear-tattooing-based, the embedded microchips or tags, hot iron, and freeze-branding-based techniques. These techniques are used to identify and track individual animal based on marking techniques. These techniques are not sufficient for the identification of animals. The permanent marking-based animal identification approaches are susceptible to theft, fraud, and duplication [9–11].

On the other hand, semi-permanent marking-based identification method procedures are less robust and reliable as compared to permanent animal identification methods. In visual animal biometrics, representation and detection of the individual animal using their phenotypic appearances and morphological characteristics are considered as unique animal biometric characteristics [10, 11]. It is similar to minutiae point recognition in human fingerprints. A phenotypic appearance of species is a composition of an organism's observation characteristic such as their morphological image pattern characteristics of biochemical and physiological biometrics [1, 3, 10, 11].

The emerging researchers in visual animal biometrics have provided a wide range of applications for recognition and tracking systems of cattle. The cattle recognition system performs the verification of animal based on their biometric characteristics and phenotypic appearances to solve the false insurance claims [10, 11]. The recognition system performs the matching of the query (test) image of a registered animal with the stored animal database to avoid the animal manipulation and classification of various livestock breeds and understanding, control, and the outbreak of critical diseases [11–13].

Visual animal biometric systems have encountered significant challenges on the performance front toward robustness of animal recognition systems due to the acquisition of poor quality images and low-illumination pictures of animals. For example, the constant movement of animals hinders the establishment of gait patterns. Addressing such challenges in the visual animal biometrics can play a significant role in providing better solutions for the problems which are inherent in the traditional animal recognition methodologies and livestock framework-based systems. Therefore, the standard animal identification systems are not capable of handling these problems.

The visual animal biometric system needs innovative research for the development of efficient algorithmic approaches and to afford better protection and management of different species or individual [15, 16]. Adopting computer vision and pattern recognition systems is necessary for animal recognition. In this regard, a collaborative effort of multidisciplinary researchers can play a major role in solving problems of animal identification, technical, computational issues, and challenges of visual animal biometrics system [17].

The objective of this paper to provide a comprehensive review of cattle recognition frameworks based on muzzle point and face image using visual animal biometrics, computer vision and pattern recognition techniques. It also highlights the major advantages and shortcoming of classical animal identification methodologies. The comprehensive review study can encourage new multidisciplinary researchers, veterinary professionals and scientists to put in efforts toward the design and development of methods, algorithms, and frameworks for solving the problems stated above. The literature review is followed by the presentation of references for more details, incorporating applications and current trends.

The rest part of the paper is organized as follows: Sect. 2 illustrates the coherent sets of fundamental concepts of visual animal biometrics. These methods can be used to recognize and classify the individual animal or species based on their phenotype appearances, the morphological image pattern, and animal biometric characteristics. Section 3 demonstrates traditional animal recognition methodologies along with major issues and challenges for the identification of livestock animals. The cattle recognition system along with a brief discussion of animal recognition using the muzzle point image and face image feature is illustrated in Sect. 4. Section 5 presents muzzle point pattern-based animal recognition systems for identification of cattle. Section 7 explains the current state of the art. Section 6 demonstrates the opportunity, issues and significant challenges in the cattle recognition and visual animal biometrics in detail. Section 7 presents the current state-of-the-art approaches in visual animal biometrics for identification and classification of different species and individual animal. Finally, Sect. 8 illustrates the conclusion and future directions.

2 Visual Animal Biometrics

Visual animal biometric system is a pattern recognition-based system. The recognition-based system captures the image of species or individual animal using intelligent sensor devices such as digital camera, smartphones, and other image acquisition devices [13–18]. After the acquisition, the discriminatory sets of biometric features are extracted from the captured image database. The recognition system compares sets of biometric features of query image of species or individual animal against the biometric feature set(s) stored in the database and executes an action based on the result of the comparison of similarity matching scores [13–19]. The complete block diagram of the visual animal biometrics-based recognition system is shown in Fig. 1.

Visual animal biometrics-based recognition system consists of steps. The steps are data acquisition, detection of species or individual animal.

The discriminatory information is phenotypic appearances of animals, anatomy, the structure of the animal body, and morphological and primary animal biometric characteristics [18]. Typically, aspects of the phenotypic appearances of animals, and movement and gait pattern are considered relevant and selected biometric characteristics for identification of individual animal [19, 20].

In data acquisition step, the images are captured using the camera of species or individual. After the data acquisition step, the computer vision and image processing techniques remove the artifacts and noises from captured images of species. Furthermore, to find the set of biometric features of the animals, statistical-based quality assessment method is applied to analyze the captured images [19–21].

The features are extracted from the preprocessed image database. After that, unique biometric features are chosen from the stored database. The extracted biometric features play a vital role in identifying individual animal or species. It also provides a better way to classify species in the different classes for the study of population of species in their habitats. However, analyzing the extracted information is a tedious process to find the suitable biometric features from captured morphological image pattern and biometric features.

Moreover, the morphological image pattern and phenotypic appearances of species or individual animal also give suitable information for classification and identification of species. The discriminatory morphological image information includes joint striped in the coat patterns for zebra's body [16] and spot pattern on the body surface of tigers [17, 18] and cheetahs [19]. The muzzle point image pattern [20–22] of cattle is also unique biometric feature for recognition of individual animals. However, not all significant visible generic biometric features are suitable for the identification of species or animal [22].

For example, any injury marks on the body surface of species such as whale sharks are most important for identification of whale shark; yet their uniqueness short-lived, injury marks heal quickly [23]. The variability in the biometric characteristics emphasizes their limitations, applications and biometric usability for the long-term studies, although suitability and evaluation of discriminatory information from these patterns of animal biometric features need the recompilations during the most studies of different species [23, 24].

For many biological studies, field conditions are required to be efficient in computation and self-reliant than those applied in the present human biometric-based recognition system [24]. Furthermore, various operations in uncontrolled and ecological suffered from the limited energy supply to the systems. This issue situates significant challenging conditions for data acquisition, storage, and processing of massive database in the visual animal biometric system. Therefore, it requires robust, reliable operations and current state-of-the-art algorithms to solve these major problems.

Visual animal biometric systems are frequently stripped down to minimalist versions of what would be used in controlled environments, and this can be adequate for many study purposes. There are following advantages of automated visual animal biometrics-based recognition system: (1) several key characteristics of visual animal biometrics-based recognition systems and their output make them promising and potentially framework, methods, tools for

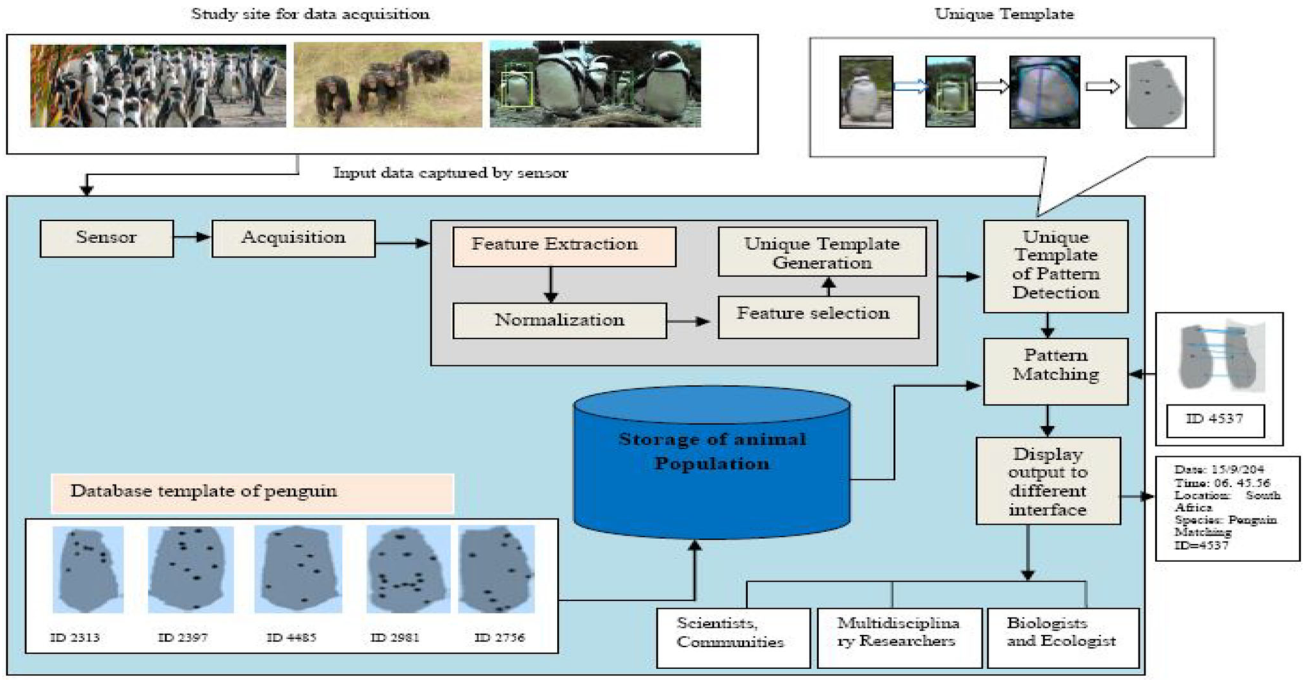


Fig. 1 The major component of a visual animal biometric system for recognition and representation of species

biometric feature studies. The quantification of phenotypic appearance and visual features cater objective measure for detecting the appearances and classifying features and identifying various species. The behavior analysis and morphology features for detecting of species. Automated system processing can be use to facilitate better study for results and standardization of methods for depth analysis. One of the many advantages, visual animal biometric-based recognition system provides standardization of the observational database for comparative research studies in multidisciplinary fields.

Visual animal biometrics can cater objective measures. It can be applied for performing the comparison across individual animal, type of species, and monitoring of its populations in similar way as in other disciplines namely remote sensing, physiology, or genetics. This output can be achieved by dividing the complex features representation and phenotypic appearance into comparable units. For example, the configurations of various landmark key-features on body of species such as coat patterns on zebra, spot points in tiger's body or the signature of locomotion on specie's body [20–25]. The comparative study of a population of different species can be achieved from variations in their morphological images pattern and biometric images. These image patterns are segmented by state-of-the-art segmentation algorithms to find out the region of interest (ROI)-based segmentation of the face images of animal. In association with this, other biometric features are also used for getting better comparable feature units or key point features for accurate matching. It can help in representing these matched key point features into the feature space for the recognition of species or individual animal.

