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Techniques and Applications

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Preface

Animal biometrics is an emerging research field for representation and detection of visual animal biometric characteristics. It provides quantified methodologies for design and development of efficient animal biometrics-based recognition systems for different species or individual animal. The animal biometrics-based recognition refers to the use of discriminatory morphological characteristics, physiological and behavioral characteristics (face images, body structure, iris, movement pattern, and gait), phenotypic appearance-based features, and visual features (coat pattern of zebra, spot point on penguin's chest, skin patterning behind the gills of each whale shark and muzzle point image pattern of cattle). The phenotype appearance-based features of species or individual depict the major composite of observable and discriminatory feature characteristics of an organism. Further, it includes the morphological characteristics (image pattern), biochemical traits, phenology, behavior and biometric characteristics for detection and representation of species or individual animal, called animal biometrics identifiers or simply animal biometrics, for automatically detecting, representing, and recognizing a species or individual animal. The research field of animal biometrics uses formal methods to represent and detect biometric features, and morphological image pattern, and phenotypic appearances of animals. It can be utilized to recognize and classify species, identify individuals, detects the occurrence of, or variation in, a distinct behavior, as well as to estimate morphological characteristics and their inter-individual variation or intra-individual differences over time. The formal feature representation based methodologies which have been applied to identify and classify the massive classes of different species for identification of individual animal in the given class. Hence, it performs the detection of animal occurrence or variation in the huge inter-individual and intra-individual classes of species.

In the available literature on animal biometrics, the classical animal recognition methodologies are mainly ear-tagging-based animal identification, freeze branding, ear tattoos, ear-tips, or ear-notches, embedding of microchips and hot iron, embedding of transponders in the animal's body for identification, monitoring, and tracking of animals. These classical animal identification methodologies are invasive approaches for the recognition, and verification of individual cattle. Moreover, the classical animal recognition-based approaches are more susceptible to massive vulnerability of loss and illegibility. It always leads to more security issues for the protection of cattle or other animals, as reported in various surveys.

Therefore, classical animal recognition methodology is unable to cater a competent level of security to individual cattle. Moreover, this methodology also fails to provide a required level of registration, identification of missed and swapped cattle, reallocation of livestock, and verification of false insurance claims. Furthermore, the classical animal recognition systems are limited in public domain due to the enormous amount of manpower requirements, high cost, and vulnerability of loss. This loss occurs due to duplication, fraudulent, and forging of embedded standard ear tags. However in the state-of-the-art-based animal recognition approaches, different governmental organizations and private animal insurance providers identify and then verify the animals to solve the biggest problem of the false insurance claims by cutting their ear or snatching the embedded label of ear tags or notches from the animal's ear. The duplication, forgery, and fraudulent processes are responsible for the falsification of the labeled ear tags. Therefore, it is tough to recognize and verify the registered insurance animals (owner of cattle) or impostor (non-insurance) animals.

Thus to provide better solutions for identification and verification of false insurance claims, monitoring of livestock, assistance during health management of animals, efficient recognition is required. The efficient recognition also prevents critical diseases and distribution of cattle in the livestock framework. These are thus the major issues of identification and monitoring of animals in the classical animal recognition approaches and traditional livestock framework-based systems. Further, these issues cannot be ignored by various scientists, veterinary professionals, animal experts, and different research communities before contributing their valuable efforts for the design and development of robust, noninvasive, and real-time animal biometrics-based recognition systems.

Therefore, it is strongly required to develop a real-time animal biometrics-based recognition system for identifying and monitoring different species or individual animal.

The animal biometrics is the emerging field and considered more reliable, like robust biometrics characteristics for verification and identification of species or individual animal than traditional animal identification-based methodologies. The animal biometrics-based recognition system can provide better security, higher efficiency, accuracy, cost-effectiveness and increased user convenience for modern livestock monitoring and frameworks. Therefore, the animal biometrics-based recognition system is used and deployed or evaluated in the livestock frameworks of private or government organizations (e.g., national Aadhar card for animals, verification of false insurance claims, analysis and study of the total species populations, monitoring of animal's health, diagnosis of widespread critical diseases) applications. Each animal biometrics identifier has its strength and weakness, and selection of particular biometric characteristics generally depends on the requirements of the applications. Any chosen biometric characteristics can also be compared on the well-defined factors such as universality, distinctiveness, permanence, collectability, performance, acceptability, and circumvention. Due to well-known distinctiveness and immutable properties of animal biometric identifiers over time, these are the most widely used identifiers for recognition and verification of animals.

In view of addressing the above challenges, this book emphasizes the progress made in the classical animal identification methodologies for species or individual animal recognition over the past few decades. The authors believe that this book would provide a sound platform for understanding not only the fundamental coherent set of ideas or concept but also the intricate details of this proliferation and a wide range of technologies of animal biometrics, computer vision, and pattern recognition. In addition, the book is also helpful for the senior undergraduate and graduate students, researcher and industry professional working in this area, and other emerging applications demanding recognition and verification of animals.

The eight chapters of the book are organized as follows:

Chapter 1 presents a brief introduction of the animal biometrics followed by the major characteristics, advantages, potential applications, and interdisciplinary relevance of animal biometrics recognition system in the field of ecology. This chapter further includes the general framework of animal biometrics recognition systems along with major components for detection and identification of species or individual animal along with some state-of-the-art animal biometrics recognition systems. Furthermore, the chapter introduces the population distribution of different species, with opportunities, technological challenges, and recommendations for animal biometrics. Finally, the community, communication, data, and tool sharing are also included to provide the better collaboration to encourage the multidisciplinary researches in the field of animal biometrics.

Chapter 2 presents a comprehensive survey on the state of the art in the field of animal biometrics. This chapter provides a brief introduction to the discipline of animal biometrics followed by the classification and identification techniques of species or individual animal. Furthermore, the potential challenges of existing techniques and research communities, tools, and data sharing are also discussed in brief.

Chapter 3 contains an overview of several reported cattle recognition frameworks based on face biometric features of cattle. Further, the authors in this chapter have developed a biometrics-based cattle recognition system for the validation of prepared face image database of cattle for recognition of individual cattle. The proposed recognition system also has been utilized to evaluate the experimental results of cattle face image by applying the existing handcrafted feature descriptor technique and appearance-based feature extraction and representation techniques.

Chapter 4 presents an automatic recognition algorithm of muzzle point image pattern of cattle for the identification of individual cattle, verification of false insurance claims, registration, and its traceability process. The proposed algorithm uses the texture feature descriptors acquired at each Gaussian smoothed level that are combined using fusion weighted sum rule method. With a muzzle point image pattern database of 500 cattle, the proposed algorithm yields the desired level of identification accuracy. In this chapter, the experimental results demonstrate that the identification accuracy performance of the proposed method is found superior to other appearance-based face recognition algorithms.

Chapter 5 presents a novel framework using hybrid texture feature extraction and classification approaches to identify cattle based on muzzle point image features. Further, the methods characterize the extracted pattern of muzzle point image for better recognition and classification of cattle, and it examines the discriminatory features of muzzle images using texture feature extraction technique and supervised machine learning-based multiclassifier techniques. Furthermore, the proposed approach is validated in this chapter by achieving the state-of-the-art accuracy on muzzle point image database of cattle with standard identification settings.

Chapter 6 presents deep learning-based cattle recognition system. It is proposed to identify the individual cattle using muzzle point image pattern. The deep learning-based feature extraction and representation approaches are applied in this chapter to learn the discriminatory texture feature representation of muzzle point images with limited training dataset. The proposed approach consists of two steps: (1) a deep mixture model to find accurate patch correspondence between muzzle point image patterns and (2) convolution neural network, deep belief network, and stacked denoising auto-encoder-based fusion network to extract the features from muzzle point image pattern. Extensive experimental results illustrate that the proposed deep learning approach outperforms state-of-the-art methods for recognition of cattle on muzzle point image database.

Chapter 7 presents a novel Fisher locality preserving projection-based cattle recognition framework for extraction and representation of cattle identification in real time. In this chapter, the efficacy of proposed muzzle point-based recognition approach for cattle is evaluated under identification settings which yields excellent recognition rate for identifying individual cattle. Further, the approach is also evaluated for the optimum recognition time for enrollment and recognition of cattle on different sizes of cattle image database.

Finally, Chap. 8 explores the emerging trends and future challenges of state-of-the-art animal recognition techniques in brief. It concludes with the findings of this book and draws potential suggestions for the future research.

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Abbreviations

AFR	Affordability requirement
Batch-CCIPCA	Batch-candid covariance-free incremental-PCA
CLAHE	Contrast limited adaptive histogram equalization
CMC	Cumulative match characteristic
CNN	Convolutional neural network
CRS	Cattle recognition system
DBN	Deep belief network
DT	Decision tree
DTM	Data transfer and management
EAD	Ease to access database
EER	Equal error rate
EN	Ear notching
EOAS	Ease of application system
FAR	False acceptance rate
FLDA	Fisher linear discriminant analysis
FLLP	Fisher locality preserving projection
FMR	False matching rate
FNMR	False non-matching rate
FRR	False rejection rate
GAR	Genuine accept rate
GMM	Gaussian mixture model
HOOG	Haar of oriented gradient
ICA	Independent component analysis
ILDA	Incremental linear discriminant analysis
IND-CCIPCA	Independent-candid covariance-free incremental-PCA
INT	Intermediate
K-NN	K-nearest neighbor
LBP	Local binary pattern
LDA	Linear discriminant analysis
LO	Low

LP	Lack of pain
LTE	Law's texture energy
MLP	Multilayer perceptron
MO	Moderate
MPI	Muzzle point images
NA	Not available
OSS	One-shot similarity
PCA	Principal component analysis
PFFD	Protection from fraud and duplication
PIM	Permanent identification methodology
PNN	Probabilistic neural network
PSDFC	Protection and security during food chain
RBM	Restricted Boltzmann machine
RFID	Radio frequency identification
RIFT	Rotation-invariant feature transformation
RPCA	Robust principal component analysis
RVP	Retinal vascular pattern
SDAE	Stacked denoising auto-encoder
SFTA	Segmentation-based fractal texture analysis
SIFT	Scale-invariant feature transform
SIM	Semi-permanent identification methodology
SOS	Scalability of system
SRORD	Success rate of reading database
SURF	Speeded-up robust feature
SVM	Support vector machine
TDL	Tucker tensor decomposition
TIM	Temporary identification methodology
UID	Unique identification number
VLAD	Vector of locally aggregated descriptors

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Chapter 1
Animal Biometrics: Concepts and Recent Application

Abstract This chapter presents a brief introduction of the animal biometrics followed by the major characteristics, advantages, potential applications, and interdisciplinary relevance of animal biometrics recognition system in the field of ecology. Further, the chapter includes the general framework of animal biometrics recognition systems along with major components for detection and identification of species or individual animal along with some state-of-the-art animal biometrics recognition systems. Furthermore, the chapter introduces the population distribution of different species, technological challenges and recommendations for animal biometrics. Finally the community, communication, data and tool sharing are also included to provide the better collaboration to encourage the multidisciplinary researches in the field of animal biometrics.

Keywords Animal biometrics · Computer vision · Pattern recognition
Phenotypic appearances · Morphological characteristics

1.1 Introduction

During the last decade, the classical animal identification methodologies were applied in detecting, representing, and identifying the species or individual animal [1]. The classical animal identification methodologies apply the coherent set of ideas of using body measurement and marking of individual animals to solve the major problems of animal identification and monitoring throughout the world [2].

The animal identification methods can be used to solve the significant problems of detecting species or individual animals [3]. The animal identification methods can be used to solve the major problems of classical animal identification frameworks or systems for detecting species or animals. These problems occur due to variety of reasons that include verification of ownership and parentages of animals, controlling bio-security, proper registration and tracking them for better research and agricultural purposes [4, 5].

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For animal identification, the classical animal identification methodologies include mainly ear-tagging-based identification systems, ear tattoos, freeze brandings, hot iron, embedding microchips, ID-collar, paint and dye-based manual approaches for identification and tracking of individual animal in the herds [5].

Despite being noninvasive approaches of animal biometrics, embedding microchips and artificial labels in the ear tags of animal can be easily lost. It can be duplicated and forged by imposters or false insurance makers. Moreover, ear-tagging-based recognition system includes various kinds of metallic clips and plastic ear tags for recognition of individual animal which are painful for the animals [6]. Ear-tagging-based identification is a method that uses a label in the ear tags with a particular identification number. This is embedded into the ear of animal breeds.

Moreover, the ear tagging and ID-collar identification -based animal marking techniques are have long been in use. However, performances of these methods are confined due to its vulnerability to losses, susceptible to damage, duplications, fraud, and significant challenges of security and management [7, 8]. The first reason is that the embedded label can also be eventually damaged easily. The animal's ear can gradually be corrupted because of the long-term usages [8, 9].

The embedded identification numbers also create various infection and critical diseases and health problems to animals. These problems occur due to contagious infections, widespread of critical diseases and many sufferings to animals and the species [5–8]. On the other hand, the contagious infections can spread. The infections can also help to fast-spreading animal diseases, such as foot-and-mouth disease to them [9]. There are no animal biometrics-based identification frameworks available in the literature to classify the suffering animals based on their images using computer vision and image processing techniques.

In this direction, some researchers have contributed to improve the performance of classical animal identification systems using computer vision and image processing approaches [10]. However, the performance of traditional animal identification methodologies is limited due to their vulnerability to losses, duplications, fraud activities, and major security challenges in the livestock framework-based systems [3, 10]. Further, the classical animal identification techniques have failed to cater the required level of security to species or individual animals.

Outstanding to their uniqueness, immutability, distinctness and cost-effectiveness, characteristics of the animal biometrics-based features mapped into automatic animal biometrics-based recognition systems have emerged as a promising research field [10, 11]. The research field of pattern recognition and computer vision has repeatedly been identified as an intellectual frontier whose boundaries of applicability are getting more proliferation due to wide application and uses. This applicability is yet to be more stipulated. This chapter explores a novel application known as animal biometrics.

Presently, animal biometrics is an emerging research discipline in computer vision, pattern recognition, and image processing and cognitive science [1, 3, 9–11].

It is a promising research field that encourages new development of quantified algorithms and methodologies for representing visual phenotypic appearances, detection of visible features, of species, individuals and recognition of animals based on their morphological and biometric characteristics [4, 11]. The animal recognition system based on animal biometrics is a pattern recognition system. It selects the prominent set of salient features from the biometric characteristics of animals [12].

The animal biometrics-based feature characteristics include joint stripe patterns (e.g., coat pattern for zebra), spot point patterning-based features (e.g., for cheetah spot pattern), and skin color patterns behind the gills of whale shark (*Rhincodon typus*), face images (for chimpanzee and chimpanzee), stripe pattern (for tiger) muzzle point image pattern (for cattle), iris-based patterns, and retinal vascular patterns of animal and species [1, 2, 10–12]. The animal biometrics-based recognition systems identify the animal that carries the Turing pattern. In animal kingdom, such visual markings are generally known as coat patterns. These coat patterns are often found on major body parts of animals as colorizations of fur, skin, features, and cuticle. These patterns are identified as visual biometric features known as smart visual design features. For example, the eyespots smart design pattern on body parts (wings) of butterfly, colorful circular design on snake body, joint striped marking on zebra's body [2–4, 13].

Moreover, the fingerprint feature-based recognition systems are also applied for the recognition of chimpanzee based on face images, footprints of fishers (*Martes pennanti*) wildebeest. The significant differences in biometric features are concentrated in the few parts of the body surface of the animal. The set of discriminatory biometric features, such as joint stripes in the coat pattern of zebra, spot patterning on the chest of African penguins, spot point configuration of the whale shark, and dense pattern of muzzle point image of cattle are the proper biometric pattern that presents unique features or combination of permanent features. These biometric features are more appropriate and accurate biometric identifiers to characterize and recognition of the individual species or animals [14].

In recent time, real-world applications of animal biometrics-based recognition system have achieved more attention due to a variety of application for animal monitoring. It also provides enhancement of quantity and quality of the collection of massive videos, captured images of species, collection of ecological data and data processing. However, advance animal biometrics requires better integration of computer vision and machine learning-based methodologies and systems among the scientific disciplines, multidisciplinary researches, ecologists for studies of animal population [15].

Such valuable efforts will be worthwhile due to the enormous perspective of approaches rest with the formal abstraction of biometric characteristics, phenotype appearances, and morphological pattern for building well-developed interfaces between different organizational levels of life [6, 16].

1.2 Interdisciplinary Relevance of Animal Biometrics

Currently, multidisciplinary researchers and various research committees study large populations about different kinds of animals or species based on source information [1–3]. The information about individual animal was captured from different sighting or sources; they always applied the methods of sampling and analysis known as capture–mark–recapture [16]. Figure 1.1 shows the six different species which are visually adapted to their habitats by developing body patterns that effectively camouflage within their environment or group of similar species (conspecies).

The capture–mark–recapture relies on the availability of the approximately vast collection of extensive data regarding repeated sighting or capture of same individual or group of animals. Bounding boxes are created around animals using computer vision techniques. It is applied for highlighting the detected body parts, biometric features characteristics, or morphological traits of interest in video or still image datasets of species or individual animal (shown in Fig.1.2) [1, 17].

Multidisciplinary researchers employ visible color patterns or unique identification number based on the ear-tagging numbers using identification system, paint or dye, sketching of body of animals, embedded of passive integrated transponder and microchips as different markers for identification of individual animal [10, 12–15].

The marking method has been precious for the understanding of population changes, identification, tracking and monitoring of individual animal and species; yet these marking-based identification systems are invasive. Species or individual animal that carries ear tags, embedding microchips and other appliances may be detrimentally affected. Markers might loosen, lost quickly, and wear out, affecting study results and possibly wrecking members of species under observation. It involves capturing and handing the animals to provide the devices [18].