In the similar direction, the visual animal biometric system is used by applying the computer vision algorithms to provide the localization of discriminatory key point features or landmarks [e.g., joint stripes on coat pattern, spot patterning on penguin, whale, muzzle point image pattern (beads and ridges pattern)] features from these segmented regions. These features are significant for the identification of different animals such as zebra, tiger, and cheetah based on their coat patterns and spot point pattern. Tiger identification and tracking are done using biometric features such as natural spot patterns of the tiger's body [17–26]. Moreover, the extraction of a discriminative set of features such as beads and ridge pattern of the muzzle point images are suitable for cattle identification [20–27]. These are the primary biometric identifiers for animal identifications.

The main motivation for the design and development of the visual animal biometric-based recognition systems or framework is to encourage innovative researchers and multidisciplinary researchers and ecologists and biologists for understanding better the animal biometrics system and monitoring system for recognizing, representing the species and classifying different species, identifying endangered species or animal. The designed handheld audio-visual devices, speech processing and recording devices, and various intelligent sensor enabled systems or devices carried by drone and aerial vehicles are used to prepare the huge document observations using the routinely procedures. This procedure generates huge quantities of recorded audiovisual databases. It is a very time consuming process. The time needed to sift through the manual data acquisition and recordings and storage to new develop system and frameworks data; visual animal biometric systems helps by providing information on the accurate occurrence of certain animal or species, analysis of their behavior, or computation of feature of morphological patterns in a fraction of this time. It also can help to perform a better evaluation of inter-class variation or intra-class variation of individual animal changes over time for population analysis across the world [25–28].

Visual animal biometric systems became a long-standing recognition problem with the computer vision, and pattern recognition field [26–30]. It is also used broadly in the tradition of recognizing ecological and evolutionary studies of documenting and indexing of animal appearances [27, 30]. It needs the ability to identify an individual despite several variations in the aspect of phenotype appearances, and movement, vocalizations, and morphological characteristics. The traditional animal recognition methodologies are illustrated in brief in the next section.

3 Classical Animal Recognition Approaches

The conventional animal recognition systems have achieved proliferations due to widespread applications [3–5, 10, 26]. It provides various beneficiaries, from different animal producers and consumers to the food industry itself. These recognition systems cater the help to mitigate the widespread of critical diseases of the animal by the outbreak, and controlling the pet vaccinations and providing the better solutions for the understanding of trajectories of such significant disease throughout the world [28–30].

The traditional animal recognition systems unable to limit more loss in term of the livestock monitoring, control of critical disease. Therefore, visual animal biometrics can provide efficient methods to reduce costs of disease eradication, livestock monitoring and to provide other facilities to the livestock. It can also minimize the losses in the potential trades of different types of animals through recognition of cattle that facilitates ownership management of animal [21–31]. The major problems of these approaches stem from ear tag duplication, and their vulnerability to losses, deformations, and fraud. The standard cattle recognition methodology is shown in Table 1. The brief description of classical cattle recognition approaches is illustrated as follows:

1. Permanent marking-based identification methodology
   Permanent marking-based identification methods are ear tips or notches, ear-tattoos, and freeze branding. These methods are also known as the mechanical type of livestock identification methods [23–27, 29–31]. These methods are discussed in brief as follows:

   A. Ear-tipping or notching method
      The ear-tipping or notching-based recognition approaches of cattle are unable to deploy at a large-scale population of livestock for identification systems. It provides the distress to livestock animals during the embodiment of ear tips in the ear of cattle. Therefore, such methods cannot mitigate the significant pain to animals. The major drawback of the ear tips or notches-based identification approaches is (1) it is not scalable to the large scale of cattle recognition and can recognize only a limited number of animals. Therefore, such recognition systems can be deployed for a medium farm.
   B. Ear-tagging-based method
      In the ear-tagging method, metal clips and plastic

Table 1 List of animal identification method

Animal identification method/parameters	Permanent animal identification technique				Semi-permanent animal identification technique		Temporary animal identification technique	
	Tattooing	Embedded microchip and devices	Ear tip/notch	Freeze brand	ID collar	Ear tagging	Paint/dye	Electrical Signal based method (RFID)
Reliability	Medium	Very high	High	Very high	Low	Low	Low	Very low
Cost	Medium	Very high	Low	Medium	Low	Low	Very low	Very low
Visibility	Very low	NA	Medium	High	Very high	Very high	Very high	NA
Longevity	High	Very high	Very high	High	Low	Low	Very low	Low
Risk of harm	Low	Very low	Medium	Low	High low	Very high	Very low	Very low
System performance (accuracy)	High	Very high	NA	Low	High	Low	Very low	High
Uniqueness	High	Very high	NA	Low	High	Medium	Very low	Very high
Database required	High	Very high	NA	Low	Low	Medium	NA	Very high

NA not available

tags are applied to the identity the cattle. The ear tags are not successful techniques for recognition of livestock because the label of ear tags can be lost easily [30]. The ear-tagging-based recognition can be susceptible to damages, duplications, losses, un-readability, and fraud of ear tags and do not perform well as a long-term recognition method. The used metals for tagging of ear-clips can increase more infections to an animal; it is reported in a study of health management of 500 sheep in Scotland. To solve these problems, it is required to develop a new identification technique using various signals for the cattle recognition and registration. However, these metal tags itself must be considered to an electrical transducer [30, 31]. Based on the presence or absence of embedded ear tags, various cattle breeds are recognized.
In the available literature, the semi-permanent-based identification ear-tagging system is not used for recognition of animal for the long term, because it can be damaged and lost quickly. Based on available literature, the ear-tagging-based identification method is applied to mark the ear of animal for identification. It is used to recognize the livestock animals using ear-tags based system. This is applied only 20–21% to tags the animal. The major drawbacks of these approaches are that they are not reliable for the recognition of cattle due to fraudulent and duplicated easily [34].

C. Freeze-Branding Method
Freeze-branding-based animal identification method works slightly different to the hot iron branding identification approach. In hot iron branding, various farm's brand, unique numbers, or symbols are applied in hot iron branding to recognize the beef animals [34]. The freeze-branding technique performs some destroying procedure of color pigment in the hair of the animal. The major shortcoming of freeze-branding, hot iron brandings, and ear-tattooing-based recognition approaches are: (1) recognition accuracy is relatively better as in one herd where the animal is identically branded. It is a more time-consuming process compared to other recognition approaches [35].

2. Semi-permanent-marking identification methodology
The semi-permanent methods are illustrated in detail for the identification of cattle. The semi-permanent marking-based approaches are discussed as follows:

- Ear-tagging-based method
According to Wardrobe [7], Johnston and Edwards [15], the ear-tagging is not a successful method for identification of animals because the reliability of the embedded label number is very low (shown in Table 1). Some deficiencies are also found in the ear-tagging-based identification systems because the label of the ear tags can be lost quickly. The fraudulent and duplication of the ear tags are practiced to get false insurance claims from different government insurance schemes by different users (e.g., owner, parentage, and others). Moreover, the label of ear tags can also be eventually damaged and corrupted because of the long-term usages. Since animal husbandry exists in our society, a secure and individual identification is a necessary need to prove ownership [36].

3. Temporary-marking identification methodology
The temporary identification approaches are mainly sketch patterning and id collar for identification of livestock animal. The sketching patterning-based identification approaches are utilized to identify the broken color on the body surface of cattle breeds (e.g., Ayrshire, Guernseys, and Holsteins) [36]. It depends on standard drawing skills. However, sketch patterning-based approaches suffer from the better quality of image pattern. Therefore, temporary identification procedures do not provide the identification accuracy for livestock animal [37].

According to available literature, animal identification approaches can be categorized based on electronic techniques, such as radio frequency identification (RFID) [30–36] to identify and trace the livestock animals. These methods primarily perform the attachment of two devices with the animals [6, 32–37]. One device keeps a unique identification number or labels, and another device is applied as a reading device for scanning or reading the symbols. Based on reading symbol, the system interprets the unique code or identification symbol to verify the cattle. The embedded devices may get lost easily, duplicated, or damaged. The performances of classical cattle recognition approaches are summarized based on various attributes as shown in Table 1.

4 Identification of Cattle Based on Muzzle Point Image Pattern

Cattle recognition system is a pattern recognition-based retrieval system. It retrieves the biometric feature for the identification of livestock. The muzzle point image and face are unique biometric features for recognizing individual cattle [11, 18, 19].

In the current scenario, visual animal biometrics-based recognition has a plethora of efficient and intelligent approaches for the identification and classification of species or individual animal [38, 39]. The identification methods extract the color features and unique and immutable biometric features characteristics [39]. The first animal biometric feature characteristics include muzzle point image pattern, face images, iris patterns, and retinal vascular patterns. The biometric characteristics-based recognition system can easily perform the accurate identification of cattle using automatic computerized recognition systems, and (2) easily monitoring and individual registration of animal using biometric features characteristics. However, it has several challenges such as the acquisition of suitable biometric identifiers, recognition rate, computation time, and overall system operability.

In the available literature, various animal breeds-based organizations for food safety and animal health guidelines have formally emphasized the significant values of the design and development of the animal recognition and traceability-based systems in the livestock [38–40]. They are advanced actively promoting a new platform for the design and development of animal biometric-based recognition system for the recognition of animals.

Cattle recognition system plays a significant role in the recognition of animal using their primary biometric characteristics and analysis of the visual features of patterns of muzzle print image [36–40]. It has been widely utilized for registration and traceability of animals as a visual clue for the owner verification and assignment of the animal to correct parentage of an animal. It is also necessary for breeding associations, production, and proper distribution of beef cattle.

Only a few researchers have been done so far to solve such major problems for recognition of animals throughout the world [37–41]. Thus, it is a need to design and develop a non-invasive, reliable, automatic, cost-effective, suitable, and robust biometric characteristics-based animal biometric-based recognition system. Such animal biometric-based recognition systems play a significant role in controlling the widespread animal diseases. It also detects the infected animals and mitigates the loss of livestock producers by tracking the history of critical illness. The following subsections emphasize on retinal vascular patterns, iris patterns, and muzzle print images for the recognition of cattle.

4.1 Retinal Vascular Patterns

The retinal vascular patterns-based primary biometric characteristics systems only depend on the retinal image recognition (RIR). The retina vessels of individual cattle are a unique and suitable biometric identifier for the recognition of livestock [34–41]. However, to get the retina images database is very tedious and reported performance measures are deficient as compared to other animal biometric-based recognition systems.

The retinal patterns are found in almost all species or individual animals. The animals have no retinal vascular pattern. Therefore, retinal pattern-based animal biometric systems can be widely deployed across an extensive variety of species or individual animals. It is also an application for recognition of sheep and goat across the world. The major shortcoming of retinal pattern-based recognition is that system can fail due to injuries to the cornea of eyes of the animal because there is no any suitable way to get the correct retinal image pattern [35–41].

4.2 DNA-Based Animal Identification Method

DNA-based animal identification methods were also proposed to identify and verify individual animal for better health management and the outbreak of critical diseases for a long time in the livestock framework-based systems. The identification of animal is produced from a given specific animal [35]. However, DNA-based animal recognition systems consume more time and the verification of DNA for the animal is costly. DNA-based animal identification systems are not non-invasive and profitable. It is also very time-consuming procedures for getting unique DNA identifiers to recognize the various animals [36–42].

In visual animal biometrics, species and individual animal have been acknowledged using first animal biometric characteristics such as unique patterns (e.g., coat pattern of zebra, spot pattern on tiger, cheetah, and various morphological patterns of different species) which are similar to minutia point's recognition in a human fingerprint. The minutiae point in the muzzle images consists of two important features known as ridge bifurcation and termination. These features are used to find the accurate correspondence based matching with datasets. Apart from minutiae point features, other biometric modality such as face recognition, iris recognition, retinal vascular pattern based recognition are also play vital role for recognition of animal or endangered species. Therefore, animal primary biometric-based system include quantifying methods to improve the accuracy by using computer vision based advanced facial recognition, and other biometric modality methods based on muzzle print image (nose print) for animal identification [37–43].

4.3 Iris Biometric-Based Animal Identification

The unique pattern of the iris is a suitable biometric identifier to recognize the species or animal. Similar to human iris pattern, iris pattern of cattle consists of discriminatory features such as rings, furrow, crypts, and corona. All animals also have similar prominent biometric features of iris pattern. The first contribution to the development of iris code was initiated by author Daugman [44] to identify the individual persons using a 2-D Gabor filter [39–43]. The low user acceptability of iris patterns renders iris capturing a difficult task.

In a similar direction, the authors proposed a framework for cattle recognition based on iris pattern using SIFT [40] feature descriptors. They are usually associated with a change in an image property, such as intensity, color, and texture features. The local features of iris recognition are computed at multiple points in the image; hence, they are immune to image scale and rotation.

Recently, a cattle recognition system is proposed based on iris biometric patterns of cattle using a 2-D complex wavelet transform (2D-CWT) features [43, 45]. A contact-free handheld device collected the iris pattern of livestock. The size of the captured image database is 60 grayscale images from six eyes of cattle with a resolution of 320 × 240. The proposed approach reported an EER of 1.55% in the verification mode and overall recognition accuracy of 98.33% in the identification mode.

The overall all performances are manifested to be high, but they have obtained experimental results on the insufficient image database of iris pattern of cattle. Similar to human iris pattern recognition, cattle recognition based on the iris image pattern faces more challenges in identifying individual cattle. New research findings have demonstrated that first animal biometric characteristics such as coat pattern, muzzle point pattern, and spot position patterning on the body surface (e.g., for tiger and penguin) are a unique and immutable identifier to identify the individual animal and significantly improve the recognition accuracy. The cattle recognition based on muzzle point image pattern is depicted in detail in the next subsection.

5 Cattle Recognition System

In this section, cattle recognition system using the muzzle point image pattern and face biometric features is illustrated in length. In the cattle recognition system, a muzzle point image is applied to the input image to classify and recognize the cattle breeds (races). According to the Baranov et al. [41], muzzle dermatoglyphics (i.e., ridges, granola, and vibrissae) from the various cattle breeds are mostly different. It is similar to the recognition of minutia points in human fingerprint [45]. Several researchers have proven that the muzzle point image is used for identification and registration of cattle.

The recognition of livestock based on muzzle point feature is similar to minutiae point recognition in human fingerprints. The muzzle point image pattern consists of dense texture pattern of different grooves or valleys known as beads and some river-like structures known as ridges. The grooves and ridges features are uniform patterns. It is distributed over the skin surface of the nose area (muzzle point) of animals. The muzzle points are also images consisting of different color attributes known as white skin grooves and black convex sector. The sectors are surrounded by grooves [41–43, 45, 46]. The color feature attributes of the muzzle point image of cattle are also used to classify the cattle breeds based on cattle. The color features of the muzzle point image of cattle are unique animal biometric feature characteristics to recognize the individual cattle.

The recent advancement in visual animal biometrics research field has achieved proliferation due to wide-range application and uses. It provided quantified methodologies for feature extraction and representation (e.g., appearance-based and texture feature-based recognition algorithms for identifying and classifying the cattle breeds). The muzzle point image pattern of livestock is a discriminatory biometric feature for classifying and identifying cattle that has achieved recent attention in the visual animal biometrics [5, 7, 43].

The cattle recognition system consists of two phases: training phase and the testing phase. In the training phase, the cattle recognition system captures the muzzle point images using sensors [43, 45]. The system creates the database and stores the captured pictures of cattle. In the testing phase, a test (query) is matched with the stored image database using similarity matching techniques. Various steps are involved in the cattle recognition system using muzzle point image, as shown in Fig. 2. The brief description of the recognition system is given as follows:

1. Data acquisition phase
   Data acquisition is an initial step of livestock recognition systems for capturing of biometric data (e.g., muzzle point images) of cattle. The image of the muzzle point (nose pattern) pattern of cattle is captured by the digital camera with resolution of 30 megapixel. Some muzzle image pattern and beads and ridges of cattle are shown in Figs. 3a, b and 4a, b, respectively.
2. Preprocessing and feature extraction phase
   The preprocessing is the essential step for the feature extraction. The cattle recognition system applies the preprocessing using image processing techniques to mitigate the noises and other specific artifacts from the captured muzzle point image database. Gaussian pyramid, a low-pass filter technique, is applied to filter the noise from the images and smoothen the images after the removal of noises at various Gaussian pyramid levels (e.g., Gaussian levels (L1), (L2), (L3), and (L4) with Gaussian factor 4), as shown in Fig. 2. After the preprocessing step, discriminatory biometric

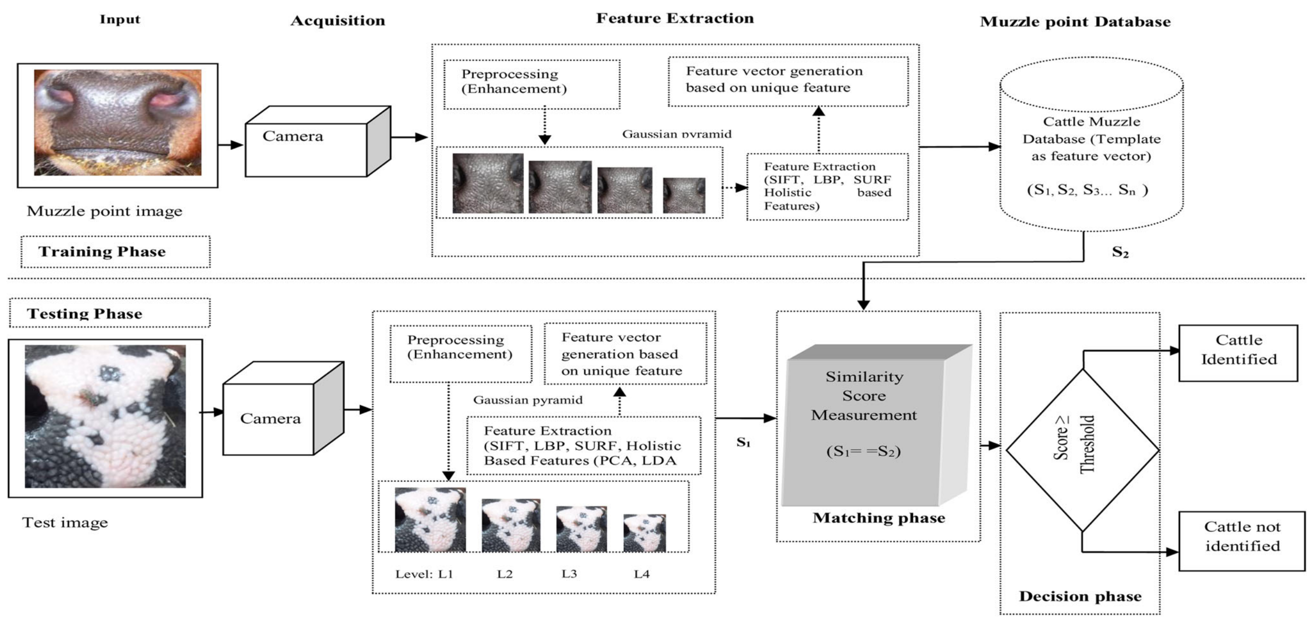


Fig. 2 Cattle recognition system based on muzzle point image pattern

Fig. 3 **a** Beads and ridges pattern of the muzzle print images, **b** segmentation of beads and ridges pattern into upper, middle, and the lower part of a muzzle print image [61]