Further, the false marking-based identification approaches mentioned above comprise significant technical–economic drawbacks: The reading of visible

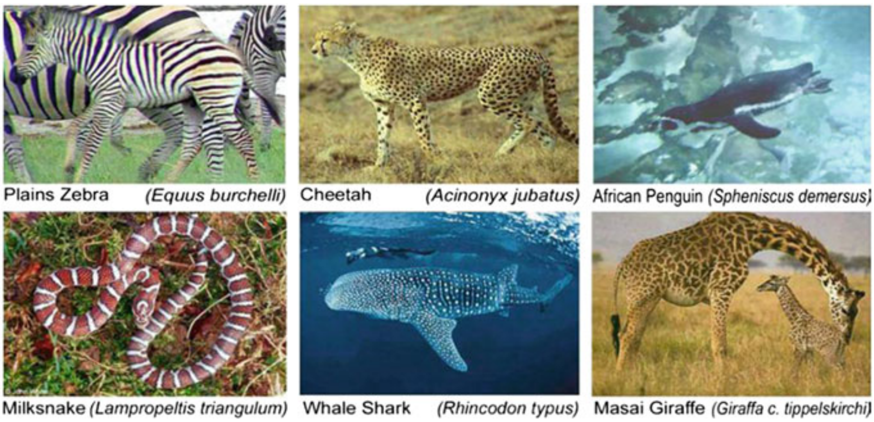

Fig. 1.1 Coat pattern structure of different species [1]

marking ear tags normally requires manual reading on a large scale, while radio- or satellite-based monitoring frameworks and tags are very costly up to 10,000 per device.

In the similar direction, for study of biological and ecological data, animal biometrics also explores novel computing paradigm, systems, and tools for analysis of biological data of species.

These computing, frameworks, and scientific tools can cater assistant to the biologists, biological engineers, multidisciplinary researchers, scientists, and engineering disciplines. Hence, animal biometrics gives quantified approach to design and development of recognition systems. These systems can be used for noninvasive-based identification, easy to use, acquisition of images or video.

These computing paradigms of animal biometrics can be relatively cheap means to identify species as well as individual animal's intimates that operated fast and robustly under field conditions and on large populations [19].

1.3 Promising Applications of Animal Biometrics-Based Recognition Systems

The detection and classification of species is rapidly evolving computer vision, pattern recognition, and image processing techniques that have been used widely in the monitoring and tracking of species. It has a very strong potential to be widely adopted in the broad range of applications and uses [20].

The automation of identification of species or individual animal would cater new avenues of efficiency and economic advantages with respect to the modern farming of cattle and livestock generally. The application of animal biometrics-based recognition system is illustrated in Table 1.1. This table illustrates the applications of animal biometrics-based recognition system. The applications and uses are categorized into three groups as follows: [3, 4, 21].

The traditionally, classical animal identification and livestock framework-based systems have used non-biometrics and invasive methodologies for verification of individual animal. Government organizations and private verification organizations have used ear tag-based identification systems, hot iron, freeze branding, and RFID-based animal identification techniques [3, 22].

The commercial applications have used knowledge-based identification systems for tracking and monitoring species or individual animal. These applications include accurate identification process of animals. It is necessary for verification of users (e.g., ownership, parentages and others) of species or individual animal. The excellent performance offered by advanced computing paradigm, machine learning technique, intelligent sensor devices, and steady improvement in wireless networking technology has made animal biometrics very attractive.

The animal biometrics-based recognition systems are now being increasingly used for all these applications. To achieve major impact, the applicability of animal

Table 1.1 Detail description of identification and verification systems for animals

Identification/Verification	Government	Commercial
Verification of false insurance claims of animal using Unique Identification (UID) Number	Enrollment of animal for UID number	Development of smart devices and android application for animal health
	Generation of National UID database number for animal	
Users (owner, parentage of animal and others) identification	Population study scheme of animals using UID number	Facilitating ownership management of animal using android-developed intelligent smart devices
Identification of registered and non-registered or insured animals using UID number	Health monitoring of animal by identifying and tracking specific animals using UID number	Telemedicine-based health monitoring system for animals using smart devices and technology
Animal biometrics-based identification system for missed or swapped animals	Controlling of critical diseases and vaccination scheme for animal	Information network for animal productivity and health
Parentage identification of animal based on UID number	Monitoring and population study of species or animal breeds	Preparation of biometric feature images of animal database
Bovine registry for seamless integration with UID number and farmer card/farmer ID (e.g., Kisan credit card number which is offered by Government)	Provide controlling schemes to check smuggling and border transfer of animal using UID number	Design smart devices for generating data of animal with demographic, health and production data

biometrics required to be widened. The scientists, engineers, and various research animal biometrics communities have attempted to design and develop tracking and recognition system for classification of endangered animals.

Research concluded that the deep learning algorithms and fundamental coherent ideas of computer vision are used for improving the performance of the systems for various attractive applications. These interesting ideas further can be included for design of robotic systems (e.g., drones) for identification and tracking of animal in their habitats.

Animal biometrics-based recognition system actively collects discriminatory data by traversing the animal habitat to improve both the quality and quantity of captured data and learning systems [1, 2]. These systems can adapt better to highly unpredictable environments, continuous proliferation of wide applications, and increase in system capabilities.

1.4 Prerequisites for Promising Applications of Animal Biometrics

Before beginning the design and development of animal biometrics-based recognition systems for the specific application, it is required to consider the major criterion for evaluating the expected performance measures, accuracy, and robustness under varying field conditions [1–3, 5]. Following are the major criteria:

1. The degree of differentiation between the classes of interest (i.e., species, individuals, behavior, and morphology) can be fundamental to how accurately automated classification can work.
2. Selected discriminatory sets of biometric features of species for class discrimination must be immutable and universally exposed within the study population and stable over time.
3. Also, the class of all selected biometric feature variants needs to be discriminated, unique enough to separate it from similar set of extracted feature patterns which are not of interest for classification of species. These biometrics properties provide a way to determine whether the class of interest of species can be captured with high probability and low misclassification rate.
4. The selection of classification algorithms for extraction of biometric features of interest in audiovisual source data can determine how well algorithms can perform for identification and classification of species.
5. Occlusion (covering and non-covering) of biometric features of interest and low illumination and poor image quality can mitigate performance measures of classification algorithms and its success rates, whereas ideal lighting conditions can provide the homogeneity of phenotypic appearance of species.
6. Similarly, the separability of extracted set of features of interest from background patterns can enhance the success rates of classification algorithms.
7. Any additional context information that can be used for discriminating classes of interest species databases. The machine vision techniques can increase classification accuracy for species classification and identification by selecting the discriminate set of biometric features from databases.
8. The emerging technology, computer vision, and pattern recognition approaches can be used for audiovisual recordings. It will determine how well an animal biometrics-based recognition system can perform the identification and classification of species based on its biometric feature in the long term.
9. Changing environmental conditions can also affect the stability of hardware system. User-friendliness, including intuitive use, software, tools stability and the use of widely accepted dataset formats, and ease of transferring data in the deployed remote systems can improve acceptance by ecologist, new practitioners, multidisciplinary researchers, and biologists.

The rest of the chapter is organized as follows: Section 1.5 presents the brief introduction of animal recognition systems. The major components of the recognition systems are illustrated in Sect. 1.6. Section 1.7 presents the current state-of-the-art animal biometrics recognition systems. Next, the summary of the chapters is given in Sect. 1.8.

1.5 Animal Biometrics Recognition System

Animal biometrics-based recognition system performs on the identification of species or individual animal using extracted features which are similar to recognition of minutiae points in human fingerprints [1–3, 23]. A feature is defined as a piece of information which is significant for solving the computational task related to a certain application. Moreover, animal biometrics can be applied to genuine understanding of feature representation of animals and classifying the phenotypic appearances of different species or animals based on feature representation of different species [23, 24].

The recognition system can be used to recognize and classify species, identification individuals, detect the occurrence of, or variation in, particular behavioral of species or individual animal. It also used to measure morphological feature characteristics and their interindividual (between individuals) variations or intra-individual (being or occurring within the individual) changes over time [1, 20–23].

The examples of animal biometrics-based recognition systems are illustrated in Fig. 1.2. The animal biometrics-based recognition system is used for detecting the animal based on their biometric features, body morphological image pattern, and

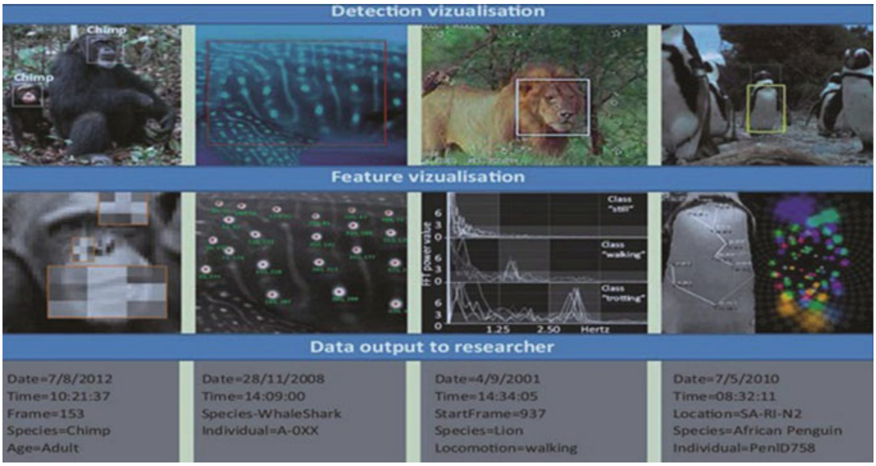

Fig. 1.2 Detection and classification of different species and individual animal using animal biometrics-based recognition system

phenotypic appearances. It also depicts the bounding boxes which highlight the detected body parts or morphological image pattern of interest in video or images.

For example, the animal biometrics-based recognition systems are (1) chimpanzee identification system using face recognition techniques, (2) identification of whale shark using computer vision techniques, (3) detection and identification of tiger using the box bounding methods, and (4) identification of penguin based on coat chest pattern feature. Figure 1.2 shows the detection and classification of different species and individual animal using animal biometrics-based recognition systems and frameworks.

The SLOOP is an animal recognition-based system. It is similar to pattern recognition-based system for recognition and classification of individual animal and species [1, 9, 14, 23]. The SLOOP animal biometrics-based recognition system retrieves the relevant morphological image pattern and biometric features from the stored biometric template database [10–12]. The retrieved information methods fetch information from the salient set of visual features, morphological image pattern, and biometric characteristics for the recognition of species and individual animal [10, 12–14].

The SLOOP animal recognition system uses the cloud computing, machine learning-based techniques, and crowdsourcing methods to greatly improve the identification accuracy of animals and tracking movement and analysis of behaviors of animals [15–17]. The brief description of the component of animal biometrics-based recognition system is discussed in the next subsection.

1.6 Major Component of Animal Biometrics-Based Recognition System

Animal biometrics-based recognition system consists of six important components—(1) sensors component (for acquisition of data), (2) detection of species based on captured image pattern and extraction of feature from image pattern and (3) storage capabilities, (4) similarity matching of query image of species with stored templates in the template database, (5) decision or action executed based on matching scores and defined threshold value, and (6) finally, utilization of extracting feature characteristics.

The expected outputs of animal biometrics-based recognition systems are combined for various applications. These expected outputs of recognition system can encourage the multidisciplinary users, newcomers, and interdisciplinary researchers for better contribution in animal biometrics [1].

Although the appropriateness of biometric characteristics needs re-evaluation in most studies, proven designs and the working prototype model of automated animal biometrics-based recognition systems all comprise five key components: (1) data acquisition phase using sensors, (2) detection and representation of biometric feature pattern, (3) matching of salient set of prominent biometric features,

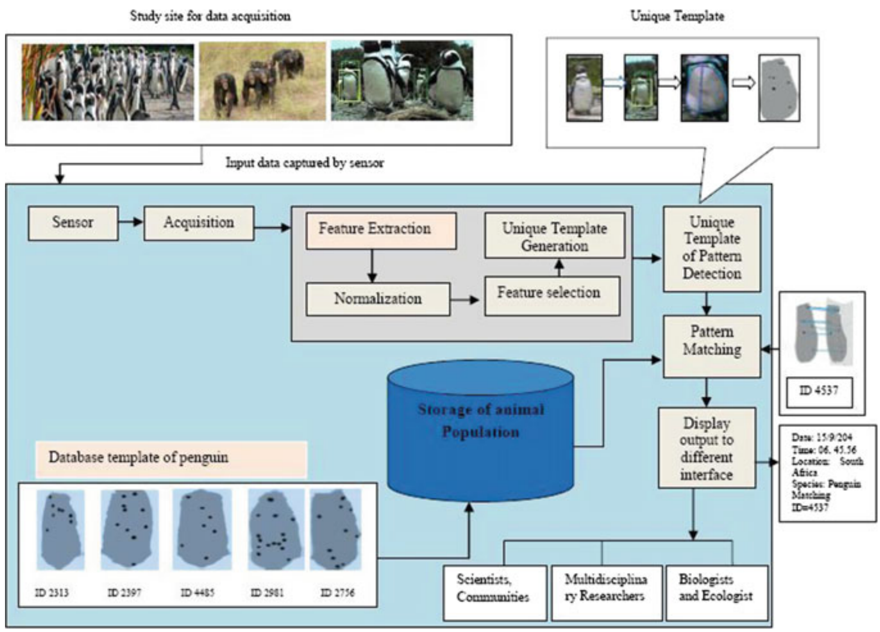

Fig. 1.3 Major components of animal biometrics recognition system

(4) preparation of database and storage capabilities, and (5) finally integrating and interfacing with wide range of applications and users that utilize the extracted feature (information) for recognition and representation of individual animals [24].

Finally, interface component reports the consistent output of the animal biometrics-based recognition system to different users such as scientists, multidisciplinary researchers, biologists and ecologists and software system for further study and analysis. In the available literature [18], the animal biometrics recognition system is developed for whale sharks based on their spot points of body surface. In this system, the whale shark photo-identification library is used for retrieving information of whale sharks.

The retrieved information is applied for whale shark monitoring program in the world. The recognition system uses photos of the spot patterning for individual whale sharks to monitor population, tracking movements and determines whether the same shark has been seen in the area before. The working of animal biometrics-based recognition system is shown in Fig. 1.3. The brief description about each component of animal biometrics recognition system has been illustrated as follows:

1.6.1 Data Acquisition and Data Preprocessing

In the acquisition step, various sensors, such as camera (e.g., surveillance camera, normal camera, trap camera), are used to capture data from the study sites. After data acquisition phase, individual species are detected based on morphological image pattern and biometric features by applying computer vision and pattern recognition algorithms. Animal biometrics-based recognition system extracts the biometric features (e.g., the spot points on the chest of penguin) from the captured data (e.g., video or image database) of animals.

The extracted features are preprocessed and normalized for better representation of extracted features in the feature space. To reduce the noises and artifacts from captured database, recognition system uses the data preprocessing algorithm to process the captured images of species. The salient set of feature vectors are chosen to generate the unique templates from extracted biometric features and stored these templates in the database.

1.6.2 Extraction and Representation of Features

Typically, aspects of the phenotypic appearance of species or individual animal, its movement characteristics, biometric and morphological traits or vocalizations are chosen and used as the biometric entity.

Moreover, determining a suitable biometric entity set for an animal in a study population is a difficult task. Representation of proper biometric features, in a quantifiable way, is also the central algorithmic challenges in the animal biometrics [1, 3]. The major difficulties are: how to capture the discriminatory features of animal body using computer vision-based approaches, pattern recognition technique, and mathematical models and selected tuning parameters of animal biometrics-based recognition. The parameter includes (1) animals are uncooperative in nature because animals actively change their body shape, and (2) pose due to their head movement and body dynamics, (3) body surfaces of animals reflect differently under various lighting, (4) animals frequently become visible as partly hidden by other content, and (5) covering and non-covering problems of animal's body, such as vegetation.

Although computer vision-based recognition techniques capture some of these aspects accurately, these techniques do not allow for an automatic association between them and input data images or video.

1.6.3 Matching of Animal Biometric Features

In matching process of animal biometric system, the small representation of scientific data (e.g., feature vectors) of each subject (animal) is matched.

In the testing phase, a test (query) image of species or individual animal is matched with the stored template database and computes the matching scores using similarity matching techniques (Euclidean distance and distance metric-based, learning-based approaches) for the identification of individual animal. Figure 1.3 shows the major components of animal biometrics recognition system.

1.7 Current State-of-the-Art Animal Biometrics Recognition Systems

In this section, animal biometrics presents the identification and classification of species or individual animal using recognition systems. The recognition systems take the biometric characteristics, morphological image pattern, and phenotypic appearances from the captured images of species or individual animal. The current state-of-the-art methods and recognition systems are illustrated as follows:

1.7.1 SLOOP: A Pattern Recognition-Based System for Animal Recognition

SLOOP is an animal biometrics-based recognition system which uses the computer vision, machine learning and crowdsourcing, and image processing techniques [1, 9, 11]. The SLOOP recognition system extracts and retrieves morphological image pattern and phenotypic appearances of species or individual from captured image pattern for identification and classification of individual animal or species.

Moreover, SLOOP animal recognition system uses pattern recognition, cloud computing, deep learning techniques to greatly improve the population study of species, movement and behavior analysis of species or individual animal. It extracts discriminatory features (information) from the morphological image pattern and biometric characteristics of species or different for the recognition purposes (source: https://sloop.mit.edu) [9].

The working block diagram of the SLOOP computer vision-based animal biometric recognition system is depicted in Fig. 1.5. It requires uploading the images of different species or individual and its metadata as necessary input images for recognition purpose. The uploaded input images are preprocessed for extraction of feature and matching process [1]. Figure 1.4 depicts the preprocessing of various species. In Fig. 1.5, the preprocessing step depicts the preprocessing and enhancement of images of different species as shown in Fig. 1.5a. It mitigates noises by using specularity removal algorithms for Fowler's toad species. By applying the specularity removal algorithm, some regions are marked for identification of species.

As reported in [9, 11], SLOOP vision-based recognition system applied mean shift-based Support Vector Machine (SVM) classification techniques and graph cut-based segmentation approach for retrieving valuable information. The SLOOP

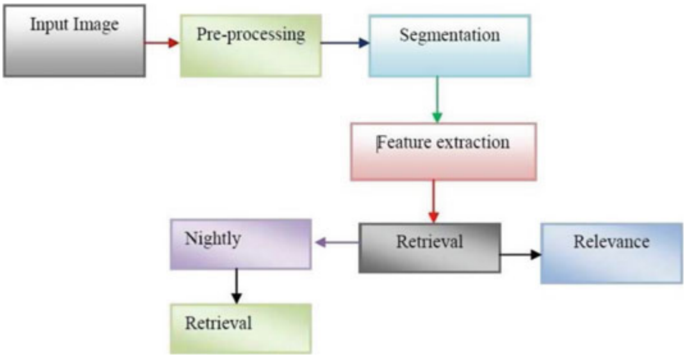

Fig. 1.4 Major components of SLOOP animal identification system

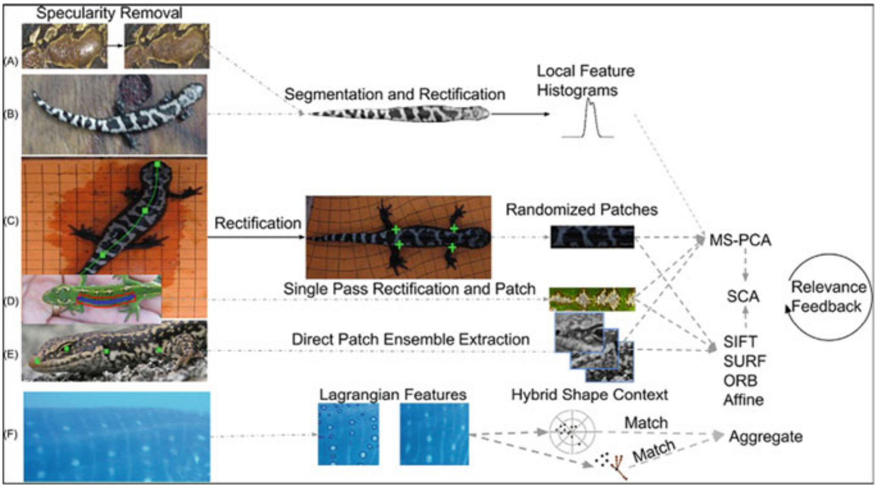

Fig. 1.5 Identification of different species using SLOOP animal identification systems [11]

recognition system also performs the classification of species based on color feature. The color features include red, blue, and green features.

The recognition system extracts the color features from the image of species. The extraction of the color texture features for classification is shown in Fig. 1.5b. Figure 1.5c, d shows a conventional mode of rectification for deformation species with substantial bilateral symmetry as marble salamander's kinks' and focus is to mark a preferred axis of symmetry. In the skins, for example, a few points mark the patches and their orientations are shown in Fig. 1.5e. In recent use, 2 to 4 feature points across the length of the species or animal are adequate to provide excellent spline candidates and rectifications. For other species, the region of interest (ROI)-based patch selection around fiducial feature points with rotation, affine or spline-based normalization, is applied. For example, in case of the skinks (lizards, the family of the Scincidae and the infraorder Scincomorpha) detection, a few points mark the patches and their orientations (see Fig. 1.5(e)) which are improved and used for matching these feature points. Finally, Lagrangian features are extracted by SLOOP system for the detection of whale shark and are depicted in Fig. 1.5f.

1.7.2 Animal Biometrics-Based Recognition System for Face Detection of Chimpanzee

Detection and identification of faces of mammal animals or species and localization of the facial-extracted feature points in the face images are essential for the identification of the individual animal.

The animal biometrics-based recognition system is used for chimpanzee animal and employs face detection-based computer vision models [25–29]. The recognition models consist of multiple classification techniques to classify the extracted set of features of animals. The face detection of the chimpanzee is depicted in Figs. 1.6

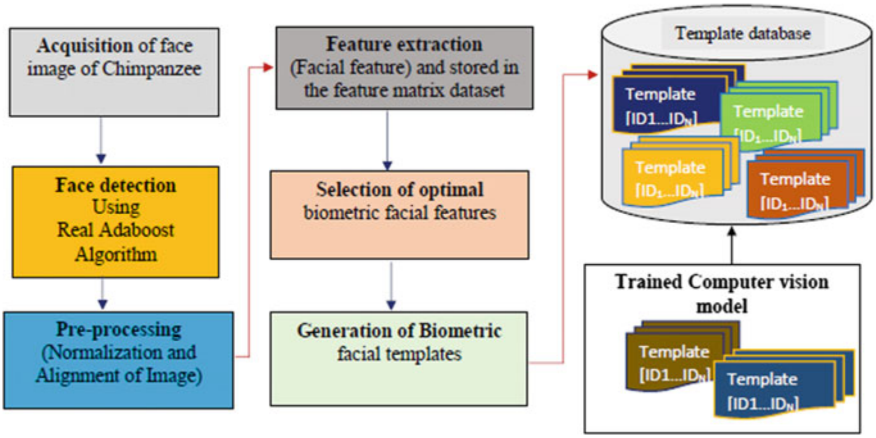

Fig. 1.6 Components of chimpanzee recognition-based systems

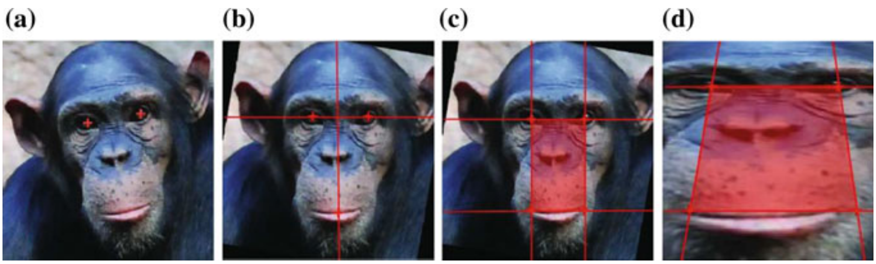

Fig. 1.7 Detection of keypoints feature of face image of chimpanzee [26]

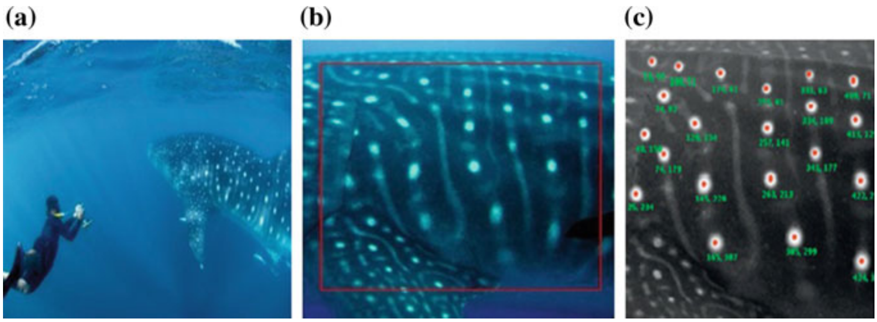

Fig. 1.8 Identification of whale shark species

and 1.7. An animal biometrics-based system comprises three main components. In the first step, chimpanzee faces in images are found and the eyes are located within the face regions.

In the second component, we apply several preprocessing steps like face alignment and lighting normalization to ensure comparability of the facial images across the entire database and improve the systems robustness against lighting changes. The third and last step recognizes the detected and normalized faces and assigns identities to them.

The following subsections explain those three parts in more detail. Figure 1.8 depicts the face alignment and extraction of detected keypoints from face image of chimpanzee.

1.7.3 ECOCEAN Whale Shark Identification System

Currently, animal biometrics has gained recent attention and proliferations due to a variety of application and use in the recognition of species or individual animal across the world. Animal biometric systems have been applied to considerably growing the quantity of uniquely spotting species or individuals based on ECOCEAN whale shark photographic-ID library [17, 21, 30, 31–39].

For the preparation of whale shark photographic-ID library database, a joint endeavor of more than 3500 multidisciplinary researchers, active volunteers, engineers, biologists, and scientists are involved. Their contributions are valuable for the acquisition of more than 43,000 images of whale sharks from more than 3800 individual subjects (whale sharks) [17] (source: http://www.whaleshark.org/). The identification of whale shark based on their Lagrangian features is shown in Fig. 1.8.

1.8 Issues and Challenges of Animal Biometrics

These problems pose a computer vision challenge robustly to extract feature from the captured massive amount of high-resolution image and video. A number of major challenging problem classes are found in the animal biometrics. It reflects the limitations of currently available coherent set of idea, technology and thereby determines the research directions for project undertaken. The major problems of animal are highlighted in the identification and classification of species or animal in the next subsection.

1.8.1 Identification of Animal Based on Coat Pattern

The compact and generic representation and comparison of biometric features for unique component of visual features (for coat pattern-based feature) have not been proposed in the literature yet. Species-specific biometric template database is not available in the literature for identification of animals [23, 24].

If exists at all, they are optimized for totally or partially manual identification of species or individual animal. Mathematical formulation of the robust visual features, morphological image pattern, and biometric characteristics-based representation methodologies for individual representation of specific animal and comparison of coat pattern feature is primary condition for handing the animal biometric identity data inherent to animal or species [24].

1.8.2 Segmentation of Background and Discriminatory Features in Natural Environments

Natural habitat of animal constitutes highly uncontrolled and clutter environments. In the natural environment, animals are free to move from one location to other location. Under these conditions, biometric feature pattern of animal is difficult to separate from background components and undergoes specific alignment and alteration while animals are being enrolled by registration of biometric features [40].

Due to high intra-class variations in the captured image or video database, appearance of same object in an image is found to be different at different times of measurements. The major alterations occurred due to low illumination, poor image quality, partial occlusion (covering and non-covering of body part of animal during vegetation).

The identification of animal in the captured image is shown in Fig. 1.9. Figure 1.9(a) depicts identification of tiger in low illumination images, occlusion and original images. Figure 1.9(b) illustrates identification of zebra based on joint

Fig. 1.9 Major components of animal biometrics recognition system [24]

striped feature representation. Figure 1.9(c) presents tracking of penguin based on chest coat pattern feature using computer vision and pattern recognition approaches.

Based on above research concluded that the emerging research field of animal biometrics is on the verge of providing efficient machine learning techniques, computer vision models, and powerful tools for multidisciplinary researchers, biologists, ecologists, and field practitioners. With the proliferation of distributed animal biometrics-based recognition systems, it has become increasingly significant for ecologists, biologists, and researchers to use to collect and process the collected information on species, individuals, and their behavior. It also provides a better platform for learning of animal biometrics techniques and emerging machine and pattern recognition techniques for training the models in a standardized way and for a broad spectrum of applications.

Although traditional animal recognition systems have bestowed that animal biometrics are feasible and useful to the ecologists, field practitioners, biometric community, and biologists; The significant issues and challenges prevail ahead to develop the field into a universally accepted and applied subjects. Numerous major challenges also lie ahead to develop the field into a widely accepted and applied subject. Bridging the gap between the different multidisciplinary involved the most significant challenge. To achieve the important impact, the applicability of animal biometrics demands to be widened. Innovative ideas and research perspectives include robotic systems, unmanned aerial vehicle (e.g., drones), internet of things (IoT) actively captured the data (multimedia data or biological databases) by traversing the animal habitat to increase both the quality and quantity of collected database. The computer vision-based learning systems and models that acclimate better to extremely unpredictable environments, continuously developing on system capabilities.

1.9 Summary

In this chapter, a comprehensive introduction of the animal biometrics followed by the major characteristics and advantages of animal biometrics is illustrated. In addition, the potential applications, computation capability of systems for feature extraction and representation, interdisciplinary relevance of animal biometrics recognition system in the field of ecology are also highlighted.

Furthermore, chapter explores the general framework of animal biometrics-based recognition systems along with brief description of each major component for detecting and identification of species or individual animal based on their biometric features, morphological image pattern, and phenotypic appearance of animals. The chapter also includes current state-of-the-art animal biometrics recognition systems. Furthermore, the chapter introduces the population distribution of different species, with opportunities, technological challenges and recommendations for animal biometrics. The workings of the art-based system are summarized. Finally, chapter provides the better collaboration to encourage the multidisciplinary researches in the field of animal biometrics.

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Chapter 2
Analytical Study of Animal Biometrics: A Technical Survey

Abstract This chapter is dedicated to the comprehensive survey on the current state-of-the-art in the field of animal biometrics. In addition to this, we have provided a brief introduction to the discipline of animal biometrics followed by the classification and identification techniques of species or individual animal using the discriminatory set of their biometric features in brief. Further, the potential challenges of existing methods and research communities, tools, and data sharing are also discussed.

Keywords Identification · Morphological image pattern · Coat pattern Detection · Feature extraction · Feature representation · Classification Computer vision · Learning model · Pattern recognition

2.1 Introduction

Over the last decades, advancements in computing paradigm and algorithms have resulted in the availability of fast, inexpensive, and advancements in computer vision and machine learning algorithms. These improvements have resulted in the availability of cost-effective and robust recognition system for identification, detection, localization, and tracking of individual species or animals. Moreover, these recognition system uses the efficient feature extraction and representation learning algorithms for classification of species or animals in their habitats.

Newly, animal biometrics research is expanding proliferation due to broad range applications and practices. It is an emerging research discipline in computer vision, pattern recognition, image analysis, and cognitive sciences. Moreover, it promotes new development of quantified algorithms and methodologies for representing, detection of the noticeable features, phenotypic appearances of species, individuals and identification of species or animals based on their morphological image, and biometric feature characteristics.

Animal biometrics further assists the study of animal trajectory and behavior analysis of the individual animal or species. However, advanced animal biometrics researchers need the better integration of computer vision-based feature extraction

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and representation methodologies and systems among the scientific disciplines, multidisciplinary researchers, and ecologists for studies of the animal population [1]. Such valuable efforts of interdisciplinary researchers, scientists, engineers, biologists, ecologists, and senior citizens will be worthwhile due to the enormous perspective of approaches rest with the formal abstraction of biometric characteristics, phenotype appearances, and morphological image pattern for building well-developed computing interfaces between different organizational levels of life. The animal biometrics-based recognition, monitoring systems, and framework perform by computing the extracted set of biometric features and representation of features for the identification and classification of species or individual animal [2]. The identification and classification of species based on the extracted salient set of biometric and morphological image features are suitable and unique features.

The recognition of animal based on discriminatory biometric feature is similar to recognition of minutiae points in human fingerprints. A feature is defined as a piece of information which is significant for solving the computational task related to the individual applications.

Moreover, this animal biometrics can be applied to the genuine understanding of feature representation of animals and classifying the phenotypic appearances of different species or animals based on feature representation of different species. It also identifies the location of the existence of our version with; recognize the individual behavior as well as to distinguish the visual representation of morphological image patterns or animal biometric characteristics of interclass variation and intraclass of species or individual animal changes over the years.

By contrast, visual representations of morphological and biometric feature can capture dynamics in deformable models. The deformable models provide a class of mathematical representational approaches which are apply to describing organic forms of different species. These models capture variations in shape and geometry as part of the model. These models perform the integration of information from different body parts of species. The body parts include various segments of a movable limb. The models learn the flexible links between them.

As with all current state-of-the-art techniques, the major challenges are how to train the models with large training datasets of different visual features and other biometric images. These datasets generally contain thousands of manually annotated images, and important computational resources (hardware, software resources, and better integrations) are needed to build learning-based deformable computing models. In the similar direction, current statistical framework and learning models are available as better alternatives for representation of features. These models are spine fitting [3, 4], diffeomorphic models [5], and shape contexts [6, 7]. Models are used for detecting flexible appearance of species or individual animal, but these models are cost-effective.

Despite efficacious applications of animal biometrics-based recognition systems and frameworks that have improved both system throughput and objectivity of different processing and classification tasks, in the current state-of-the-art method, there is no computer vision-based models and pattern recognition-based frameworks are available for identification and classification of species based on their morphological image pattern, biometric characteristics, and visual phenotypic appearances.

The animal biometrics can challenge the accuracy of the focused human experts in differentiating species or individual animal and analysis of animal behaviors. The identification of animal using embedded marking-based identifiers such as ear tags, hot iron, ear-notches, and sketching patterns are not provide required level of security to animal.

The coming generation of computer vision-based models and animal biometrics-based recognition systems can begin to incorporate population-wide variance information into the recognition process using face detection and synthesis in the higher dimension using 3D face recognition and representational computing models [8].

The effort involved may have to be substantial, because constructions of computer vision models can need computationally extensive resources using 3D population scanning system and frameworks to extract the variation of population-wide anatomical species or individual animal on the level required. The detailed description of classical animal identification methodologies is illustrated in the next subsection.

2.2 Classical Animal Identification Methodology

An essential factor in an accurate and efficient cattle identification scheme is achieving a measured, collectible, innocuous, and time-immutable identifier for each animal [9]. The critical considerations for a secure animal identification method incorporate the practical, dependable, and accurate acquisition of information in a manner that precludes fraud and allows for safe data storage and retrieval [10]. In short, there is the indication of a massive demand for a competent and efficient system of identifying individual cattle [3, 9, 11–14] in the classical animal identification frameworks.