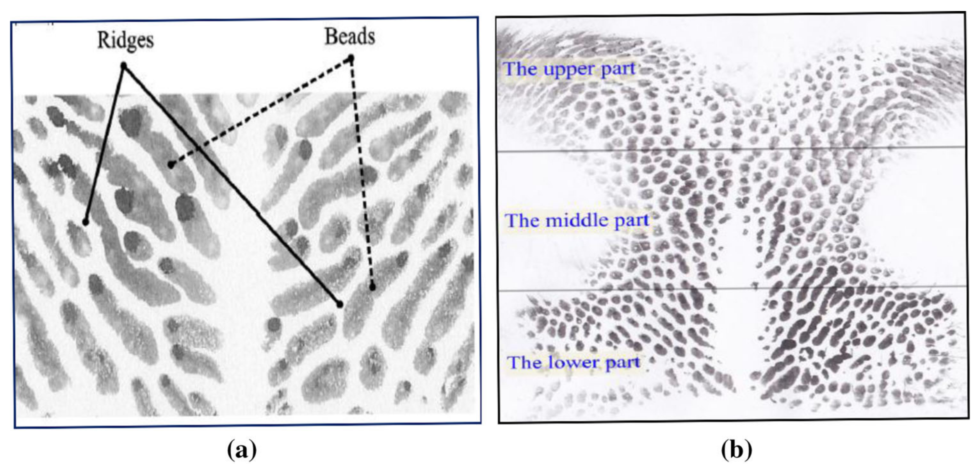
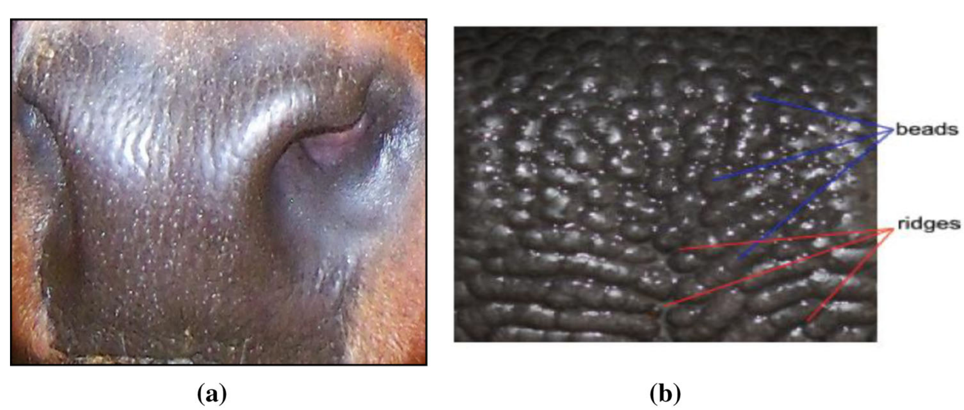
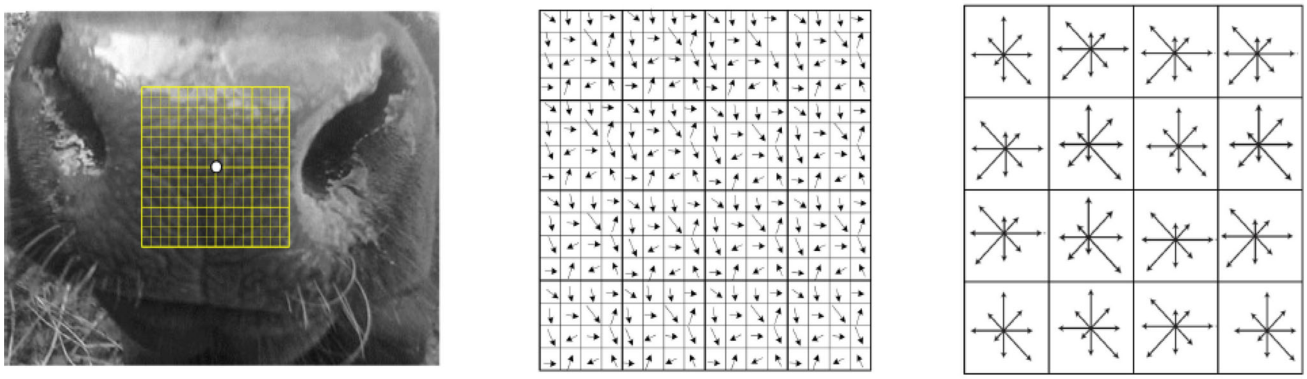


Fig. 4 **a** Sample image of the muzzle point image pattern of cattle, **b** illustrates the beads and ridges pattern in a muzzle pattern image [62]



features are extracted from the muzzle point images database of cattle. Scale-invariant feature transform (SIFT) [40–42], speeded up robust feature (SURF) [43, 45–47], and holistic (appearance-based feature extraction and representation approach) [46] are used

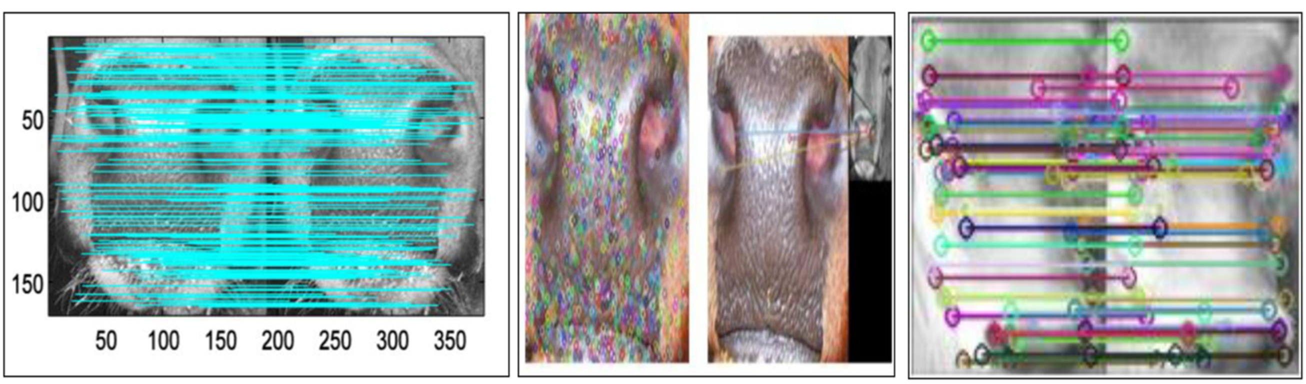


(a) (b) (c)

Fig. 5 The process of building a single SIFT key point muzzle point descriptor: **a** single SIFT key points selected from the muzzle print image, **b** calculation of 16 × 16 pixel gradients from each descriptor window, **c** calculation of 4 × 4 cells key point descriptor with 8-pixel orientations each, **d** the default length of a single SIFT key point descriptor is 4 × 4 × 8 = 128 element [63]

Fig. 6 The process of the main points localization of muzzle point images using SIFT descriptor approach [63]

(a) (b)



(a) (b) (c)

Fig. 7 **a** Matching of SIFT key points of muzzle point image from the test image, **b** recognition of muzzle pattern image based on similarity scores of SIFT key points and **c** matching of SIFT key points for face images of cattle [63]

based on feature extraction and representation algorithms.

3. Generation of template phase
After feature extraction steps, unique sets of features are selected from the extracted features for the generation of muzzle image template for matching muzzle point images. The generated muzzle image templates are stored in the database.
4. Key point localization and similarity matching phase
In the testing phase, the test image of muzzle point image of cattle is considered for matching of test muzzle image with stored muzzle image database using similarity matching techniques (SIFT technique)

[40]. During matching of muzzle point image, first SIFT key points are detected in the muzzle point images; after that, SIFT key points are selected as feature vectors using the SIFT feature descriptor method. The process of building a SIFT key points descriptor of muzzle pattern of cattle is shown in Figs. 5, 6 and 7, respectively.

5. Decision phase
   The decision or action has been executed based on matching similarity scores of key points of muzzle point images. The computed matching scores are compared with defined threshold values for evaluation of recognition accuracy of cattle.

6 Opportunity, Issues, and Challenges

Visual animal biometrics has provided many opportunities for veterinary officers, biologists, computer scientists, research communities, and multidisciplinary researchers for the development of efficient algorithms for recognition of cattle and study of the huge population of various animals. Visual animal biometrics has given better perspectives for supporting the documentation, filtering, and indexation of symbolic data, audiovisual recorded data, and taxonomic content generation for animal recognition in many ecological and evolutionary studies for a wide variety of biological species or individual.

To the best of our knowledge, there is no public availability of first animal biometric characteristics-based database for the animal recognition, and it can be therefore used to estimate the current state-of-the-art recognition systems and develop new algorithms. However, conventional biometrics and non-biometrics techniques for identification of animal are mainly routine, and manual procedures of specimens for the taxonomic impediment to the animal.

The conventional identification systems produce a massive amount of raw data that are often at the time limit of what can be processed by traditional methods. Traditional non-biometrics-based techniques include the ear-tags, and others which are suffered from the duplication and fraudulent activities. Therefore, traditional techniques are unable to cater suitable solutions for identification and verification of cattle.

On the other hand, animal recognition systems based on taxonomic impediment to biodiversity studies are multi-faceted. However, the animal biometric system has several problems of species recognition with documentation of a large population of species. The challenging problems are illustrated as follows:

1. In the recognition methods, there is a lack of standard benchmark datasets of different species animal in the public domain.
2. Traditional animal recognition systems are not able to present the highly biased nature of the sets of species or individuals dataset that has been formally described.
3. The existing documentation-based animal recognition systems are used for the retrieval of the information from a stored database. The preparation of database includes the name of species, and color features and other relevant information. This system is unable to perform the identification of animal based on the massive amount of database. It consumes more time for searching the name of query species or individual in the database.
4. Difficulties in becoming proficient in the identification of many text document for identification of species or individual animal.
5. Difficulties of using traditional taxonomic products without adequate reference collections and extensive knowledge of arcane specialist terminology [57].
6. The existing system takes a massive number of specimens or sample dataset (often of common species) for which routine identifications are required.

Visual animal biometrics-based recognition system also has several major challenges for the representations, detecting phenotypic appearances, individual, and behavior analysis in their habitats. The biggest challenges are given as follows:

- How can visual animal biometric-based recognition systems generate biometric templates and morphological image pattern-based metadata automatically for different study site fields?
- During recognition and detection of the phenotypic appearance of different species or individual, the previously developed algorithms do not solve the problems of poor eliminations, low quality of images, and occlusions (covering body parts) during vegetations of different species or individual animals.
- In the case of recognition of species or individual animals, animal first animal biometric modalities databases such as facial image, muzzle point image pattern, and natural spot pattern of animals (e.g., tiger, cheetah, and whale shark) in public domains are not available.
- The cattle recognition is still in its infancy and remains an open research field in visual animal biometrics. However, visual animal biometrics is a highly interdisciplinary field that needs various inputs from an extensive variety of disciplines to develop truly automatic, robust system and widely applicable and advantageous tools. Therefore, the parallel proliferation of the

rate of progress is made that will depend largely on successful collaborations and sharing of diverse expertise among member of the different scientific communities.