Classical animal identification methodologies have extended deployments, long-time utilization, and documented research investigations. The modern animal biometrics-based identification methodologies demand further research before large-scale applicability and uses. The traditional animal identification methodologies can be grouped into the following groups: (1) permanent animal identification methodology (PIM), (2) semipermanent animal identification methodology (SIM), and (3) temporary animal identification methodology (TIM) [12]. The complete group division of classification of traditional animal identification methodologies is depicted in Fig. 2.1.

The major problems of classical animal methodology and recognition systems stem from their vulnerability to losses, deformations, duplication, and fraud of artificial marking identifiers (such as ear tags, tattoos, and sketch pattern on the animal body), not to mention animal welfare concerns [13]. The current trends of animal recognition methodologies help to solve the major problem using animal biometrics techniques.

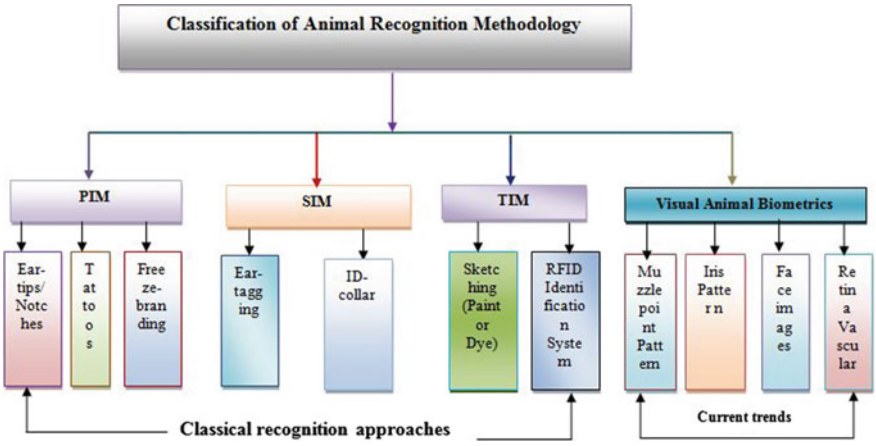

Fig. 2.1 Classical animal identification methods

The current trend-based animal biometric recognition methodologies include biometric-based animal identification. The discriminatory set of biometric features such as visual features, phenotypic appearances, muzzle point pattern, iris pattern, and retinal vascular patterns of species are taken into consideration by the animal biometrics-based recognition systems. The brief description of different animal identification methodologies is depicted in the next subsections.

2.2.1 Permanent Identification Methodology

The permanent identification methodologies generally include manual identification-based marking schemes such as ear tattoos, embodiment of micro-chips, ear-tips or notches, hot iron, and freeze-branding for the identification of individual cattle [3, 14]. The complete description of permanent identification methodologies is given as follows:

2.2.1.1 Ear-Notching-Based Cattle Identification

In classical animal identification framework, the ear-notching-based identification method is a well-known approach. It is a manual procedure for identification of the animal. In the system, this method comprises the process marking the ear of live-stock animals. It performs the V-shaped marking identifier on the section of the right and left ears of the livestock animal. The position of the ear-notch represents the identification of animal based on their labeled numbers.

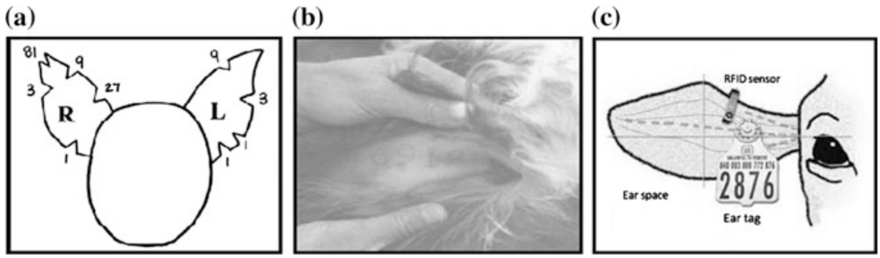

Fig. 2.2 **(a)** Process of ear-notching process of cattle, **(b)** tattooing process on ear of cattle, and **(c)** embedding of ear tag with radio frequency identification (RFID) sensor

It utilizes a compound of right ear notching and left ear notching (animal's number) for uniquely identifying individual livestock animal. This method applies a combination of right-ear notching (litter number) and left-ear notching (animal's number) for uniquely identifying and classifying individual animal. For instance, an animal identified as 18-2 which is recognized as the second animal in the group of 18. Two notches each would mark this animal at the position 9 on the right ear and two notches at the position 1 on the left ear of the animal. Two ear-notches would mark the animal, each ear of the animal at the position nine on the right ear of the animal and two ear-notches at the spot one on the left ear of animal [9, 15]. The resultant outcomes of the ear-notching operations and the marking scheme on the left ear and the right ear of animal are depicted in Fig. 2.2. Ear-notching-based marking methods are also employed for identification of domestic animal such as pet animal, goats, sheep, and pigs.

However, ear-notch-based identification marking technique is not a suitable for medium- and large-sized farms [16], because it requires more caring about the embedded ear-notches. Due to some critical infections, the embedded ear-notches cause critical diseases. Therefore, the ear-notching-based animal identification

Fig. 2.3 Cattle's breed ears have been hurt and disintegrated by ear tags. *Source* Dairying and Husbandry, Institute of Agriculture Sciences, (BHU, Varanasi)

method is not suitable for identification of pet animals. Figure 2.3 illustrates the cattle's breed ears using ear tags. Cattle's ear has been hurt and disintegrated by labeling ear tags in the ear of cattle.

2.2.1.2 Ear-Tattooing-Based Marking Method for Animal

Ear-tattooing-based marking technique is a classical animal identification methodology. It is extensively used for identification of different animals [17]. The ear-tattooing-based marking method uses the letters, numbers, or a combination of letters and numbers.

Special ear tattoo pliers have been practiced to place ear tattoo holes inside the animal's ear, and then, a permanent paint is tapped into the pits, wherever it is confined under the skin's covering and shows up as characters or number [17].

The major advantages of the ear –tattoo-based identification approaches are given as follows: (1) It avoids the problem of distress to the animal; (2) however, it is highly susceptible to alteration, duplication, and removal and fading of colored ink of marked tattoos. Besides, the ear-tattooing-based identification schemes have limited scalability for cattle identification [16].

The major shortcoming of ear tattoo-based identification is depicted as follows: (a) the ear tattoo-based identification is time-consuming, (b) laborious operation for marking the ear of livestock animal and individual cattle, and (c) it is always needed to check, read, and record tattoos for identification of individual cattle in real-time scenario.

2.2.1.3 Hot iron-Branding-Based Marking Method for Animal

hot iron-branding-based marking method is another permanent identification system for identification and tracking of the individual animal in the herd. It uses a farm's brand, letters, or unique numbers which are impacted on the body of the animal to recognize different animals visually.

The hot-brand-bearing identifier is heated to a proper temperature, firmly impacted on the body surface of the animal, and liquidated the hot impacts immediately. It is an invasive approach for identification of individual cattle. The invasive method performs the marking with particular care to the temperature of the branding tool.

Hot iron branding appears to be a simple identification method. However, the significant drawbacks of this approach are as follows: (1) it provides low identification accuracy; (2) the marked symbol can be easily counterfeited, eliminated, or modified; and (3) hot iron branding marking is an invasive procedure. Therefore, it is not sufficient for animal classification.

The hot iron-based marking technique is banned in the UK due to welfare concerns of livestock animal and species [18]. The branding system is utilized for recognizing an animal's ownership preferably that of the animal's identity, which is not practiced for future modern development of the system for animals.

2.2.1.4 Freeze-Branding-Based Animal Marking Method for Animal

Freeze branding is permanent identification approach. It was initially used by Dr. Keith Farrell of Pullman, Washington, for identification of animals in Sweden around 1966. Freeze branding-based marking scheme works differently to the hot iron-based branding method. It depends on destroying the natural pigment in the hair of the animals. The freeze branding operation provides white-hair growth in the area of skin the iron touches. Although this approach is simple, its disadvantage lies in its lack of applicability to white animals. Furthermore, such brands can be tentatively hidden by changing the white color of the brand to mingle with the animal's original color. The freeze branding-based invasive marking and identification method are very simple for marking the individual animal for identification purpose.

The major shortcomings of this approach are as follows: (i) it cannot be performed for marking to white animals; (ii) it is an invasive identification technique, (iii) freeze-brands can be obscured by changing the white color of the brand to blend with the animal's original color, and (iv) it takes more time to do accurately than hot iron-based technique and requires a lot of specialized equipment.

The freeze-branding-based marking and identification schemes are performed for identification of the animals to verify the ownership or parentage of cattle with the matching of the stored personal database. However, some states of country have considered it as the proper marking technique for identification of animals.

2.2.2 Semipermanent Animal Identification Methodology

In the classical cattle identification approaches, semipermanent identification methodology (SIM) is used to provide a required level of security to livestock animals by using ID-collar and ear tag-based identification techniques. The brief description of the SIM-based identification approaches for identification of individual animal breeds is discussed in the next subsections:

2.2.2.1 Collar-Based Marking Method for Cattle Identification

Animal collar-based identification is a semipermanent identification approach. In this method, collar devices are attached to the neck of the animal or cattle to allow it to be harnessed and tied up for various other reasons.

A unique identification number is embedded in a piece of material. The embedded numbers are frequently placed on collars for controlling and tracking of the animal. Similarly, collar-based identification systems are also utilized for monitoring and tracking of non-pet animals throughout the world.

Further, the collar-based identification systems can also be used for zoo animals and domestic animals including cattle or calves, goats, and sheep. The major shortcoming of collar-based identification approach is that it can be dangerous for pets that live in crates or which might get stuck in tree branches and that is why safety collars have been developed. Breakaway collars are specially designed to prevent the pet from choking or getting stuck because of their collar [15, 19].

2.2.2.2 Ear-Tagging-Based Animal Identification Method

Ear-tagging-based identification method is one of the numerous widely applicable and accepted identification methods for livestock animals in the different country. Ear tagging is a method that uses a label with a particular identification number which is attached to the ear of breeds. Ear tagging system provides convenient and low-cost identification of individual cattle. It also reduces manual marking-based identification problems in the conventional animal identification techniques and livestock framework-based system. However, It such as suffering to the animal and difficulties about the visual investigation by humans [9, 14, 19]. The first reason is that the ear-tag label can be lost easily. The label can also be eventually damaged, and the ear will gradually be corrupted because of the long-term usage.

Ear tags can be formed from metal or plastic material components. It can be identified with barcodes, numbers, or color-based attributes [20]. The ear tags are associated with wireless chips [16].

The design considerations of any ear tag should present the item tamperproof and visually legible, and the cards should live attached without harming the animal [17, 18, 21]. The ear-tagging-based identification techniques have been progressed for cattle identification in some ways. However, there is also being a limitation with ear-tagging-based identification systems for recognition of beef cattle because ear tags can be scratched from the cattle's ear and it destroys the ear of cattle in the long-term usages.

The ear-tagged labels have been missed if it is not applied correctly to cattle's ear [21]. The different interdisciplinary researchers, animal monitoring, and tracking professional [22, 23] decided that the embedded labels of ear tags could also be ultimately damaging and corrupt the ear of animal because of the long-term usages.

The low reliability and recognition rate (accuracy) are also significant problems for identification of individual animal [24]. Therefore, ear-tagging-based techniques for animal identification are unable to cater the required level of better monitoring and security to the animal in the traditional animal identification methodologies [25].

2.2.3 Temporary Animal Identification Methodology

The electric signal-based techniques such as radio frequency-based identification (RFID) and sketch pattering (e.g., paint or dye-based marking techniques)-based identification approaches are known as temporary identification method (TIM) [24]. The detailed description of the temporary animal identification methodology for animal identification is given in the next subsections.

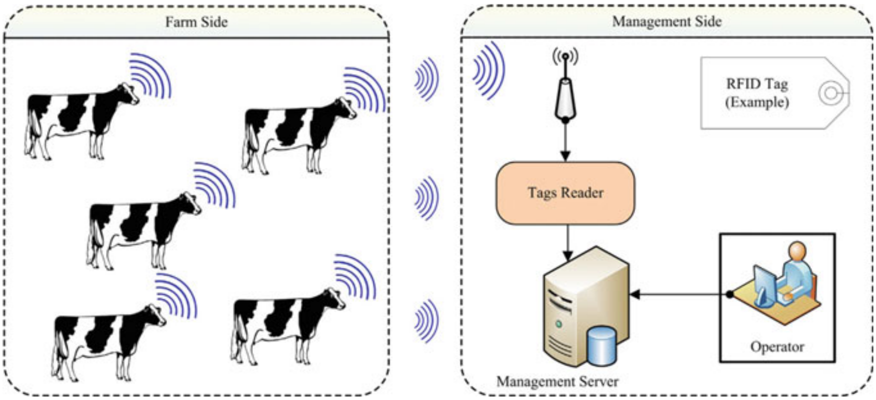

Fig. 2.4 Cattle monitoring and tracking using RFID-based sensor network

2.2.3.1 RFID-Based Identification Method of Animals

RFID system deploys radio waves for identification of human or objects [25].

RFID-based frameworks are extensively used for tracking the animals throughout the world. It is recognized as a suitable system in a wide range of industries and applications, including cultivation, access control, supply-chain product tracking, vehicle parking system and tracking the objects, software systems as working models for library books to keep the record tracking, and smart systems for shopping [26, 27].

A generic RFID system consists essentially of RFID tags (transponders), an RFID scanner reader, and a management host or server [4–8, 27–30].

The general structure of an RFID-based framework and system for cattle monitoring and tracking is shown in Fig. 2.4.

2.2.3.2 Sketch Pattern-Based Animal Identification

The sketching pattern-based animal identification is a manual approach. The sketch pattern-based identification system uses the broken color information of animal breeds (e.g., Ayrshire's, Guernsey's, and Holstein's cattle breeds). However, the sketch marking-based patterning-based methods need better drawing ability of persons for coloring and making sketch pattern on the body surface of cattle [31, 32].

The comparative analysis of classical animal identification methodologies is illustrated in Table 2.1. The comparison of classical animal methodologies for identification of animal is depicted based on different attributes such as reliability of approaches, computationally expensive (cost analysis) for design and development of the animal identification-based framework systems, and livestock monitoring systems [32, 33]. The comparative analysis of different techniques also plays a vital role indesigning the animal monitoring systems for modern farmhouses.

Table 2.1 Comparative analysis of cattle identification

Identification/ attribute	PIM				SIM		TIM	
	Tattoo	MC	ET	FB	Collar	ETG	Paint/ dye	RFID
Reliability	M	VH	H	VH	LO	LO	LO	VL
Cost analysis	M	VH	LO	M	LO	LO	VL	VL
Visibility	VL	NAT	M	H	VH	VH	VH	NAT
Longevity	H	VH	VH	H	LO	LO	VL	LO
Risk of harm	LO	VL	M	LO	HL	VH	VL	VL
Accuracy	H	VH	NAT	LO	H	LO	VL	H
Uniqueness	H	VH	NAT	LO	H	M	VL	VH
DBR	H	VH	NAT	LO	LO	M	NAT	VH

MC microchip, *ET* ear tattoos, *FB* freeze branding, *ETG* ear tag, *RFID* radio frequency identification, *SIM* semipermanent identification method (SIM), *PIM* permanent identification method, *TIM* temporary identification method, *DBR* database required, *NAT* not available, *M* medium, *H* high, *VH* very high, *VL* very low

The different comparison factors are analyzed for comparing the cost of various systems and devices.

In the available literature of classical animal identification methods, the selection of the most appropriate identification method for the animal from the list of classical methods is not the simple task. The selection of technique involves different parameters such as farm size, number of herds, and number of animal or species in each herd on top of the evaluation factors. The different cost analyses such as the predicted cost, protection, and security of animal identification and operability are presented in Tables 2.2 and 2.3, respectively.

On small-scale-based farmhouses and livestock framework in the world, the deployment costs of the livestock monitoring systems are a big challenge for the different government organization. These significant challenges play vital roles for modern livestock farmhouses when selecting the identification methods [34]. However, the large-scale-based animal identification methods are not required on such livestock frameworks or farms due to the limited number of registered animals [35–37].

The classical animal identification techniques fail to cater solutions using the artificial marking techniques. Due to artificial markings such as tattooing on the animal's ear seem to be a simple identification method it does not contribute enough accuracy and reliability as it can be easily duplicated, removed, or altered. Therefore, these classical animal identification techniques are unable to identify the cattle.

Visual animal biometrics-based solutions can provide efficient solution for accurate identification of animal. For cattle, muzzle point image is primary biometrics features. Baranov et al. [38] has shown that muzzle dermatoglyphics (i.e., ridges, granula, and vibrissae) from various animal breeds are mostly differences which are similar to the recognition of human’s fingerprint. Visual animal

Table 2.2 Comparison of classical identification methods for animals

Classical methods		Livestock related		Marker-based identification					Operability	
		LPPSDFC		EAD	SRORD	PFFD	DTM	AFF	EA	SS
PIM	Ear notching	MO	NA	INT	INT	INT	LO	High	LO	LO
	Ear tattooing	MO	NA	MO	MO	INT	LO	High	MO	LO
	Hot branding	LO	NA	MO	High	INT	LO	High	MO	LO
	Freeze branding	High	NA	MO	MO	INT	LO	INT	MO	LO
SIM	Collar-RFID	High	High	MO	MO	LO	High	High	High	MO
	Ear tags	High	LO	LO	LO	INT	MO	MO	MO	LO
TIM	Injectable RFID	MO	LO	High	INT	INT	High	LO	INT	INT
	Paint/dye	LO	LO	LO	LO	LO	INT	LO	INT	LO
	Plastic bar code	High	High	LO	MO	LO	LO	MO	High	MO
	Embedded metal ear clip	INT	High	MO	INT	LO	LO	High	High	MO

MO moderate, *LO* low, *NA* not available, *INT* intermediate

biometrics develops quantified methods for representing and detecting the phenotypic appearance of animal or species, individuals, behaviors, morphological traits and biometric feature-based animal identification. The current trends in recognition methods for species are described in the next section.

Table 2.3 Comparative study and cost estimation of various classification approaches

Classical methods		Marker related		Operability		Unbound Cost	Longevity	Predicted Cost
		POFAFF		EA	SS			
PIM	Ear notching	INT	High	MO	LO	High	High	High
	Ear tattooing	INT	High	LO	LO	LO	High	INT
	Hot branding	INT	High	MO	LO	LO	High	High
	Freeze branding	INT	INT	MO	LO	MO	INT	High
SIM	Collar-RFID	High	High	High	MO	LO	LO	MO
	Ear tags	High	LO	MO	LO	LO	LO	INT
TIM	Injectable RFID	MO	LO	INT	INT	MO	LO	INT
	Paint/dye	LO	LO	INT	LO	MO	LO	LO
	Plastic bar code	High	High	High	MO	LO	High	LO
	Embedded metal ear clip	INT	High	High	MO	NA	MO	High

PSDFC protection and security during food chain, *LP* lack of pain, *EAD* ease to access database, *SRORD* success rate of reading database, *PFFD* protection from fraud and duplication, *DTM* data transfer and management, *AFR* affordability requirement, *EOAS* ease of application system, *SOS* scalability of system, *MO* moderate, *LO* low, *NA* not available, *INT* intermediate, *LP* lack of pain

2.3 Visual Animal Biometrics: Current Trends of Animal Recognition Methodologies

In this subsection, overview of current trends of animal recognition methodologies is discussed in detail [35]. The comparison of different methods for identification of cattle is also illustrated in the next subsections.

2.3.1 Retinal Vascular Pattern-Based Cattle Identification

Retinal vascular patterns are one of the most biometric features for identification of cattle. It is similar to human retinal scans. These retinal scans are not changeable over time [31, 32]. The acquisition of retinal image pattern of cattle using enrollment process is shown in Fig. 2.5.

Furthermore, injuries to the eyes cornea do not interfere with the ability to obtain an accurate retinal image. The raw retinal image used for enrollment and the physiological structure of retinal vascular patterns are shown in Fig. 2.6.

Similar to human retinal patterns, the retinal vascular pattern of individual cattle is confronted with the same challenges of acceptability, collectability, and processing time in recognition of livestock based on their retina pattern [33].

These significant problems that arise in the identification of animal encompass the difficulty for capturing the retinal images of animals due to eye diseases and a failure to control the movement of the animal long enough to capture the retinal images accurately. Retinal imaging is a primary biometric trait for the identification of animals. Based on available literature, retinal image-based cattle identification

Fig. 2.5 Enrollment of retinal image pattern of cattle

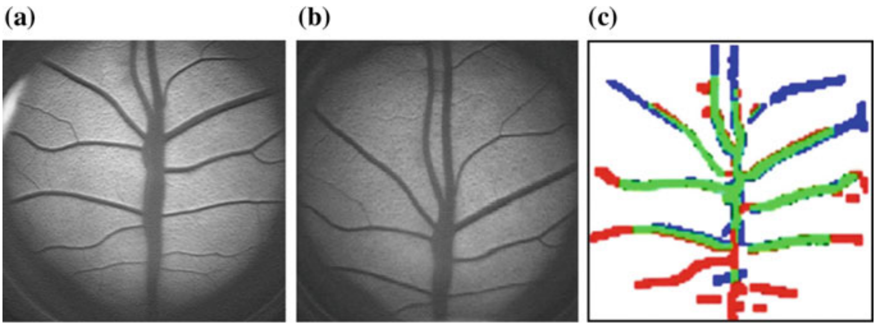

Fig. 2.6 **a** Enrollment of cattle using retinal pattern, **b** image of same retinal pattern, **c** extracted features [31]

systems have been gaining more advancement for registration of different livestock animals.

In [39], the authors proposed a computer vision-based approach for identification of 4-H beef and sheep. In their research study, the experimental results are evaluated based on the captured retinal image pattern of cattle using retinal imaging technology as a means of permanent identification of 4-H beef and sheep.

The retinal image pattern of 491 beef races and 220 sheep were captured using OPT reader device during enrollment for 4-H beef and sheep. The verification accuracies were 96.2 and 100% that were reported for beef cattle and sheep, respectively.

In the similar direction, authors Rojas-Olivares et al. [40] proposed a biometric recognition system for identification of sheep based on their retinal image. The complete description of the experimental results is given in [41–43].

The author, Barron et al. [43], reported the retinal recognition as a biometric method for sheep identification. The objective of this study was to assess the accuracy of a commercially available retina biometric-based method for sheep identification [44, 45].

In the similar direction, the author Corkery et al. [10] reported the biometric framework-based face recognition for sheep. The captured face image database of sheep is used for feature extraction by using holistic feature extraction and representation technique. The independent component technique is also used to compute the independent feature component from extracted facial features. The 180–200 salient set of feature components were extracted from database.

The experimental results are performed to evaluate the performance of proposed approach independently on several normalized facial images from 50 sheep (sets of two, three, and four training images per sheep). The performance of proposed approach is evaluated on a separate set of face images. The three normalized facial images per sheep have been considered for training the proposed system. The similarity matching scores are measured using the cosine distance-based classification method. The proposed approach yielded 95.30–96% classification accuracy.

In the similar direction, the author Shanahan et al. [46] proposed biometrics recognition-based framework for traceability of beef cattle. The underlying idea is that proposed system has been applied radio frequency-based identifiaction (RFID) for the tracking of individual cattle and the biometric identifier (retinal) for verification of cattle identity. The bio-track database has been outlined for the storage of retinal images.

Allen et al. [31] proposed cattle identification framework based on retina image pattern of cattle. For the evaluation of experimental results, 869 bovine animals were used to capture 1738 retinal image modalities (from both eyes), with a maximum achieved identification rate of 98.30%.

2.3.2 Iris Pattern-Based Cattle Identification

Iris pattern is a dominant biometric characteristic for identification of the individual animal. The animal biometrics-based recognition system extracts the iris pattern as the prominent feature for identification of animal or species. It is similar to human iris pattern-based recognition. The iris image pattern of human has the discriminatory set of biometric features such as furrows, rings, crypts, and a corona in the iris pattern.

The author, Daugman [47], illustrates an accurate and reliable recognition of individual based on iris patterns using 2D Gabor filtering [48]-based recognition approach that is used to modulate iris phase information [49–51].

The authors, Lu et al. [51], proposed the biometrics-based system for cattle identification based on iris pattern of cattle. The proposed system based on iris analysis includes iris imaging, iris detection, and recognition. In the initial phase, the image quality of the biometric features of captured sequences is first assessed in order to determine the quality of biometric features of iris pattern and a clear iris image is selected for the subsequent process.

In the second phase, the inner and outer boundaries of iris image pattern of cattle are fitted, respectively, as two ellipses based on the edge images during image segmentation. After that, segmented iris pattern of cattle is obtained on which normalization of extracted features from the segmented image pattern is performed using the geometric method.

Finally, 2D complex wavelet transform (2D-CWT) technique is applied to extract local features and global characteristics of the iris pattern of cattle, and the phase of the filtered cow iris is encoded as features. Experimental results indicate the effectiveness of the proposed approach.

The muzzle print images (nose print pattern of cattle) are unique and suitable biometric characteristics for identification individual cattle [35, 52, 53]. The complete description of the cattle identification based on muzzle print images is given in the next subsections.

2.3.3 Cattle Identification Using Biometric Features

A fundamental problem with traditional cattle identification systems in the classical animal identification is that systems or frameworks all depend on artificial devices. These devices are attached and embedded in the animal's body. Biometric characteristics of cattle are employed for identification of livestock. The muzzle point image, face biometric features, spot points on tiger's body, coat pattern (e.g., standard striped-based coat pattern for zebra), iris pattern, and retinal imaging are the biometric features of individual cattle. The biometrics-based solutions offer a rapid and secure mechanism for providing an actual identification and verification of animals or species using animal biometrics-based recognition systems.

The recognition system ensures the identification and traceability of animals back to the farm of origin [14, 54, 55]. In animal biometrics research, cattle identification is an essential issue in the modern livestock management frameworks and traditional animal recognition systems. Cattle identification provides a method for registration and traceability of individual cattle. The listing of cattle is known as enrollment process of livestock using their biometric features such as muzzle point images or face images.

Cattle identification plays a vital role in animal breeding, production, and distribution of the animal races. The major biometric characterizes of cattle can be categorized into three groups: (1) muzzle print image-based cattle identification using manual approaches, (2) muzzle point image pattern-based identification of livestock using smart devices, and (3) face biometric feature-based identification of cattle.

2.3.4 Muzzle Print Image-Based Cattle Identification

Muzzle print image-based cattle recognition is a classical animal identification approach for identification of individual cattle. The muzzle print images of cattle as a mean of cattle identification have been done research and studied since 1921 [44].

The muzzle print image capturing devices, equipment, and materials is used in the capturing process of muzzle print image of cattle for identification of cattle. The equipment is used in the image acquisition of cattle's muzzle print which is depicted as (1) white paper (e.g., A5-size white papers are used for taking print image on it), (2) stamp black or blue ink, (3) soft cottons, and (4) tissues for cleaning the snot from nose of cattle [45, 46].

The muzzle print image pattern of cattle is a unique biometric feature for unique identification and classification of animal breeds. In the muzzle print image-based cattle identification system, it includes well-defined procedures for capturing and digitization of captured muzzle print image of cattle. The classical cattle recognition systems and frameworks include capturing devices using blue or black ink. The ink is first spread over nose of cattle. The soft cottons and tissues are used to clean the nose of cattle before data acquisition. After that, the inked nose is impacted on white A-5 papers in the multiple sessions for preparing the database of muzzle print image of cattle.

The acquisition procedure of muzzle print image of cattle needs better assistants from staff members of dairying and husbandry department to keep still the head of cattle using strong ropes, because animals are not cooperative in nature for animal biometrics-based recognition systems. The well-defined procedures of capturing of muzzle print image of cattle are depicted as follows (procedure 1): The identification procedure of cattle based on muzzle print image is given as follows (shown in Algorithm 2.1):

Algorithm 2.1: Data acquisition algorithm/procedure for muzzle print image of cattle

1. The head of cattle has to be kept still using a strong rope.
2. **Cleaning process**: Cleaning the muzzle print image (nose) of cattle to remove snot using soft cotton and tissues.
3. **Removal of noise**: Once the snot is removed from nose, use a thin blue ink layer using soft cottons on the muzzle point of cattle.
4. **Alignment and movement**: Muzzle print image of cattle is taken on the A-5 white paper with upward rolling movement.
5. Repeating steps 2, 3, and 4 until the number of muzzle print image is adequate.
6. The lifted muzzle print image of cattle captured on A-5 white paper.
7. **Transformation of image**: Captured muzzle print images are required to convert into the digital images using image processing technique with resolution 300 dpi.
8. **Preprocessing of muzzle print image**: The last step of data capturing and preparation is digitalization and preprocessing of captured muzzle print images for cattle identification.

The muzzle print image-based identification of cattle needs some improvement to process the captured images of muzzle print of cattle, because the image is captured with blue ink using manual approaches (shown in Algorithm 2.1). The muzzle print-based cattle recognition system is shown in Fig. 2.7.

Figure 2.7 presents all the steps of cattle recognition. It illustrates the acquisition of muzzle print image using blue ink with the help of dairying and husbandry staffs. The captured print images are preprocessed using image processing technique and segmentation of preprocessed image. After segmentation of muzzle print image, the bead and ridge features are extracted from selected region of interest-based images and features are stored in database. The feature of query print image is matched with stored feature templates.

The similarity matching of muzzle print images is done at two refinement levels. In first level, muzzle features are matched with query image, but some false matches (reported in red circle and triangular figures in the test and trained images) are reported in this experiment. The false matches are taken consideration by refining strategy at level 2 for improving the identification accuracy for cattle recognition.

The digitalization of captured print images of cattle is done by performing the preprocessing and transformation of the print image into the grayscale image using image processing techniques. The impacted muzzle print images of cattle are poor quality of the image. Therefore, muzzle print image is required to transform by

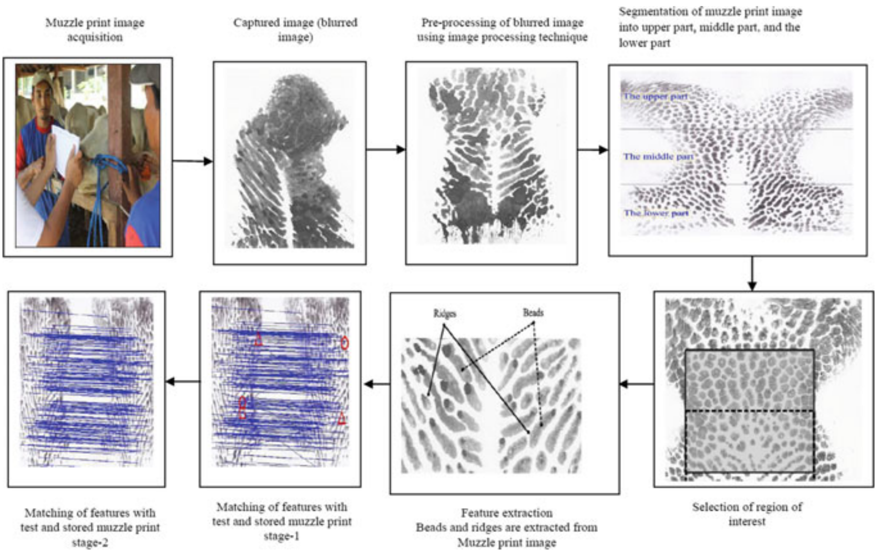

Fig. 2.7 Block diagram of cattle recognition based on muzzle print images of cattle

converting and transformed into 300 dots per inch (dpi) muzzle print images for identification of individual cattle. Digitization and transformation process consumes more time-consuming processes for the large-scale database of muzzle print image of cattle. Therefore, muzzle print image-based cattle identification fails to yield better identification accuracy using classical muzzle print image-based cattle identification approaches.

The acquisition phases of muzzle print image-based identification systems do not include the intelligent sensors (digital camera, smartphones, and others). High-quality images are not captured. Only blue ink-based muzzle print images are captured in the acquisition step. The blue ink-based captured muzzle print image includes various artifacts and noises with the print image of muzzle pattern of cattle. Therefore, it needs the efficient computer vision, pattern recognition, and image processing techniques to get better quality of the muzzle print image for identification of individual cattle.

Over the past few years, advancement in classical muzzle print image-based recognition system has resulted in the availability of fast and inexpensive processors, smart devices, and advancements in data capturing devices and communication technology in visual animal biometrics.

Recently, Interdisciplinary researchers, scientists, engineers, ecologists, biologists and research communities of animal biometrics have started designing and developing of automatic identification, tracking, and representation systems and framework for animals or species based on their biometric features, and morphological image pattern. These research groups also performed the identification, monitoring, and tracking of individual endangered species or animal using smart devices such as camera, smartphones, and other intelligent capturing and computing devices and systems.

Currently, in visual animal biometrics, muzzle point image-based cattle identification has been achieved more attention for identification, monitoring and tracking of livestock animals and species. The author Mishra et al. [56], Johansson [57] and Baranov et al [38] have proven that the muzzle point image pattern of cattle has discriminatory biometric feature pattern. The biometric feature of muzzle point image is known as immutable biometric characteristics for identification of individual cattle.

The identification of individual cattle using muzzle point image pattern has characteristic like the fingerprint recognition of human. The identification of cattle based on muzzle point image is shown in Fig. 2.7. Figure 2.7 depicts the recognition of minutiae point in human fingerprint which is similar to muzzle point feature of cattle.

Several biometric traits of animals have been investigated, among them being muzzle print image pattern [58], iris patterns [59], retinal vascular pattern, facial image of cattle [60, 61, 62], and DNA profiles [63]. Each of these biometrics characteristics can be measured and recorded in the database, providing each animal with a unique identity that remains associated with that animal for life.

The muzzle print image of cattle is also a suitable biometric feature for identification of individual cattle. The muzzle print feature can provide better platform for registration and verification of cattle.

The muzzle point image consists of two patterns: (1) bead image pattern and (2) ridge image feature pattern. The minutiae points are formed by ridge bifurcation and ridge termination feature points. The two most discriminatory biometric pattern structures are known as ridge endings and ridge bifurcations. These biometric features form immutable and unique feature called minutiae point.

Figure 2.8 depicts the examples of ridge terminal (endings) and ridge bifurcations. Based on this observations, it is concluded that feature representation of minutiae points in fingerprint is similar to bead and ridge feature representation in muzzle point features for identification of cattle.