Thus, there is the need to cater to an emerging research perspective to multidisciplinary researchers, veterinary officers, and scientists for the recognition of animals using the visual animal biometric techniques. There are significant issues related to the availability of consistent muzzle point image pattern, and facial or coat pattern databases in the public domain along with standard benchmark and train and test splits of recognition systems. Although existing framework and recognition systems have demonstrated that visual animal biometrics are available with feasible and useful application across the several disciplines such as biological, ecological, biometrics and animal science. Few challenges lie ahead to design and develop field into a widely accepted and applied subject. Bridging the research gap between the different disciplines involved remains the significant challenges. To obtain major impact over these challenges, the applicability of visual animal biometrics requires to be more widened. Moreover, these major challenges can be solved by different researchers and ecologists, and biologist. They will inspire other researchers to obtain the solutions for these problems and perform the comparative results across obtained solutions for ecological and evolutionary studies.

Visual animal biometric systems can be of the huge assistance by giving information on the precise occurrence of particular species, individual's behavior, or morphological patterns of interest in a fraction of this time. Furthermore, monitoring and ecological population-based studies of biodiversity have a significant role in visual animal biometrics for recognition, classification, environmental data analysis, and ecology and behavior.

7 Current State of the Art: Visual Animal Biometrics

The animal biometrics-based system is a pattern recognition system recognizing the individual animal based on their visual biometric features, morphological feature characteristics, and phenotypic appearance animals. The animal recognition system uses computer vision and pattern recognition methods to extract the biometric features for identification of the individual animal. The visual animal biometric-based recognition system consists of two phases: (1) the training phase and (2) testing phase. In the training phase, the proposed recognition system first acquires the biometric data from an individual animal using sensors and creates the image database. It extracts a set of salient feature of the captured biometric data. The proposed visual animal biometric system is shown in Fig. 8.

The visual recognition system is applied to extract the different biometric features such as facial features, morphological body features, and phenotypic appearance features, and visual features from captured biometric images or videos. The captured biometric database is used for preprocessing and enhancement process. After that, the system generates the unique feature templates from the extracted biometric features. These feature templates are stored in the template database. The biometric feature set of query images is matched and compared with a stored feature in the animal database. After that, the recognition system executes an action based on the result of the comparison.

In the training phase, discriminating features are extracted from the captured image of a database of species or individual animal using different feature extraction techniques. Scale-invariant feature transform (SIFT) [40], speeded up robust feature (SURF) [46] and local binary pattern (LBP) methods [51] are used to extract texture features of the muzzle point. Moreover, the holistic feature extraction and representation techniques such as principal component analysis (PCA) [47], linear discriminant analysis (LDA) [59], and independent component analysis (ICA) [60, 61] methods are used to extract the biometric features from captured multimedia biometric database such as video and images of species or individual animal.

In the testing phase, the comparison is made with the features sets (s), stored in the animal databases in the form of template feature. The proposed animal biometric system plays a major role in multiple disciplines (e.g., biometrics, biography, ecology, population, computer vision, and behavioral research). Further, the animal biometric system utilizes both the variability and uniqueness of vocalizations, coat patterns, body dynamics, and morphologies as unique biometric traits. The coat pattern of zebra, tiger (spot point features), penguin and muzzle point of cattle serve the same purpose as human fingerprints do with a biometric system.

In this section, the current state-of-the-art animal recognition systems and framework are illustrated for identification and verification of livestock animals and endangered species. The steps involved in the proposed animal biometrics-based recognition system with a complete description of each component are also discussed. The identification of animal and species based on phenotypic appearance and biometrics feature is illustrated in the subsections.

7.1 Visual Animal Biometrics-Based Livestock Identification System Based on Face and Muzzle Print Image Features

The identification of cattle in a classical animal identification system and livestock management framework is a major challenging problem based on invasive and artificial marking methods. Cattle identification is related to registration and traceability of individual cattle that are significant for animal breeding, production, and proper distribution of the livestock animals. The muzzle print (nose) pattern is a suitable identification method for cattle in livestock management framework.

The biometric feature characteristics of the muzzle image pattern of cattle are similar to fingerprint recognition of an individual. Mishra et al. [43] studied that the artifacts of muzzle print image of cattle. Based on their survey study, the muzzle print image is divided into two essential features known as beads feature and ridge feature. The patterns of bead feature are irregular structures. The shape of the bead is similar to the islands. On the other hand, the shape and structure of the ridge pattern are like rivers. The author Noviyanto and Arymurthy [4] proposed an animal biometrics-based identification system for cattle using SIFT descriptor technique. The accuracy of the system reported 0.0167 equal error rate (EER) for cattle identification. Furthermore, the author customized the SIFT matching method for accurate identification of cattle. The refinement SIFT method yielded 0.0028 equal error rate (EER) for individual cattle, which is better than the original SIFT method.

In a similar direction, the author Mingawa et al. [21] proposed a cattle recognition system using muzzle (nose) print images of cattle. The filtering techniques are applied to remove the noises from muzzle print of cattle database. To provide a better accuracy of the system, author Barry et al. [22] proposed a method for cattle identification-based muzzle print images using different image processing techniques. The proposed method of Barry et al. [22] is similar to the proposed approach of Mingawa et al. [21].

Furthermore, Awad et al. [38] proposed a recognition system for individual cattle. The system uses the SIFT feature descriptor-based matching technique to detect the key points for the matching of muzzle biometric features. Random sample consensus (RANSAC) classification technique is applied to classify the extracted features of muzzle print image (shown in Fig. 9).

Noviyanto and Arymurth proposed a method for the identification of cattle using uniform-speeded up robust feature (U-SURF) technique [46]. Keeping these principles in mind, the author Tharwat et al. [48] proposed a method for the identification of cattle using the local binary patterns (LBP) technique [48–51]. The local texture features are extracted from the muzzle point image under reduced

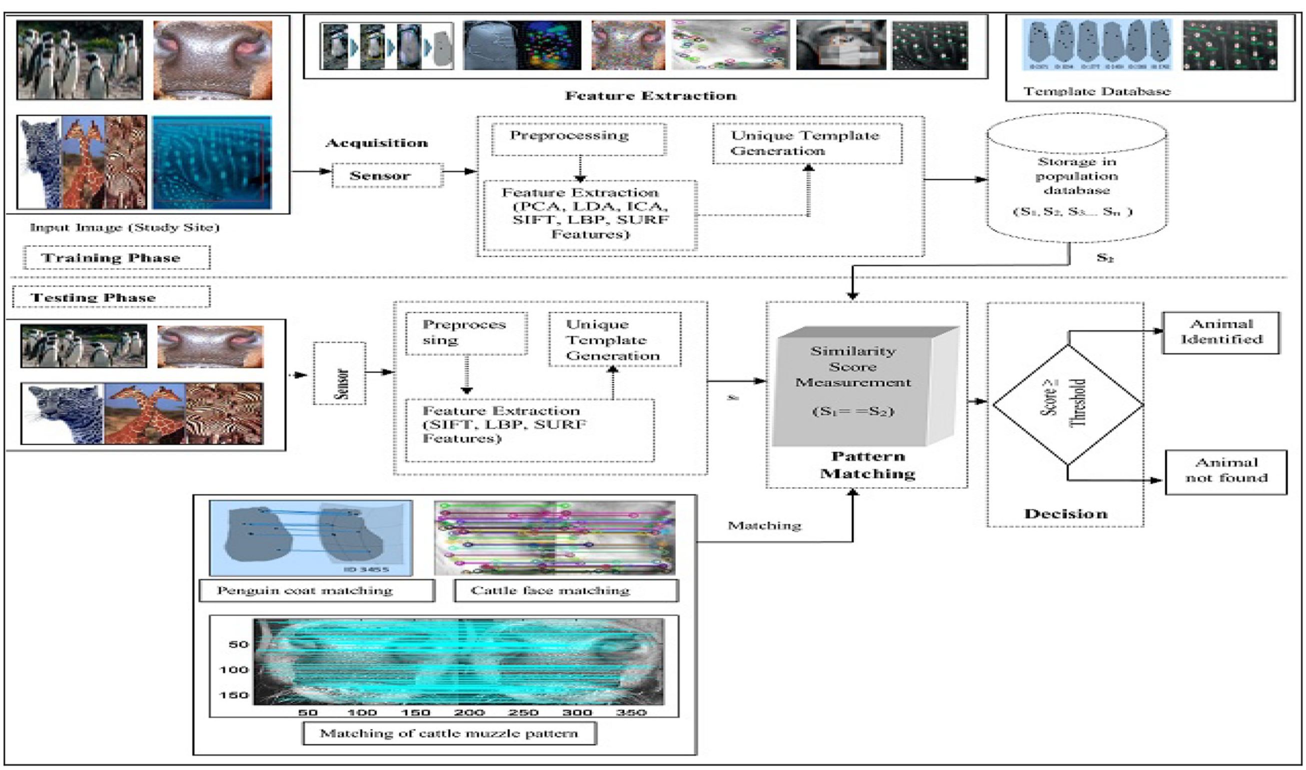


Fig. 8 Visual animal biometric system for different species or individuals

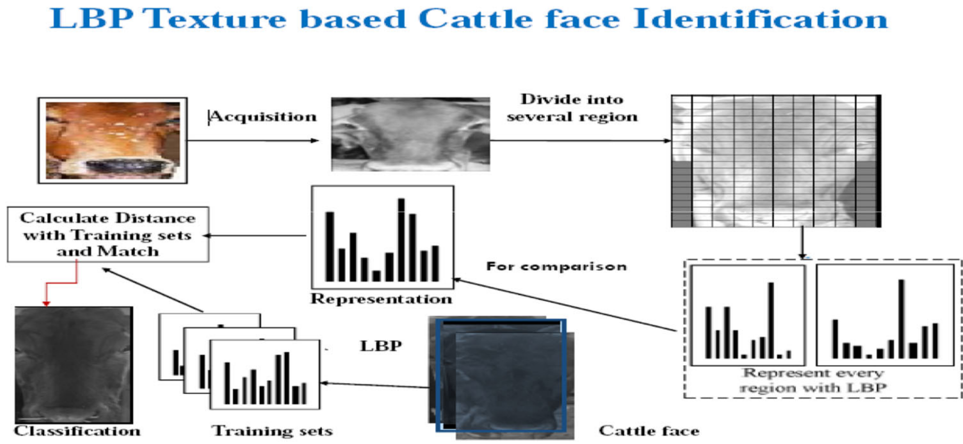


Fig. 9 The identification of face image of livestock (cow) using local binary pattern descriptor feature method

illumination and occlusion of the muzzle pictures. For the classification of cattle breeds, they tested four different classification models (e.g., nearest neighborhood (NN), K-nearest neighborhood (K-NN), support vector machine (SVM) and naive Bayes classification techniques) to classify the extracted set of features from the muzzle image database into different classes for cattle identification.