Cattle identification system refers to the process of matching a test muzzle point image against a stored muzzle point image database to find out similarity matching

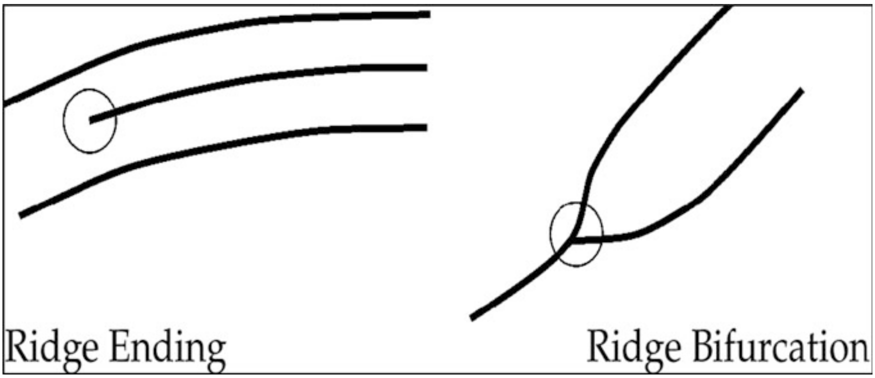

Fig. 2.8 Ridge ending and ridge bifurcation of muzzle point image pattern of cattle

score for establishing the identity of individual cattle. The main objective of cattle recognition system is to quickly determine whether a test muzzle point image pattern is present in the stored muzzle image database of cattle and to retrieve those which are most similar to the test from the stored database.

On the other hand, cattle identification system faces the great challenges with respect to collectability and accuracy of system, and as such, it is considered as a research field still in the development [64, 65]. The similarity matching between muzzle point features and minutiae point feature of human is shown in Fig. 2.8, respectively. The complete description of cattle recognition using muzzle print image of cattle is illustrated in the given subsections.

2.3.5 Muzzle Point Image Pattern-Based Cattle Identification

Similar to the recognition of minutiae points in human fingerprint, the captured images of cattle also present different biometrics characteristics, such as grooves, or valleys, ridges, and bead structural patterns in the muzzle point image (MPI) of cattle. These uneven muzzle image features, distributed over the dense skin surface of the nose area of the cattle, are represented by white skin grooves and by black convex areas girdled by the grooves.

A muzzle print image of the animal can be recognized as an accurate biometric identifier, time-immutable identifier, and proper biometric characteristics, one distinguishing enough to identify an animal with accuracy comparable to that accomplished by human fingerprints [63]. The muzzle print images of animal have been examined since 1921 [66]. The muzzle point image pattern-based identification of cattle is shown in Fig. 2.9, respectively.

The author Minagawa et al. [67] proposed the first biometric-based framework for identification of individual cattle in which the joint pixel intensity feature of the grooves was extracted by applying the image processing techniques (e.g., filtering, binary transformation of captured image, and thinning).

The identification was then achieved by matching the joint pixels of an image of cattle with stored image database to itself. The experiments of their proposed approach were conducted on the prepared muzzle print image database of 43 subjects (cattle). In this experiment, the similarity matching score is achieved at 12% and maximum scores at 60%. The experimental results also illustrated that the identification accuracy was around 30%.

In the similar direction, feature descriptor-based feature extraction and representation techniques such as scale-invariant feature transform (SIFT), speeded up robust feature (SURF) and its variant Uniform-SURF (U-SURF), local binary pattern (LBP), Dense-SIFT are used to extract the muzzle print images of cattle for unique identification of cattle [10].

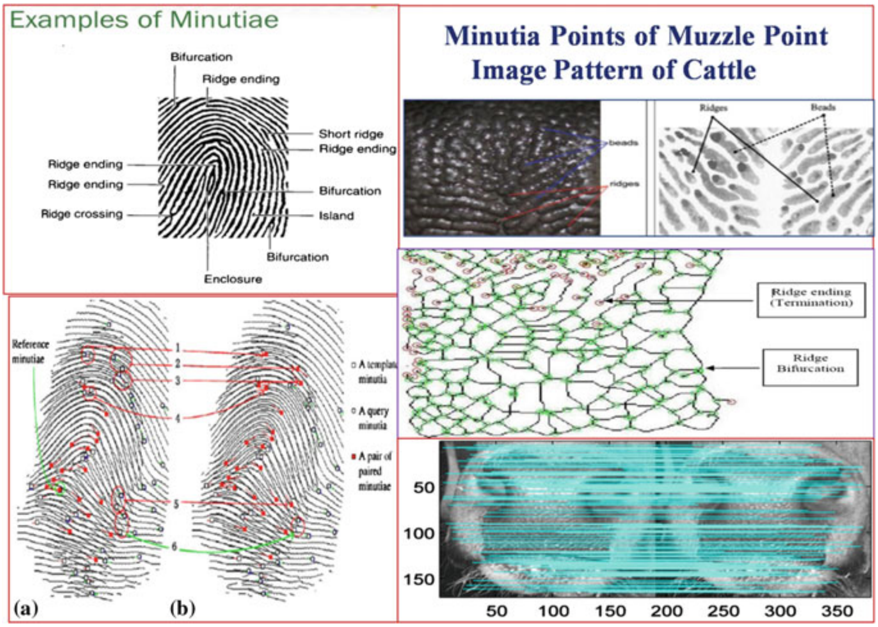

Fig. 2.9 Muzzle point-based cattle identification

Noviyanto and Arymurthy [35] proposed a method for extracting the texture features of muzzle print images of cattle. They performed the experimentation on the 15 muzzle print image database of cattle to validate the experimental results for the identification of cattle. The authors have applied only 10 images to train the proposed model in the training phase, and 5 images were used in the testing phase. The SURF-based feature extraction-based descriptor technique was found superior to U-SURF-based technique, one as the former achieved 90% identification accuracy against rotation conditions.

Awad et al. [36] presented a proposed method for classification of cattle breeds based on their extracted set of biometric muzzle point features. The complete experiments were performed based on muzzle print features that exhibit unique identification of individual cattle.

In [68], the author proposed a system for identification of cattle using muzzle print images. The identification of cattle is performed using supervised classification techniques on the computed principal component features of muzzle print images.

The support vector machine (SVM) [69], linear discriminate analysis (LDA), and Tucker tensor decomposition (TDL) classification techniques are applied to classify the extracted features. The performances of these classifiers are compared on the same dataset of muzzle images with different experiment settings. The experimental results are evaluated by F-score which is equal to 0.750.

The author, El-Bakry et al. [70], presented a method to identify the bovine (cattle races)-based muzzle pattern identification. The proposed approach extracts the texture features of muzzle print images using texture feature method. The proposed method has been implemented by using box-counting-based fractal dimension-based technique. The experimental results illustrated that feature vector for different muzzle print images of cattle is highly symmetry.

In [71], the authors proposed a muzzle-based classification system for cattle using multiclass support vector machines (MSVMs). The box-counting algorithm is applied to compute the feature vectors after detection of keypoints of muzzle images as feature of cattle.

The experimental results reported that advancement of the presented system based on muzzle print features using classification techniques performed the best and achieved 96% classification accuracy in case of increasing number of classified group to ten compared to 90% classification accuracy achieved by traditional classification system.

In [72], Hosseini et al. proposed a recognition system for scanning and identification of cattle based on muzzle pattern of an animal. The proposed system comprises a scanning segment configured to fit over the muzzle (nose) of the animal and a plurality of scanning cameras attached to capture the muzzle image pattern of cattle from different angles. The recognition system considerably comprises an image processor for combining and processing scanned muzzle patterns from the plurality of scanning cameras and presenting the processed muzzle pattern on an image viewer. A handle segment has been incorporated a plurality of control buttons and a communication interface for connecting and transferring data to an external device.

In the similar direction, the authors Tharwat et al. [73] proposed a method for identification of cattle using local binary pattern-based feature extraction and representation technique. The local binary pattern-based feature descriptor technique was done as it extracts robust texture features which are invariant to rotation and occlusion of the muzzle print images. The results showed that their proposed approach achieved 99.50% identification accuracy.

In [74], the authors proposed a framework for identification of cattle breeds. The proposed system presents an invariant biometric-based identification system to identify cattle based on their muzzle print images. The recognition system extracts the muzzle print feature using speeded up robust feature (SURF) extraction technique. The extracted features are matched and classified by minimum distance and support vector machine (SVM) classifiers. The proposed framework is tested on a 217 muzzle print images of cattle to evaluate the performance of the algorithm for cattle identification and yields the accuracy of 90 %.

Author, El-Henawy et al. [75], proposed an artificial neural networks (ANNs) based on the identification model of cattle. The proposed model is applied to perform the preprocessing, feature extraction, and identification of individual cattle based on extracted features. For feature extraction, box-counting and segmentation-based fractal texture analysis (SFTA) algorithms are utilized.

Box-counting algorithm provides a feature vector of 8 texture features, and SFTA feature extraction technique gives 18 features for each cattle image.

For identification of livestock, proposed system compares the similarity between test images of muzzle image feature with stored database. The experimental results reported that SFTA approach had achieved better identification accuracy among all other identification techniques. The proposed approach is superior to previous work. The proposed approach achieved the highest identification precision of 99.97% to recognize cattle.

In [76], the muzzle print image-based cattle recognition system is proposed. The recognition system takes different feature patterns of muzzle print for cattle identification, and there are uneven features for their skin surface. These muzzle point image patterns are different from each other similar to fingerprints of the human. The authors proposed fuzzy-based cattle identification system for identification of cattle based on muzzle print images using principal component analysis technique.

2.3.6 Identification of Cattle Based on Face Biometric Feature

The author Cai et al. [60] proposed a novel facial representation model of cattle identification using local binary pattern (LBP) texture features of face image of cattle. They have combined normalized gray-level feature of cattle face images. Algorithm training was performed independently on 900 face images of cattle (e.g., 30 subjects (cattle) × 30 face images). Each cattle has a set of 6, 7, 8, and 9 face images, respectively. The face image-based identification of cattle is shown in Fig. 2.10.

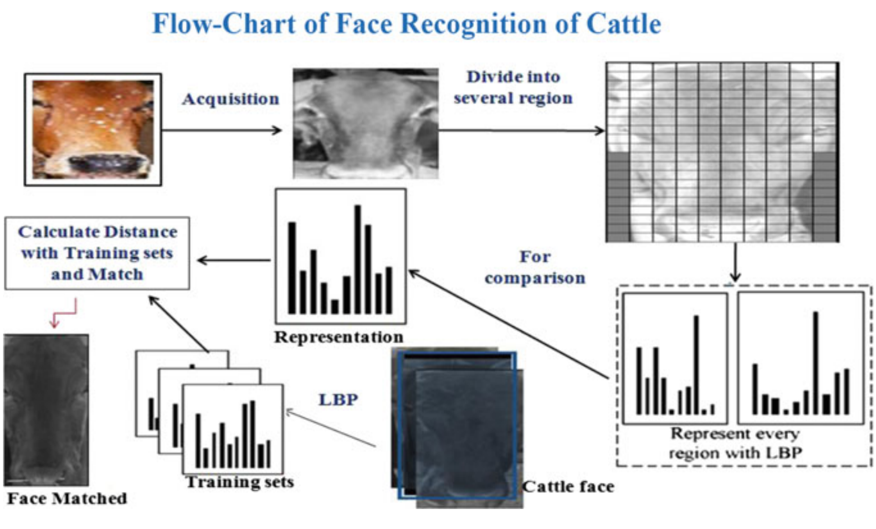

Fig. 2.10 Flowchart for cattle identification using face image biometric feature

To improve the performance, alignment of images is done by applying the sparse and low-rank decomposition technique. These techniques were also applied to align technique for the face images of cattle. The variations in illumination, image misalignment, and occlusion provided different representations of features in the feature space during the testing and matching phase of proposed model. The working of face recognition system for cattle is shown in Fig. 2.10.

In [61], Kumar et al. proposed a cattle recognition system using appearance-based face recognition and texture feature-based descriptor techniques for recognition of individual cattle. In the proposed recognition system, facial features (pixel value of face image) are extracted using these techniques and the proposed recognition system consists of various components (phases). The proposed approach yields the 86.56% identification accuracy.

2.4 Morphological Image Pattern-Based Animal Identification

In this section, identification of animal using morphological image pattern, biometric features, and visual features of species or individual animal are illustrated in detail. The morphological image pattern and biometric feature-based identification of species or individual animal uses morphological image processing techniques. It selects the differences in the morphological features to distinguish species.

In existing work, species or individual animals were taken as inalterable units. After morphological concepts of Charles Darwin, published in his book 'On the Origin of Species by Means of Natural Selection' (1859), the morphological image-based identification method has been used under the assumption that similar identical morphological biometric characteristics would reflect relatedness and therefore result in a natural systematic.

The classification of species is divided into several categories, which is based on different morphological features such as (1) representation and identification of species based on morphological features using computer vision models, (2) texture feature of morphological image pattern of species or animal using computer vision approaches, and (3) detection of species based on visual appearance-based image approach. The description of different approaches for identification of species based on morphological image pattern is depicted in Table 2.4.

The better representation of the extracted sets of morphological image and biometric feature of species or animal is also required to perform the preprocessing using image processing techniques.

The computer vision models do not capture the discriminatory biometric feature or morphological image patterns of animals because the species or individual animal alters their body shape and pose under different lighting. The reflections occur from their body surface. In this case, animals are exhibited under constant

Table 2.4 Identification of species based on morphological image features

Name of species/ Animal	Biometric feature, morphological image feature	Technique used	Provided solutions	Issues and challenges	Ref.
Whale Shark specie	Spot pattern behind the gills of the whale shark Database size: 35,000	Computer vision technique, Sloop Algorithms	Representation of biometric feature for Identification of whale shark		[2]
Frog	Morphological image pattern feature	Computer vision and pattern recognition	Representation of morphological image feature is done by rough mask-based method based on the intensity and saturation of the captured images of species	1. Glare from captured images cannot mitigated by using existing techniques 2. Secular reflections in the image are major problem	[10, 77]
Tod, Lizard, and other species	Morphological image pattern feature	Computer vision, image processing techniques (such filtering, segmentation image classification techniques)	Image patch-based identification technique	Inaccurate color filling to identify the Tod, Lizard and species especially from the background of the image	[78]
Marbled salamanders	Morphological image and biometric features Database size: 6000 images	Deformation-invariant matching technique, scale-cascaded alignment-based techniques, MS-PCA technique	Body shape recognition-based solution	Low lighting, noise, glare, and a number of challenging factors are not solved by deformation-invariant match-based on-scale-cascaded alignment to a problem in conservation biology	[78, 79]

lighting conditions. Individual animals often become visible as partially hidden by vegetation.

To solve these essential, challenging problems, advanced computer vision system, animal biometrics techniques, and recognition frameworks also have been implemented recently to represent the morphological biometric traits of the animals. However, traditional computer graphical and statistical visual computing models are unable to explain the compact description of the extracted set of salient morphological biometric feature and biometric images of species [80].

Texture feature descriptor techniques are fast to compute and invariant to monotonic grayscale changes of the image of species. However, the most prominent limitation of local texture feature extraction technique is its small spatial support area.

Texture feature-based descriptor techniques such as scale-invariant feature transform (SIFT) [18, 21] Dense-SIFT, rotation-invariant feature transformation (RIFT), local binary pattern (LBP), speeded up robust feature (SURF) [22] descriptor-based recognition algorithms have been applied to recognize species or individual animal using small region features effectively to represent morphological image pattern and visual appearance of animals. RIFT is a rotation-invariant generalization of SIFT techniques. The descriptor of RIFT is constructed with circular normalized image patches. The pseudocode of texture feature-based descriptor technique is illustrated as follows (shown in Algorithm 2.2):

Algorithm 2.2: Texture feature-based descriptor technique

1. **Initialize image phase**: Image [*M*, *N*] is taken as input, where *M* and *N* are dimension,
2. Preprocessing phase: The image *I* is preprocessed using image processing techniques,
3. **Size of texture feature descriptor (*W*)**: Initial size of texture feature descriptor with window size (W) = 3 $\times$ 3 neighborhood of image (I),
4. **Generation of binary features**: The texture feature descriptor binaries the local neighborhood of each pixel values of image (I),
5. **Generation of histogram (H) phase**: The descriptor technique builds the histogram on these binary neighborhood patterns of pixel values,
6. **Matching of and classification of histogram phase**: Similarity matching of histogram is performed by similarity matching techniques, linear discriminant analysis techniques, support vector machine classification model, and one-shot similarity matching technique.

Figure 2.11 illustrates the encoding of pixel values of images of species which are selected from the database images with descriptor window size 3 $\times$ 3. After that, the center (C) pixel value is chosen as threshold value of pixel values.

The center value is compared with all neighbor pixel value of the descriptor window. The neighbor value is greater than the centre value, and then, 1 is assigned, otherwise zero is assigned to the respective value. Figure 2.11 depicts the encoding mechanism and generation of LBP codes for better representation of species or animal in the feature space. The major component of animal biometrics-based recognition system is shown in Fig. 2.12.

Figure 2.13 presents the identification of tortoise species by extracting the feature interest points from the images of tortoise.

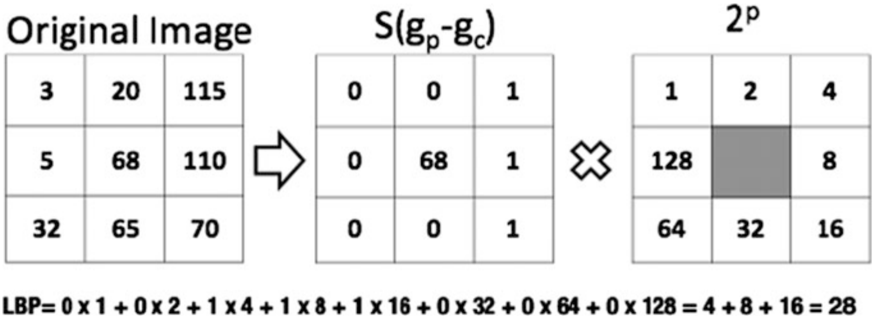

Fig. 2.11 Generation of encoded feature using local binary pattern (LBP) technique

Therefore, the widespread application and uses of these devices are getting more proliferations for behavior analysis and identification, tracking, monitoring, research, and conservation of wildlife [25, 26, 81]. The animal biometrics-based recognition system provides well-defined techniques for profiling the species behaviors.