The author, Cheng and Li [49], proposed a cattle recognition framework using local features descriptor method such as local binary pattern (LBP) [50, 51]. The proposed cattle recognition framework is shown in Fig. 8. The author, Gaber et al. [50], proposed a cattle recognition system based on the captured muzzle print images using Weber local descriptor (WLD) techniques to extract discriminatory features for identification of cattle. The proposed system was trained with the size of the 217 muzzle print database. The muzzle point images are captured from the 31 subjects (cattle). For testing the query muzzle point image, seven muzzle print images are used for it. The AdaBoost classification method is applied to classify the extracted WLD features from the face images to recognize the cattle.

Kumar et al. [58] proposed a system to recognize individual cattle in real time using computer vision techniques and wireless multimedia networks. In the system, the muzzle point images are captured using the digital camera with 30 megapixel resolution. The captured images are transferred to the server of cattle recognition system using Wi-Fi communication technology [61–62]. The cattle recognition system performs the image preprocessing on the captured muzzle point image database to reduce and filter the noises. The recognition system uses a support vector machine model to classify the extracted set of features of the muzzle of cattle. After that, the similarity score measurement method is applied to compute the matching scores to perform the comparison with threshold value for classifying the test muzzle point images. The matching of test images is done with the stored muzzle images database of cattle [61] (Table 2).

7.2 Visual animal Biometric System for Animal Identification Based on Phenotypic and Morphological Feature Characteristics

The animal biometrics-based identification system uses the computer vision, pattern recognition techniques to identification of individual animal. The system extracts the biometric features, morphological traits, visual features as well as behavioral feature characteristics for identification and verification of species. In similar direction, Duyck et al. [2] designed an animal biometrics-based system known as SLOOP system for classification of endangered species based on their phenotypic and visual features. The animal biometrics-based SLOOP framework extracts the discriminatory features and retrieves the discriminatory set of features from the morphological image of endangered species. The identification of endangered species using the SLOOP system is shown in Fig. 10. The SLOOP system uses the interactive preprocessing techniques for segmentation of the captured images. The biometrics features such as generic visual features and phenotypic appearance features are extracted from the segmented images. In phenotypic appearance features, the image patches, local visual features, and regular joint features with scale-cascaded alignment are extracted for classification of species or individual animal.

The captured images of the species are given as input to the SLOOP system. The captured images are preprocessed using the image processing techniques to mitigate the noises and other artifacts from the images. In a given system workflow, the segmentation of images and marked key points are extracted to capture the image patches. The histogram (bin) and location features of different species are extracted from the local image patches at various scales.

Dividing the holistic images into local patches methods helps to enhance the quality of images by removal of

Table 2 Cattle recognition based on muzzle point image pattern and face images

Authors	Biometric features/modality	Features extraction	Database size	Accuracy (%)	Comments
Noviyanto et al. [4]	Muzzle point features with single modality	SIFT method	48 Cattle	0.0.0167 (EER)	Noise and Outlier are problems
Hagar et al. [20]	Muzzle point features single modality	ANN + K-NN + SVM	28 Cattle	92.76%	No validation process for experimental results is done
Minagawa et al. [21]	Muzzle point features (joint features)	Computer vision	43 Cattle	30%	Feature extraction and selection are not done
Barry et al. [22].	Muzzle pattern (bead feature)	Manual marking and identification method	20 Cattle	60%	No computer vision and image processing is used
Kumar et al. [33]	Face biometric images of cattle	PCA + LDA + ICA	300 Cattle	86.95%	Database is not available in the public domain Face biometric-based system for cattle face identification
Corkery et al. [36]	Face biometrics image	PCA + ICA	50 sheep	96%	The proposed method is applied for sheep identification
Awad et al. [38]	Muzzle point pattern	SIFT + RANSAC	15 Cattle face image	93.30%	Outlier and segmentation of muzzle point images are a major problems
Kumar et al. [43]	Face biometric feature	LBP	400 Dog faces	94.86%	Noise removal preprocessing is used
Kumar et al. [45]	Muzzle point pattern	PCA + LDA + DCT	120 Cattle	90%	Appearance-based face recognition is used
Tharwat et al. [48]	Muzzle pattern	Gabor Feature extraction method + SVM– classification method	31 Cattle	99.50%	Not mentioned
Cai and Li [49]	Face biometric features of cattle	RASL + WLBP	30 Cattle	95.30%	Texture feature-based method is used for identification of cattle No cross-validation of experimental results
Gaber et al. [50]		WLD + ABD	31 cattle	99%	It is powerful and robust local feature descriptor method
Kim et al. [52]	Face biometric feature	ANMA	12 cattle	90%	The proposed method used image processing techniques to process the captured images of black-and-white patterns of the Holstein However, Japanese and Korean cattle races do not have a consistent discriminatory feature pattern on their body, therefore, identification of these cattle races by feature pattern is impossible. They have designed algorithm to find the set of featured for cattle identification
Noviyanto et al. [53]	Muzzle print pattern	SURF	8 cattle	90.60%	Muzzle print image database is minimal for this approach No validation of obtained accuracy of the system
Arslan et al. [54]	Muzzle point	KBS + PCA + SVM + RANSAC	10 cattle	80%	Holistic feature extraction method is used The accuracy of the system is affected from the reduction of the feature of muzzle print image database
Mahmoud et al. [55]	Muzzle print image pattern	BCA + MSVM	54 cattle	96%	Feature selection is done with bacterial foraging optimization method

Table 2 continued

Authors	Biometric features/modality	Features extraction	Database size	Accuracy (%)	Comments
El-Henawy et al. [56]	Muzzle point pattern	ANN + SFTA + BCA	52 cattle	99.97%	Feature extraction and selection is done with bacterial foraging optimization method and artificial neural network method Number of hidden layer is more in this experimental evaluation of the proposed method

WLD Weber's local descriptor, *ADB* AdaBoost classifier, *ANMA* associate neural memory algorithm (ANMA), *WLBP* Weber's local binary pattern descriptor, *RANSAC* random sample consensus algorithm, *SIFT* scale-invariant feature transform, *SURF* speeded up robust features, *SVM* support vector machine classifier, *PCA* principal component analysis, *ICA* independent component analysis, *LBP* local binary pattern, *DCT* discrete cosine transform, *LDA* local discriminant analysis, *HCPSO* hybrid chaos particle swarm optimization, *BFO* bacterial foraging optimization, *ANN* artificial neural network, *K-NN* K-nearest neighbor classifier, *SFTA* segmentation-based fractal texture analysis, *KBS* kinect-based system, *BCA* box-counting algorithm, *MSVM* multiclass support vector machines

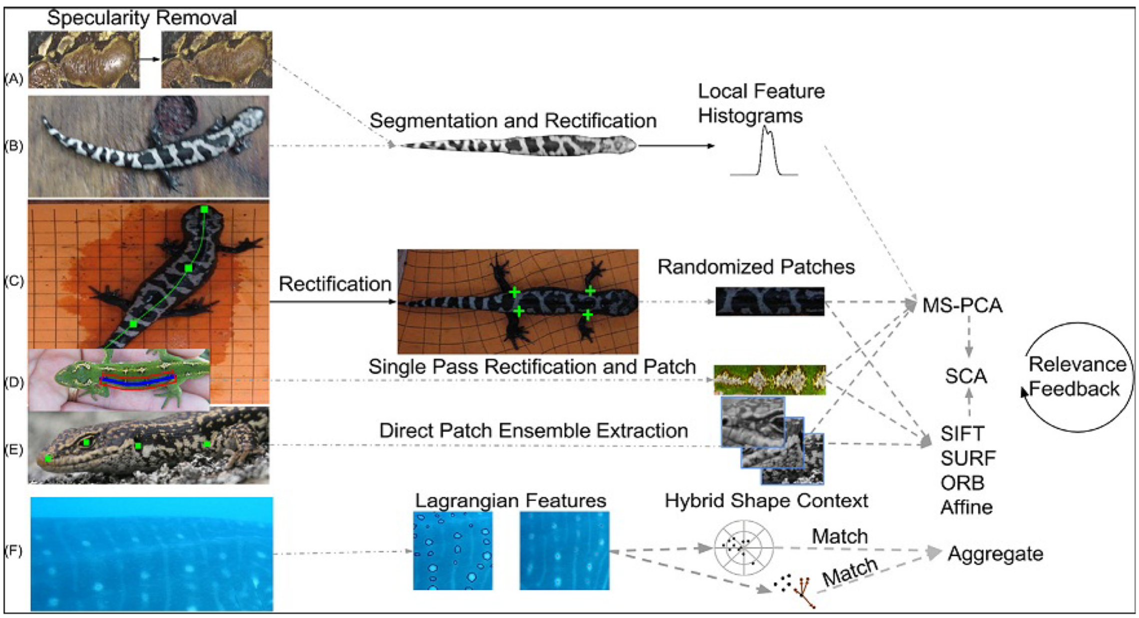


Fig. 10 The identification of species using SLOOP animal identification system [63]

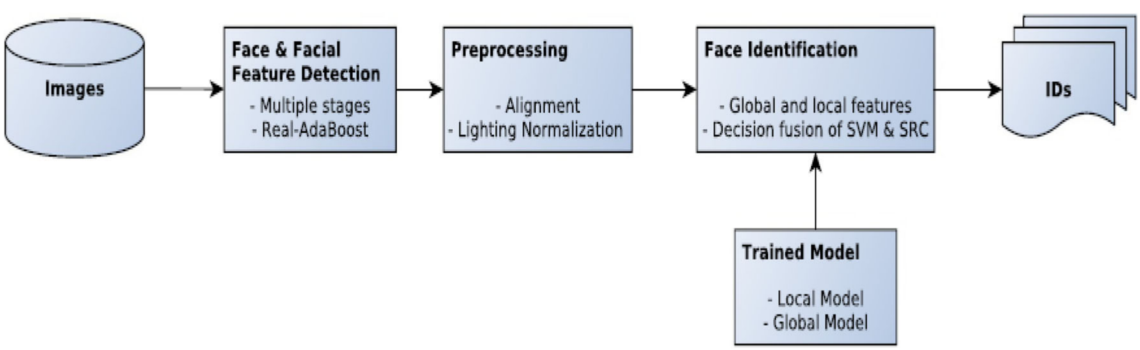


Fig. 11 The recognition system for identification of chimpanzee based on their face images [63]

specularity from the local image patches. Figure 10a shows the specularity removal algorithm within SLOOP system for Fowler's toad species. In the specularity removal algorithm, the user marks a few specular and normal regions into local patches. The marked key point features, the system contains mean-shift feature extraction methods, support vector method and graph-cut segmentation methods are used to extract the color features from the on color-texture features, shown in Fig. 10b.