2.4.1 Identification and Classification of Animal Using Profiling Behavior

In the available literature, the behavioral phenotype of captive mice is found first time using animal biometrics-based automatic recognition system for the behavior analysis. The system takes the input as different behavioral data of different animals. It provides differentiation of behavior of species.

It includes drinking, grooming, and resting state of species [76]. The animal biometrics-based recognition system generally performs the behavioral analysis of species or individual animal. It extracts the different behavioral data from the species in controlled environment [82].

Classification of species or individual animal into recognizable and distinguishable entities is a scientific model or tool in the animal biometrics [83]. It helps ecologists and biologists observe and interpret the natural world. Nowadays, the most promising computer vision methods for appropriately identifying species, as well as demarcating between-species boundaries, is to incorporate many types of information into the same study. It also assists the behavior analysis of species based on different behavioral characteristics of species.

The first automatic identification methods for behavioral phenotyping of captive mice are available in the literature [51], allowing for classification of behavioral characteristics such as drinking, grooming, and resting features. However, animal biometrics-based applications explicitly extract behavior characteristics are intrinsically bound to controlled environments. Simplified animal biometrics methods emphasize on analyzing footage in wildlife database [34] [84], flock or group

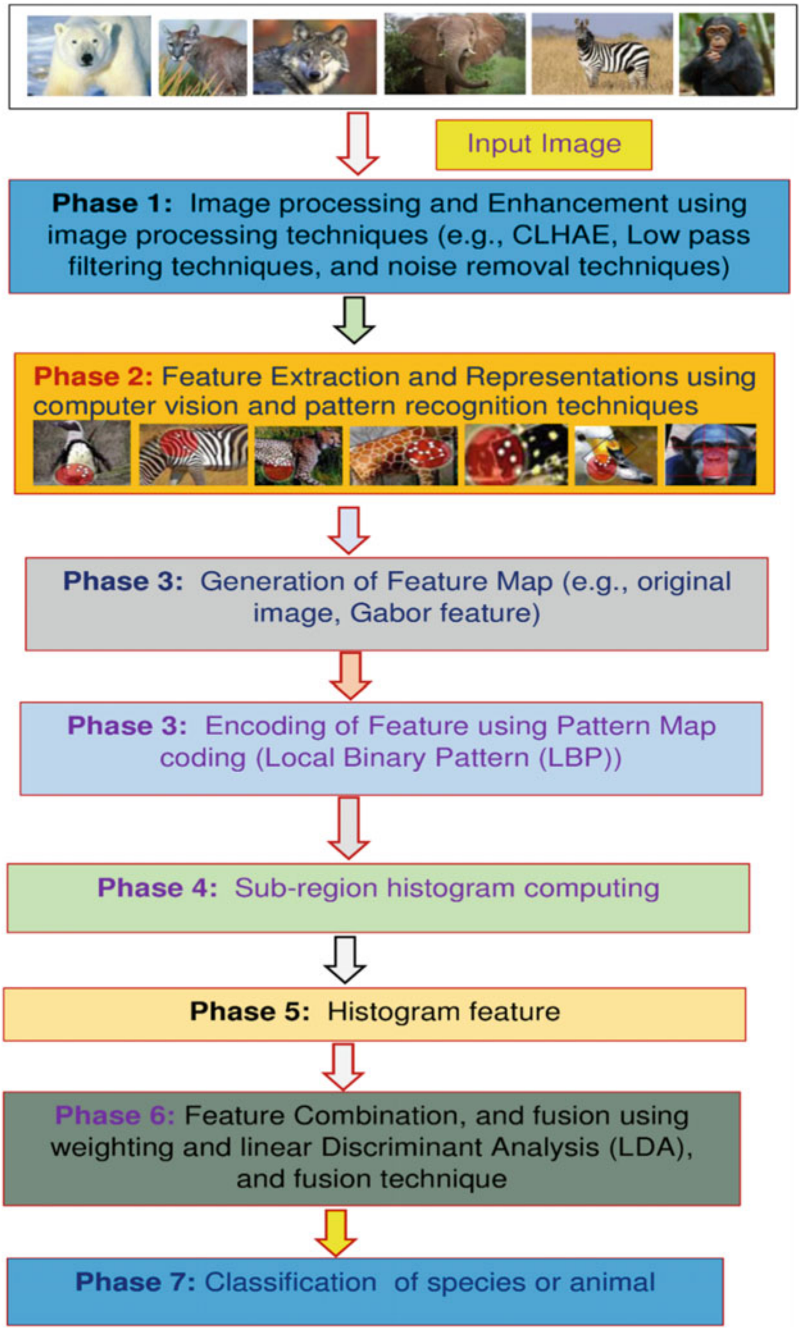

Fig. 2.12 Working of animal biometrics-based recognition system in the various phases and pipeline of local statistical feature-based face recognition

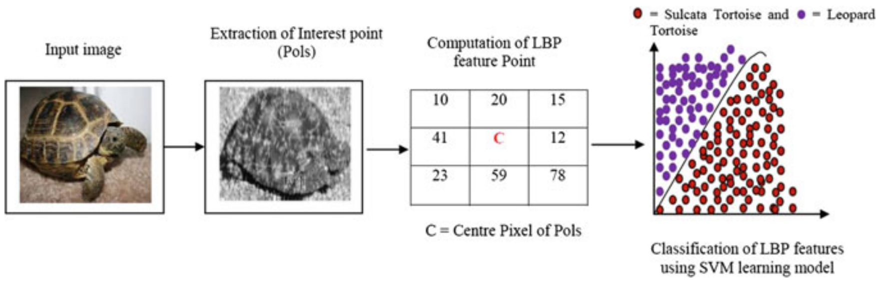

Fig. 2.13 Tortoise identification using local binary pattern-based feature descriptor techniques

movements, as developed for bees [85], fish [86], or birds [87]. Distinctive locomotive movements including quadruped gait [28] that provide motion signatures of species. These are enough to determine animal presence from the multimedia database and classify behavioral activities such as trotting, walking, or stalking [34]. Techniques in the field of animal biometrics have high potential, and suitable recognition methods are plentiful. Yet, the design and development of automatic audiovisual behavior detection systems remain to be implemented and tested for the wild species. It also takes less complex tasks for classification and identification [88, 85].

The animal biometrics system classifies the movements of flock or group of species based on behavioral data and profiling behavioral activities. The profiling behavior includes movement and behavior of honeybees [88], birds, fish [89], or ants [87] and locomotive activities such as quadruped gait of species [90], walking, running, trotting, moving, sleeping or stalking [87, 91, 92]. The species are identified by classifying the behavioral activities using learning computer vision models.

The comprehensive literature of identification and classification of species or individual animal using learning models, pattern recognition, and computer vision approaches is depicted in Table 2.4.

For the matching of extracted set of biometric features, and morphological image features, different similarity matching techniques and algorithms are also depicted in Table 2.4. The localization of different features and detecting various parts of body of animal using computer vision-based techniques, image annotation techniques such as descriptors of localization of body, matching of localized features in the body using sliding windows, grab-cut, segment compactness are given in Tables 2.5, 2.6, and 2.7, respectively.

Table 2.5 illustrates the recognition of species using animal biometrics-based recognition system. These techniques include various modeling and biometric feature learning techniques to represent the shapes and body surface of animal.

In animal biometrics, automatic image annotation is also needed. The image annotation is defined as a process by which an automatic computing system automatically assigns metadata in the form of captioning or keywords to a digital image. The wide application of image annotation of computer vision approaches is

Table 2.5 Computer vision and pattern recognition techniques

Type of Species		Identification	Computer vision and pattern recognition techniques			Annotation requirements	References
			Modeling and learning algorithms	Model representation	Matching and localization techniques		
Chimpanzee Gorilla, Monkey Apes		Facial images (Rigid Spatial Decomposition) and (Representation of Facial Features)	– AdaBoost classifiers – Indexing – Lookup tables	– Bounded box-based features – Census features – HOG features	– Cascaded rules – Sliding window-based algorithms	Annotation of facial region using bounding box	[93, 94]
Cat, Tiger, Lion, Panda, Fox, Cheetah		Head counting-based feature of animal (Deformable Decomposition of Head Shape and Texture)	– Boosting – SVM classification	– Box-bounding features – Census features – Haar of oriented. gradients (HOOG) Features	– Dual approach – Sliding windows	-Annotation of head and facial features	[95–97]
Pet animal (Cat, Dog)		Shape and texture features, facial, body, and nose print (for cat) (Deformable decomposition of face features and uniform body texture)	– Sparse representation – Latent SVM – Color Histograms, Gabor, – Descriptor model	– Geometric model, – Active appearance models -Deformable model, – HOG features, – Pixel color	– Descriptors of part localization, – Matching -Sliding Windows – Grab-cut – Segment Compactness	– Facial region, annotation using bounding box	[97–100]
Various Species of Insect	Drosophila melanogaster	Local pattern and texture features	– Deep neural network, – Maximum correntropy criterion (MCC)	– Stacked denoising auto-encoder, (SDA), – Pixel intensity of images	– Correntropy matching and second-order statistics (MSE)	– Not required	[101]
	Musca domestica (flies).	Patches and Texture Pattern	– Stacked denoise auto-encoder (SDA), – SVM	– Pixel intensity of images, – Deep learning	– Similarity matching entropy Matching	– Not required	
	Scorpions Centruroides limpidus and Centruroides noxius	Shape features	– Image processing, techniques, – ANN	– Texture feature (aspect ratio, rectangularity compactness, roundness, solidity, and eccentricity)	– Similarity matching, – Regression tree, – Random forest classifiers	– Not required	[102]

(continued)

Table 2.5 (continued)

Type of Species		Identification	Computer vision and pattern recognition techniques			Annotation requirements	References
			Modeling and learning algorithms	Model representation	Matching and localization techniques		
	Mosquitoes	Audio feature Features using speech and audio	– Feature-based classification models	– Temporal and spectral representations	Similarity-based classification	– Not required	[103]
	Other insect species	Distinctive Local Body Features (Local Gradient Distributions)	– Gradient histograms	– SIFT – Local feature concatenated histograms	– Scale-space extrema – k-D Tree matching	– Not required	[104]
	Tephritidae (fruit fly)	Local body features Texture feature	– SVM – Local soft coding (LSoft) Discriminative Local Soft (DLSoft) Method	– SIFT features – Patches (densely sampled from each image)	– Sparse coding – Spatial pyramid matching (ScSPM)	– Not required	[105–107]
Birds (NABirds, dataset containing 48,562 images)		Color feature	– Machine learning – MTurkers	– Pixel intensity of bird images	– Machine learning (SVM) classification	– Body color	[108]
		Image pixel intensity features	– Deep Convolution neural network, (CNN), – SVM	– Convolution neural network (CNN), – FCNs	– AdaBoost with Haar-like feature super-Parsing – AdaBoost, with Haar-like feature	– Not required	[109]
Bird species		Image feature (pixel intensity)	Multimodal recognition algorithm	– SIFT – Body tracking algorithm (BTA)	– SIFT keypoints – Similarity matching of keypoints	– Not required	[110]
Oriole bird (Baltimore oriole (Icterus galbula)		Color feature	– Deep learning, – CNN feature baselines	– LDA, – Entropy-Rank curve	– Grab-cut mask, – Fine-tuned CNN features	Bounding box	[111, 112]

(continued)

Table 2.5 (continued)

Type of Species	Identification	Computer vision and pattern recognition techniques			Annotation requirements	References
		Modeling and learning algorithms	Model representation	Matching and localization techniques		
African penguins Spheniscus Demersus South Polar Skuas and Adélie Penguins	Chest patterns (Body) natural markings in the chest plumage	– Computer vision models – Features procrustes + mean square error -Regression models	– Chest pattern Features	– Matching software, – Cascaded rules	Image annotation technique	[113]
Quadrupeds	Gait motion (spatiotemporal configuration of body part of animal	– PCA – LDA – Normalized convolution deep learning, SVM, KNN	– Principal component of motion fields, – KNN Search,	– Sparse, – Kanade Lucas-Tomasi tracking algorithms	Training based on video clip and motion clip for classification	[30, 113]
Ivory-Billed Woodpecker	Flying characteristics	– Image processing – Nonparametric motion filtering	– Nonparametric motion filtering	– Bird filter algorithm, -Similarity matching algorithm	– Not required	[114, 115]
Ivory-Billed Woodpecker	Flight characteristics (speed) + Silhouette information	– Binary segmentation (against sky)	– Principal axes of silhouette – velocity and its derivatives	– Spatiotemporal filters	– Not required	[116, 117]

Table 2.6 Complete descriptions of computer vision techniques for identification of species

Name of animals/ species	Animal recognition based on primary biometric features	Computer vision and pattern recognition techniques			Image Annotation	References
		System modeling and feature learning principles	Image representation-based models	Matching and localization techniques		
Elephants	Ear pattern (Shape of ear silhouette sections)	– Edge tracing	– Shape texture features of ear silhouette	– Local edge refinement	– Rough ear-line annotation	[118–120]
Grey seal (Halichoerus grypus)	Texture features (Dense skin texture body)	– Gradient of texture feature-based histograms	– Binaries surface Texture descriptor model	– Covariance-based texture matching	– Control points	[121]
Zebra	Body joint stripes (Binary pattern formed by stripe paths)	– Median filter binarization – Run-length coding	– Joint stripe (Strip junction) strings	– Dynamic programming – Edit distance	– Bounding-box around body side	[122, 123]
Masai giraffe	Head/body surface texture (Distinctive gradient orientation of head or body texture)	– Computer vision	– SIFT descriptor approach – Local feature	– k-D Tree – Similarity Matching	– Not required	[124–127]
Chimpanzee, Gorilla	Facial features (conglomerate of local and global face characteristics)	– Computer vision model – Appearance random faces	– Appearance features and texture features (global and local features)	– Random selection of facial features Random Faces	– Not required	[128]
African penguin	Chest spot points (configuration of discrete landmarks on chest feathers)	– Polar spatial histograms	– Shape contexts (Feature descriptor)	– Earth mover distance – Phase curls	– Not required	[129, 130]
Salamander	Body texture (blob-like shape of markings over main body segment)	– Coarse-to-fine decomposition using Gabor filters	– None, the method produces match decisions for input pairs	– Scale-cascaded diffeomorphic alignment	– Not required	[131]
Whale Shark (Rhincodon typus)	Spotting points on body surface (configuration of discriminatory landmarks on body surface)	– Min–Max – Normalization, – Descriptor learning model	– Localization of landmarks	– Pattern-matching algorithm (based on Groth's algorithm)	– Spot pattering-based verification	[132–134]

(continued)

Table 2.6 (continued)

Name of animals/ species	Animal recognition based on primary biometric features	Computer vision and pattern recognition techniques			Image Annotation	References
		System modeling and feature learning principles	Image representation-based models	Matching and localization techniques		
Cheetah (Acinonyx jubatus) Tiger (Panthera tigris)	Body spot pattering structures and thin stripes (configuration of discriminatory points on Body)	– Spline-model-based Texture feature	-Spot pattering and landmarks neural network (NN) (backprojection method)	– Similarity-based distance measure between spot patterings	– Body landmarks annotated for training the systems	[135–137]
Leatherback Turtle	Image feature of their plastron (bright red regions located on the outer perimeter of the plastron)	– Computer vision and pattern recognition	– Image processing – Neural networks (multilayer perceptron (MLP)	– Color-based thresholding	– Not required	[138]
Ridleys turtle (Lepidochelys)	Shape, texture features (length, breadth), color extraction	– Computer vision, – Pattern recognition	– MATLAB software tool – Shape descriptor	– SIFT keypoints-based matching	– Not required	[139]
Fish species	Color, texture, and shape features (gray-level image binarization features)	– MATLAB software, computer vision model (active appearance)	– PCA technique	– Fisher classification model – Mahalanobis distance model – SPSS statistical model	– Not required	[140]
	Shape features, local features, texture, geometry features	– Bag-of-words model (BoW) Computer vision model	– Histogram of oriented gradient (HOG) descriptor – Discrete cosine transformation (DCT)	– Random forest (RF) classification -Similarity matching	– Not required	[141–144]
	Texture features (head, Caudal (Tail)	– Pattern recognition and computer vision models	– LBP texture feature Technique	– SIFT descriptor - Similarity matching	– Not required	[145]
		– Non-rigid part model,	– SIFT descriptor		– Not required	[146, 147]

(continued)

Table 2.6 (continued)

Name of animals/ species	Animal recognition based on primary biometric features	Computer vision and pattern recognition techniques			Image Annotation	References
		System modeling and feature learning principles	Image representation-based models	Matching and localization techniques		
	Texture features, Shape features, (head, Caudal (Tail)	Feature descriptors	– Radial basis function (RBF)	– Hierarchical partial classifier, trajectory voting scheme		
Chimpanzee	Facial images (identification of age group and gender)	– Deep learning model – Convolution neural network (CNN)	– Appearance features	-Log-Euclidean model for similarity matching	-Not required	[144]
Manta Ray species	Body spot pattering (localization and configuration of discriminatory landmark body surface)	– Procrustes' alignment-based model	Discriminatory landmarks body surface	– Euclidean norm – L2 distance measures – Entropy calculation	-Spot pattering as annotation	[148, 149]

Table 2.7 Classification of species based on animal behavior

Type of species	Types of behavior/activity of species	Behavior analysis and recognition of species			References
		Modeling and machine learning strategies	Model representation for behavioral activities	Matching techniques	
Honey bees	**Shimmering Behavior** (3D movements of hive)	– Template matching	– 3D position estimation of individual bees	– Triangulation of corresponding templates	[17]
Mice	**Home-cage activity** (major characteristics of particular activities in Spatiotemporal domain)	– Spatiotemporal volume analysis	– Motion, position and velocity features	– SVM-based classifier	[40]
Birds	**Nesting behavior** (Bird presence/ absence at nest, egg count)	– Classification based on local spatial frequency	– SIFT scale information	– Fisher linear discriminant – Hidden Markov models	[35]
Wild type (WT) and Fmr1-KO (Mice species)	**Abnormal behavior** (Video tracking)	– Passive RFID in ultrahigh frequency (UHF) band	– Robust principal component analysis (RPCA)	– K-NN classification	[134]
	Home-cage activity	– Permutation entropy	– Not required	– Piezoelectric pressure sensors	[135]
Mice	**Mouse movement behavior**	– HCI-based behavior	– Computer vision	– SVM classification	[136]
Blackcap (Sylvia atricapilla)	**Migratory behavior** (timing, duration, and direction of migration)	– Bias-adjustment algorithm that adjusts radar measures	– Spatial displacement of radar targets	– Correspondence matching between radar reflectivity data	[43, 150]
	Flocking behavior (trajectory in bird flock)	– Tracking by positional beliefs	– Particle cloud and coordinate system	– Condensation algorithm	
Drosophila (Fruit flies)	**Standing, walking** off (not in physical contact with egg-laying)	– Convolution neural networks (CNNs) (2-layer CNN)	– CNN feature-based representation model	– Euclidean distance-based similarity matching	[151]

(continued)

Table 2.7 (continued)

Type of species	Types of behavior/activity of species	Behavior analysis and recognition of species			References
		Modeling and machine learning strategies	Model representation for behavioral activities	Matching techniques	
	Flocking behavior	– Ellipse model	– AdaBoost classifier	Not required	[152]
Laboratory animals	**Home-cage, postures, and activity behavior**	– Model-based articulated body parts, Gradient vector flow (GVF)-based technique	– Kalman filtering method, Classification model	– Euclidean distance-based similarity matching	[153]

used in image retrieval systems to organize and locate captured species images of interest from an image database. Therefore, captured images of species are required to accurate image annotation to provide label during the retrieval of images.