An example of this process is shown in Fig. 10c, d for a marbled salamander and gecko. In the skinks, for instance, a few points mark the patches and their orientations (Fig. 10e) which are rectified and used for matching. Finally, Lagrangian features are also used for representing the species. The spot point features, both manually marked and automatically detected key point features (in addition to invariant feature detectors for feature matching), are available and used in whale sharks (shown in Fig. 10f). Therefore, in this paper we propose, design, and evaluate an automated face detection and recognition system for chimpanzees in wildlife environments. In a similar direction, Kumar et al. [3] proposed a cattle recognition system to identify and verify the cattle based on their facial images. The proposed system extracts the set of discriminatory features of the face images database using computer vision-based face recognition algorithms.

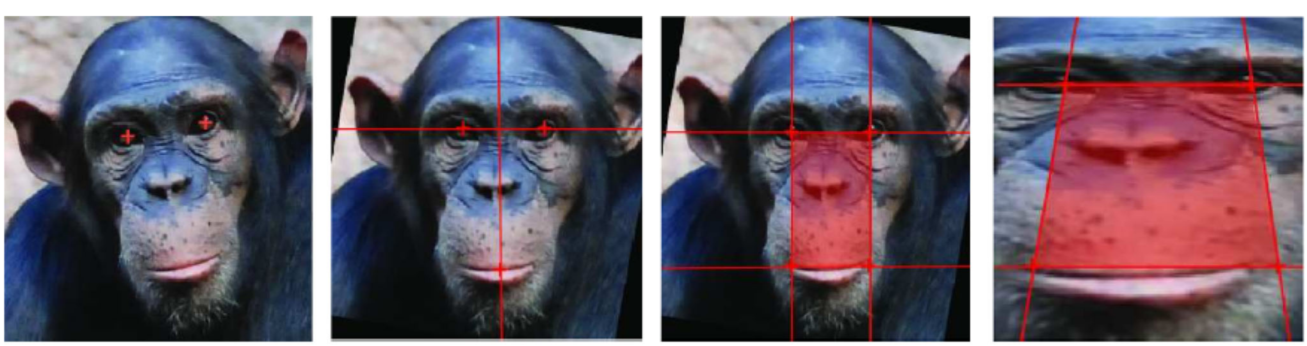
7.3 Visual Animal Biometrics-Based Recognition for Chimpanzee

The visual animal biometrics-based recognition system is also used for identification of chimpanzee based on their face image features (shown in Fig. 11). The recognition system consists of the following steps: The first step is used to detect the face of a chimpanzee. After detection of the face image, the eyes are located within the face image regions. The affine image alignment technique is applied to provide the alignment of the captured face image of a chimpanzee. The lighting normalization method is also used to get the comparability of the facial images of chimpanzee across the entire captured face image database.

The preprocessing and lighting normalization methods improve the robustness of the proposed animal biometrics-based recognition system against low illumination and light changes. The last step of the proposed recognition system is to recognize the detected and normalized chimpanzee's face image, and the system assigns identities to them based on similarity matching scores of face images database. The similarity scores are measured after the matching the test face image with stored face images. Figure 11 and 12 depict the overview of face recognition system for chimpanzee.

After all possible faces of a chimpanzee, each face is aligned using a projective transform technique. This alignment process aligns the detected face image. The aligned face images are used for comparisons across the entire face image dataset. The contrast histogram equalization technique is applied to enhance the robustness of the recognition system for identification for a chimpanzee. The performance of the system also is affected due to lighting conditions and poor image quality of face images of a chimpanzee. The faces are detected and aligned using a combination of global feature and local facial features. The alignment of the face image of a chimpanzee is shown in Fig. 11.

Figure 11 illustrates the face alignment procedure for a chimpanzee. In the face alignment procedure, the coordinate values of the detected eye provide the correct position of the mouth estimation. Figure 11a presents the detection of the eye of a chimpanzee. In Figure 11b, face alignment procedure performs the few rotations to align the face image. After rotating the facial image of a chimpanzee into an upright position, both eyes of a chimpanzee lie on a horizontal line and the left and the right corner of the chimpanzee's mouth is calculated (shown in Fig. 11c). The author Loos et al. [62] found the four points and applied a projective transformation for alignment of faces (shown in Fig. 11d). The facial features include eyes, nose, and mouth for identification of chimpanzee. These are located approximately in the same positions throughout the entire face image database. It is a prerequisite for the accurate identification of chimpanzee.



(a) (b) (c) (d)

Fig. 12 The face alignment of a chimpanzee [63]

8 Conclusion and Future Directions

This paper provides a comprehensive review of animal identification based on physiological, morphological image characteristics, and biometrics characteristics. It also provides a coherent set of fundamental and techniques for identification of individual cattle based on their muzzle point image pattern and faces images. This paper illustrates what real-world applications gaining momentum to determine and augmenting the quality of the different animal database, data collection, and preprocessing of the database are?

The comprehensive review paper illustrates the computer vision, image processing, and pattern recognition approaches to identify and verifies the animals or cattle using their muzzle point image pattern. In this article, visual animal biometric-based cattle recognition systems (using the muzzle point pictures and false pictures of cattle) are demonstrated to solve the biggest problems of missed, swapped, false insurance claim, and reallocation at slaughterhouses of animals (especially cattle) by recognizing the biometric characteristics. The cattle recognition system is also essential for the registration and tracking of livestock.

Moreover, in this paper, various computer vision-based frameworks and approaches are demonstrated for the identification of different species based on phenotypic appearances. The phenotypic appearances include coat pattern (vectorized of joint stripe), spot points on tiger and penguin, and muzzle point image pattern of animals. These features are suitable for the identification of different species [64, 65].

The promising research field of the visual animal biometrics is in the open. It caters an opportunity to ecologists, biologists, scientists, and research communities and new practitioners in the development of new methodologies for recognizing the various species in the ecology fields [66–71]. Therefore, it is on the edge of providing powerful computing models, tools, recognition frameworks, and efficient framework for capturing the database, collecting and processing the database, and extraction of phenotypes appearances features for different species. While existing animal identification systems have demonstrated that visual animal biometrics are feasible and beneficial to the biologists. For achieving a significant impact, the applicability of visual animal biometrics needs to be widened. Current technologies provide algorithmic approaches for automatic robotic systems (drones) for actively seeking the several essential data by traversing the habitat to improve both the quality and quantity of acquired data.

Although visual animal biometric systems are of use for a broad range of disciplines, they may show the greatest potential in the emerging field of phenomics. Formalized phenotypic appearance information is a key for linking the phenotype of an organism to other organizational levels of life. The complexity of the recognition system design demands a new breed of biologically knowledgeable engineers, scientist, multidisciplinary researchers, and technically inspired biologists. They include cross-disciplinary scientists who have an intimate understanding of the target endangered animal or species as well as the technical tools, systems, and coherent set of fundamental concepts that underpin practical engineering solutions.

References

1. Kühl HS, Burghardt T (2013) Animal biometrics: quantifying and detecting phenotypic appearance. Trends Ecol Evol 28(7):432–441
2. Duyck J, Finn C, Hutcheon A, Vera P, Salas J, Ravela S (2015) Sloop: a pattern retrieval engine for individual animal identification. Pattern Recogn 48(4):1059–1073
3. Kumar S, Tiwari S, Singh SK (2016) Face recognition of cattle: can it be done? Proc Natl Acad Sci India Sect A Phys Sci 86(2):137–148
4. Noviyanto A, Arymurthy AM (2016) Beef cattle identification based on muzzle pattern using a matching refinement technique in the sift method. Comput Electron Agric 99:77–84
5. Kumar S, Singh SK, Dutta T, Gupta HP (2016) Poster: a real-time cattle recognition system using wireless multimedia networks. In: Proceedings of the 14th annual international conference on mobile systems, applications, and services companion, Singapore, p 48
6. Edwin A, Mary G (2016) Fuzzy noise extraction from muzzle images for cattle identification. Int J Res Educ Sci Methods (IJARESM) 4(7):367–371
7. Wardrope DD (2009) Problems with the use of ear tags in cattle. Vet Rec (United Kingdom) 37(26):675
8. Jarraya I, Wael O, Adel MA (2015) A preliminary investigation on horses recognition using facial texture features. In: Proceeding of IEEE international conference on systems, man, and cybernetics (SMC), pp 2803–2808
9. Awad AI (2016) From classical methods to animal biometrics: a review on cattle identification and tracking. Comput Electron Agric 123:423–435
10. Kumar S, Singh SK, Datta T, Gupta HP (2016) A fast cattle recognition system using smart devices. In: Proceedings of the ACM conference on multimedia, pp 742–743
11. Petersen WE (1922) The identification of the bovine by means of nose-prints. J Dairy Sci 5(3):249–258
12. Pennington JA (2012) Tattooing of cattle and goats, University of Arkansas, United States Department of Agriculture, and County Governments Cooperating
13. Jain AK, Ross A, Prabhakar S (2004) An introduction to biometric recognition. IEEE Trans Circuits Syst Video Technol 14(1):4–20
14. Karu K, Jain AK (1996) Fingerprint classification. Pattern Recogn 29(3):389–404
15. Johnston AM, Edwards DS (1996) Welfare implications of identification of cattle by ear tags. Vet Rec 138(25):612–614
16. Lahiri, M, Chayant T, Rosemary W, Daniel IR, Berger-Wolf TY (2006) Biometric animal databases from field photographs:

Identification of individual zebra in the wild. In: Proceedings of the 1st ACM international conference on multimedia retrieval, p 6
17. Hiby L, Lovell P (1990) Computer-aided matching of natural markings: a prototype system for grey seals. In: Report of the International Whaling Commission, pp 57–61
18. Hiby L, Phil L, Patil N, Samba KN, Gopalaswamy AM, Karanth KU (2009) A tiger cannot change its stripes: using a three-dimensional model to match images of living tigers and tiger skins. Biol Let 5(3):383–386
19. Kelly Marcella J (2001) Computer-aided photograph matching in studies using individual identification: an example from Serengeti cheetahs. J Mammal 82:440–449
20. Hadad El, Hagar M, Hamdi AM, Farid AM (2015) Bovines muzzle classification based on machine learning techniques. Procedia Comput Sci 65:864–871
21. Minagawa H, Fujimura T, Ichiyanagi M, Tanaka K, Fangquan M (2002) Identification of beef cattle by analyzing images of their muzzle patterns lifted on paper, In AFITA 2002: Asian agricultural information technology & management. In: Proceedings of the 3rd Asian conference for information technology in agriculture, pp. 596–600
22. Barry B, Barron UG, McDonnell K, Butler F, Ward S (2008) Using muzzle pattern recognition as a biometric approach for cattle identification. Trans ASABE 50(3):1073–1080
23. SallyA Mizroch, Harkness S (2003) A test of computer-assisted matching using the North Pacific humpback whale, *Megaptera novaeangliae*, tail flukes photograph collection. Mar Fish Rev 65:25–37
24. Jain A, Maltoni D, Maio D, Wayman J (2005) Biometric systems: technology, design and performance evaluation. Springer, Berlin
25. Barron Ursula G, Butler F, McDonnell K, Ward S (2009) The end of the identity crisis? Advances in biometric markers for animal identification. Ir Vet J 62(3):204–208
26. Burghardt T, Calic J (2006) Real-time face detection and tracking of animals. In: Proceedings of 8th IEEE seminar on neural network applications in electrical engineering, pp 27–32
27. Geers R, Puers B, Goedseels V, Wouters P (1997) Electronic identification, monitoring and tracking of animals. CAB International, Oxford, pp 25–38
28. Vlad M, Parvulet RA, Vlad MS (2012) A survey of livestock identification systems. In: Proceedings of 13th WSEAS international conference on automation and information (ICAI), pp 165–170
29. Kumar S, Singh SK (2015) Feature selection and recognition of face by using hybrid chaotic PSO-BFO and appearance-based recognition algorithm. Int J Nat Comput Res (IJNCR) 5(3):26–53
30. Wang Z, Fu Z, Chen Wei HuJ (2010) A RFID-based traceability system for cattle breeding in China. Proc Int Conf Comput Appl Syst Model (ICCASM) 2:V2–V567
31. Allen A, Golden BL, Taylor M, Skuce R (2008) Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland. Livest Sci 116(1):42–52
32. Tillett RD, Onyango CM, Marchant JA (1997) Using model-based image processing to track animal movements. Comput Electron Agric 17(2):249–261
33. Kumar S, Tiwari S, Singh SK (2015) Face recognition for cattle. In: Proceeding of 3rd IEEE international conference on image information processing (ICIIP), pp 65–72
34. Rusk CP, Blomeke CC, Mark Balschweid, Elliot SJ, Dan Baker (2012) An evaluation of retinal imaging technology for 4-H beef and sheep identification. J Ext 44(5):1–33
35. Shadduck JA, Golden BL (2002) Retinal imaging in secure identification and source verification of livestock. In: Proceedings ID/INFO Expo 2002, National Institute for Animal Agriculture
36. Barron UG, Corkery Barry B, Butler F, McDonnell K, Ward S (2002) Assessment of retinal recognition technology as a biometric method for sheep identification. Comput Electron Agric 60(2):156–166
37. Adell N, Puig P, Rojas-Olivares A, Gerard Caja, Sergi Carné, Ahmed Salama (2012) A bivariate model for retinal image identification in lambs. Comput Electron Agric 87:108–112
38. Awad AI, Zawbaa HM, Mahmoud Hossam A, Nabi EH, Fayed Rabie Hassan, Hassanien AE (2013) A robust cattle identification scheme using muzzle print images. In: Proceedings of IEEE federated conference on computer science and information systems (FedCSIS), pp 529–534
39. Gaber T, Tharwat A, Hassanien AE, Snasel V (2016) Biometric cattle identification approach based on Weber's Local Descriptor and AdaBoost classifier. Comput Electron Agric 122:55–66
40. Lowe DG (1999) Object recognition from local scale-invariant features. In: Proceedings of the 7th IEEE international conference on computer vision, vol 2, pp 1150–1157
41. Baranov AS, Graml R, Pirchner F, Schmid DO (1993) Breed differences and intra-breed genetic variability of a dermatoglyphic pattern of cattle. J Anim Breed Genet 110(1–6):385–395
42. Mishra S, Tomer OS, Kalm E (1995) Muzzle dermatoglypics: a new method to identify bovines. Asian Livestock (FAO)
43. Kumar S, Singh SK (2014) Biometric recognition for pet animal. J Softw Eng Appl 7(5):470–482
44. Daugman J (2009) How iris recognition works. In: The essential guide to image processing. Academic Press, pp 715–739
45. Kumar S, Singh SK (2016) Feature selection and recognition of muzzle point image pattern of cattle by using hybrid chaos bfo and pso algorithms. In: Advances in Chaos theory and intelligent control. Springer, Cham, pp 719–751
46. Bay H, Ess A, Tuytelaars T, Van Gool L (2008) Speeded-up robust features (SURF). Comput Vis Image Underst 110(3):346–359
47. Turk Matthew A, Pentland AP (1991) Face recognition using eigenfaces. In: Proceedings of IEEE computer vision and pattern recognition, pp 586–591
48. Tharwat A, Gaber T, Hassanien AE (2014) Cattle identification based on muzzle images using Gabor features and SVM classifier. In: Proceedings of international conference on advanced machine learning technologies and applications, pp 236–247
49. Cai C, Li J (2013) Cattle face recognition using local binary pattern descriptor. In: Proceeding of IEEE, annual summit and conference on signal and information processing association (APSIPA), Asia-Pacific, pp 1–4
50. Mishra S, Dubey A, Khune V (2011) Muzzle print characteristics of pure bred Sahiwal. Indian Vet J 88(12):20–21
51. Ahonen T, Hadid A, Pietikainen M (2006) Face description with local binary patterns: application to face recognition. IEEE Trans Pattern Anal Mach Intell 28:2037–2041
52. Kim HT, Ikeda Y, Choi HL (2005) The identification of Japanese black cattle by their faces. Asian-Aust J Anim Sci 18(6):868–872
53. Noviyanto A, Arymurthy AM (2012) Automatic cattle identification based on muzzle photo using speed-up robust features approach. In Proceedings of the 3rd European conference of computer science (ECCS), vol 110, p 114
54. Arslan AC, Akar M, Alagöz F (2014) 3D cow identification in cattle farms. In: Proceedings of IEEE signal processing and communications applications conference (SIU), pp 1347–1350
55. Mahmoud HA, Hadad HM (2015) An automatic cattle muzzle print classification system using multiclass support vector machine. Int J Image Min 1(1):126–140
56. El-Henawy I, El Bakry HM, El Hadad HM (2016) Cattle identification using segmentation-based fractal texture analysis and artificial neural networks. Int J Electron Inf Eng 4(2):82–93

57. Weeks PJ, O'Neill MA, Gaston KJ, Gauld ID (1999) Automating insect identification: exploring the limitations of a prototype system. J Appl Entomol 123:1–8
58. Kumar S, Singh SK (2016) Hybrid BFO and PSO swarm intelligence approach for biometric feature optimization. Int J Swarm Intell Res (IJSIR) 7(2):36–62
59. Belhumeur PN, Hespanha JP, Kriegman DJ (1997) Eigenfaces vs. fisher faces: recognition using class specific linear projection. IEEE Trans Pattern Anal Mach Intell 19(7):711–720
60. Bartlett MS, Movellan JR, Sejnowski TJ (2002) Face recognition by independent component analysis. IEEE Trans Neural Networks 13(6):1450–1464
61. Kumar S, Singh SK (2016) Monitoring of pet animal in smart cities using animal biometrics. Future Gener Comput Syst 83:553–563
62. Kumar S, Singh SK (2017) Automatic identification of cattle using muzzle point pattern: a hybrid feature extraction and classification paradigm. Multimed Tools Appl 76(24):26551–26580
63. Kumar S, Singh SK (2016) Visual animal biometrics: survey. IET Biom 6(3):139–156
64. Shanahan C, Kernan B, Ayalew G, McDonnell K, Butler F, Ward S (2009) A framework for beef traceability from farm to slaughter using global standards: an Irish perspective. J Comput Electron Agric 66(1):62–69
65. Worapan K, Anuwat W, Udom C, Sarattha K, Thanandon I (2018) Automatic cattle identification based on fusion of texture features extracted from muzzle images. In: Proceeding of IEEE international conference on industrial technology (ICIT), pp 1484–1489
66. Kumar Santosh, Amit Pandey K, Satwik Sai Ram, Kumar Sunil, Singh Sanjay Kumar, Singh Amit Kumar, Mohan Anand (2018) Deep learning framework for recognition of cattle using muzzle point image pattern. Measurement 116:1–17
67. Kumar S, Singh SK, Singh RS, Singh AK, Tiwari S (2017) Real-time cattle recognition using animal biometrics. J Real-Time Image Process 13(3):505–526
68. Loos A, Ernst A (2013) An automated chimpanzee identification system using face detection and recognition. EURASIP J Video Process 2013(1):49
69. Kumar S, Singh SK, Singh AK (2017) Muzzle point pattern-based techniques for individual cattle identification. IET Image Process 11:805–814
70. Kumar S, Singh SK, Singh AK, Tiwari S, Singh RS (2018) Privacy preserving security using biometrics in cloud computing. Multimed Tools Appl 77(9):11017–11039
71. Kumar S, Singh SK (2016) Visual animal biometrics: a survey. IET Biom 6(3):139–156