These techniques can be classified into different categories such as (1) multiclass image classification of species with the massive number of species classes. In this case, the size of vocabulary can increase, (2) texture feature and active appearances-based classification models. The active appearance-based model and texture feature descriptor techniques take the holistic phenotypic appearance information and texture feature of species. In this case, the size of vocabulary can increase.

In the image analysis field, the features are extracted from the images and features are stored into feature vectors; the training annotation words are applied by machine learning approaches and image representation-based learning models to attempt to automatically apply annotations to new images of species. It also provides help in filtering the captured image datasets and indexing of audiovisual information using image annotation techniques that is progressively more produced in many ecological and evolutionary studies. The recognition of individual animal based on their primary biometric and morphological feature characteristics is shown in Table 2.5.

The promising applications of individual animal identification using pattern recognition techniques are highlighted in Table 2.6. It also includes these biometric and morphological image pattern-based representations using various computer vision models.

These techniques includes active appearance-based feature extraction and representation models, SIFT-based texture feature descriptor techniques [speeded up robust feature, local binary pattern histogram (LBPH) techniques, Circular-LBPH, multiblock LBP, transition local binary pattern (tLBP: binary value of transition-coded local binary pattern is composed of neighbor pixel comparisons in clockwise direction for all pixels except the central)], volume-LBP (it is defined as a set of volumes in the coordinate (X, Y, T) space. The coordinates X, Y, and T depict the spatial coordinates and the frame index, respectively, local feature-based computer vision models, local- and global feature-based representation models. The learning model and feature representation techniques are used to analysis the behavior of species or individual animal for recognition and detection of species. These techniques are also in Table 2.6.

Current state-of-the-art-based machine learning models and recognition algorithms have been used to assist the preclinical research of different species or individual animals based on behavioral activities. In the traditional animal monitoring systems, animal behavior is measured manually using movement pattern or gait pattern of species. It is slow and laborious. Besides, human observers always fail to produce the experimental results of behavior analysis since the decision is subjective. The behavioral evaluations are too fast, and human observers can miss due to flagging attention.

To overcome major limitations, computer vision and animal biometrics have provided automatic recognition systems for representation of behaviors of different animals. The recognition system and models help biologists and ecologists for better analysis of behavior. New practitioners and multidisciplinary researchers also used these systems and techniques to perform the experimental operations to get the better results and save considerable time and efforts.

The behavioral analysis of species is done by matching the similar activities of species by using similarity matching techniques. The similarity matching techniques perform the similarity between the query image and stored database images. For the recognition and analysis of mice behavior, home-cage activities are analyzed. For the analysis of mice behavior, motion and different activities are captured in spatiotemporal domain (X, Y, and T). The behaviors of species or individual animal are classified by support vector machine (SVM) classification model [148, 154–157].

2.5 Research Contribution, Communities, Simulation Tools, and Sharing of Database

Animal biometrics is yet in their childhood. However, animal biometrics is also a profoundly interdisciplinary field that needs input from various disciplines to design and develop genuinely the robust, widely applicable, and useful frameworks and powerful tools to capture and quantify phenotypic appearance. The rate of progress in the newly emerging field of phenomics [72] will be crucially dependent on the availability of powerful tools to capture and quantify phenotypic appearance. If widely accepted standards for phenotypic appearance data analysis were available similar to those in the genetic and physiological domain, it would considerably advance genotype-phenotype comparisons [58]. Such studies, with free-ranging animals under natural conditions, have yet to be performed. Hence, the rate of progress that is made will depend mainly on flourishing collaborations and sharing of expertise amongst members of the different research and scientific communities. The successful collaborations and expertise domain knowledge will provide a lot of opportunities for contributing the efforts to design and development of recognition frameworks and models by researchers, scientists, ecologist, biologists and experts in this open research field. It offered a platform of extremely interdisciplinary field that accumulates different inputs from various multidisciplinary areas to design and develop an automatic, noninvasive, accurate, cost-effective, robust, and universally applicable well-developed tools and approaches. The complete descriptions about the research contributions, research communities, available simulation tools, and shared database of images of species or individual animal are provided in [2, 77]. Few descriptions are available for solving the identification problem of species and also provided in Table 2.8.

Table 2.8 illustrates the existing animal biometric system, research communities, tools and data sharing for the ecologists, biologist, new user, and as well new research communities.

Table 2.8 Ongoing projects of animal biometrics

	Projects	Species	Modality	Resources	Ref.
1	[a]SLOOP	Whale sharks	Visual	[b]Envision	[2]
2	RBT + ACONE	Birds	Visual	http://rbt.cse.tamu.edu	[12]
3	ECOCEAN	Whale sharks	Visual	http://www.whaleshark.org	[13]
4	Conservation research	Animal	Visual	http://www.conservationresearch.co.uk	[18]
5	Stripes potter	Zebra	Coat pattern	http://code.google.com/p/stripespotter	[21]
6	White shark	White shark	Spot points	http://www.marinecsi.org/white-shark/	[41]
7	SAISBECO	Ape	Face	http://www.saisbeco.de	[42]
8	Database	Asian elephant	Ear	http://www.asianelephant.net/index.html	[101]
9	Cheetah database	Cheetah	Visual	http://cheetahdatabase.sourceforge.net	[102]
10	RhODIS database	Rhino	DNA	http://rhodis.co.za/	[105]
11	The Serengeti	Lions	Spots	www.snapshotserengeti.org	[107]
12	Shepherd database	Shepherd	Visual	http://www.ecoceanusa.org/shepherd	[108]
13	iBATsID	Batspecies	Acoustic	https://sites.google.com/site/ibatsresources/home	[100]
14	Shark identification	Shark	Visual	http://sharkidnetwork.com/about	[97]
15	THERIA	Mammalian	Visual	http://sharkidnetwork.com/about	[98]
16	PAM	Humpbackwhales	Acoustic		[99]
17	BEEtag-tracking system	Animal	Visual	http://biorxiv.org/content/early/2015/06/03/020347	[106]
18	CSIRO wild life collection	Wild life species	Sound archive	http://www.csiro.au/OrganisationStructure/Divisions/Ecosystem-Sciences/ANWC-Sound-Archive	[109]
19	Fish datasets	Fish	Visual	http://groups.inf.ed.ac.uk/f4k/GROUNDTRUTH/BEHAVIOR	[80]
20	The APRS	Penguins	Visual	http://www.penguinid.com	[17, 96]
21	Discover	Life species	Visual	http://www.discoverlife.org	[103, 104]

[a]SLOOP = SLOOP: Photographic Animal ID System
[b]Others = Salamanders, grand skinks, Otago skinks, geckos, visual features = appearance (patches, local features), geometry (scale-cascaded alignment), [b]Envision = http://ecovision.mit.edu/~sloop/SloopProject/SLOOP.html

2.6 Current Trends and Methods

The animal biometrics is anactive research field. It provides the wide range of efficient algorithms, robust systems, tools and method for preparation of image database of species. The animal biometrics-based system performs pattern detection, matching of biometric features and the morphological image pattern of species. Moreover, animal biometrics also caters the method to generate the storage capabilities, as well as for interfacing with applications or users that utilize the extracted information from the stored database for the study of multidisciplinary researchers, scientists, engineers, ecologists, and biologists.

Huge diversity of animal biometrics and computer vision and pattern recognition approaches often proscribes the transferability of these methods across interdisciplinary studies, which, incongruously, is one of the major goals of emerging animal biometrics.

The animal biometric-based recognition systems exist today utilize a broad spectrum of techniques for database acquisition, detection, matching, storage, and interfacing. This heterogeneity of methods usually prevents their transferability across studies, which is one of the objectives of the emerging field of the animal biometrics. Classifying well-known methods, techniques and introducing further modular systems or framework designs, customizable to individual studies, is an important goal to make solutions more generic, and cheaper to build and maintain.

Any progress towards to achieve this object will help to standardize the field and develop its more extensive applications. Unique algorithmic issues and challenges lie in coping with dynamic changes in lighting, covering and non-covering of the aniaml body due to partial occlusion, complicated organic deformation, and the requirement to annotate manually large image sets to train systems or models using advanced learning methods. Current progress in computer vision, pattern recognition, deep learning modeling and learning commitment to address these major issues and challenges.

The identification of existing handcrafted feature extraction and representation approaches provides more modular computer vision system and designs which are customizable for individual studies of species behavior, and it is a life-threatening objective to build and develop the better solutions more generic and cheaper to produce working prototype model and systems. The cooperation of individuals and researcher's efforts will help to fulfill this objective. This will assist to design and develop of systems and standardize these approaches for field studies and promote its wider application [154, 158].

The algorithmic challenges of animal biometrics lie in surviving with low lighting, partial covering and non-covering of body (occlusion problem), deformation of complex organic of species, and requirement to annotate manually large set of image database to train the designed and developed methods and recognition systems. Current advances in computer vision-based computing and modeling techniques and machine learning approaches [60] promise to address these major challenges [155].

However, the substantial progress has been made in incorporating the coherent set of ideas and knowledge on error rates for false identification in the study of ecological data analysis [11, 12]. Further to mitigate these errors and provide more advancements in the existing statistical tools, simulation systems, methods with good integration of output of animal biometrics-based recognition systems is required. Novel opportunities could recline in trading spatial for the temporal resolution to estimate density. For example, camera traps produce high temporal resolution however typically cover only a small area. Although, such a scenario can be used to determine population density of endangered species or animals. Adjusting capture–mark–recapture (CMR) identification methods for using uncertain sighting data beyond the state-of-the-art is further likely to attract increasing interest [54, 55].

To provide a great impact on existing capture–mark–recapture (CMR) identification methods for species or identification of animals using uncertain sighting data beyond the current state of the art is also likely to get more attraction to increase the interest [11, 12, 61].

To create the most efficient and robust recognition systems will need careful consideration of each components and workflows [159], so as to cater a continuous integration of human and machine capabilities. The current state of the art of based animal biometric system is shown in Fig. 2.14.

Figure 2.14 presents a flowchart of the current state-of-the-art animal biometrics-based methodologies for identification species or individual animal. It also illustrates the acquisition of high-quality data (e.g., ecological data, biometric feature, morphological image pattern, phenotypic appearances).

The current state-of-the-art-based recognition systems perform detection of morphological image pattern of species. It detects and represents the phenotypic appearances of animals using similarity matching of image pattern template with stored templates in the database. The animal biometrics-based systems also manage the large storage capacity of biometric feature templates and interfacing the relevant outputs among different interdisciplinary researchers, scientists, biologists, ecologists, and research communities for better study and analysis of captured ecological database.

Figure 2.12 depicts the working flow block diagram of current state-of-the-art-based animal biometrics-based recognition system. The animal biometrics-based recognition system consists of two components such as (1) training component and (2) testing component. In the training component, the recognition system captured the images of species or individual animal using sensing devices (e.g., digital camera, smartphone, advanced data acquisition devices, and technology).

Capturing of biometric data from different study site is used by various sensors known as acquisition phase. After data acquisition, the captured images are preprocessed using image filtering techniques.

In order to improve the quality of preprocessed images, contrast limited adaptive histogram equalization image enhancement technique is used. After that,

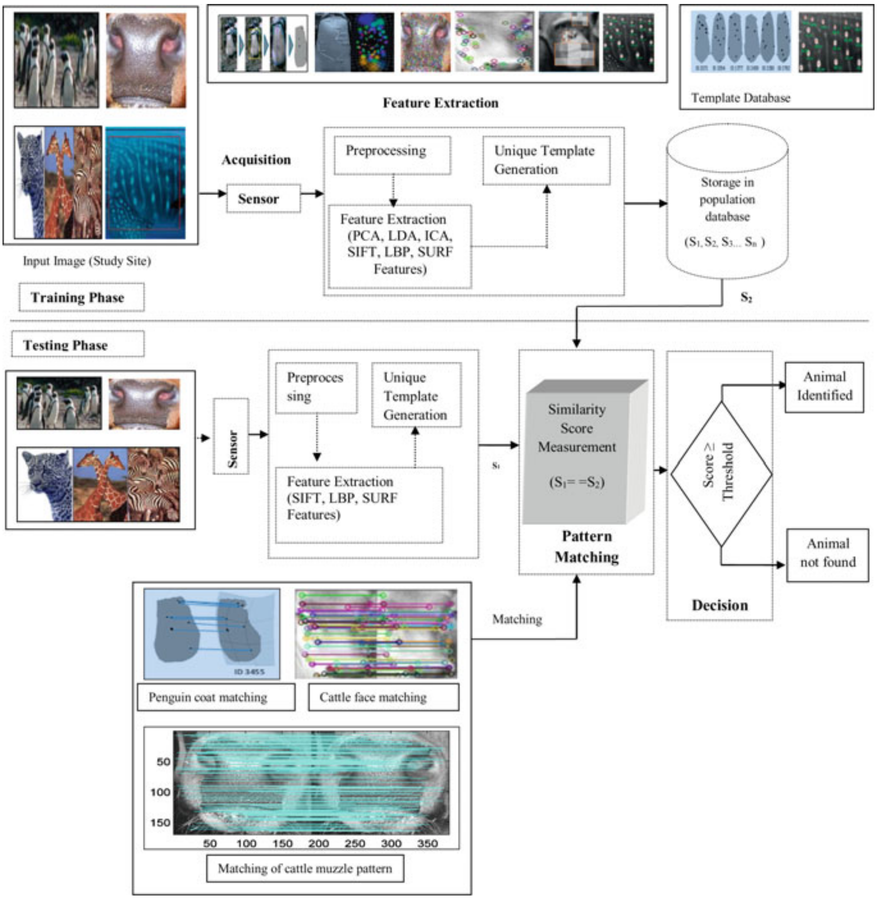

Fig. 2.14 Working prototype model of animal biometrics for identification of species

discriminative set of features are extracted from morphological image pattern and texture features of enhanced images using computer vision, pattern recognition, and machine learning approaches. The feature extraction approaches are mainly principal component analysis (PCA) [116, 160], linear discriminant analysis (LDA) [161, 162], independent component analysis (ICA) [150], and geometrical and shape features and its other variants. The local texture feature-based descriptor approaches are local binary pattern (LBP) [163], Circular-LBP [163], volume-LBP, speeded up robust feature (SURF) [164, 165], and scale-invariant feature transform (SIFT) [166, 167].

In the testing phase, unknown query images are matched with stored images for identification of species [58, 80, 81, 168–172].

2.7 Technical Issues and Challenges

Animal biometrics exists with a variety of broad spectrum of techniques to the input data acquisition, detection of the visual feature of species, matching algorithms, storage of different template generation, and various interfacing.

Figure 2.15 depicts the complete description of technical issues and challenges in the field of animal biometrics. It also includes major challenges for feature extraction and representation of biometric characteristics using holistic and existing handcrafted texture feature descriptor approaches. The major challenges for animal identification in the animal biometrics research field are illustrated as follows:

2.7.1 Algorithmic Challenges

Animal biometrics-based recognition systems are found today that use various approaches for data acquisition, feature detection, and representation of visual features of species, feature matching, preparation of database and storage capabilities as well as for interfacing with applications or users that utilize the extracted information. The extracted information of systems and framework can be very useful for identification and behaviour analysis of species by different researchers, scientists, and engineers in the animal biometrics.

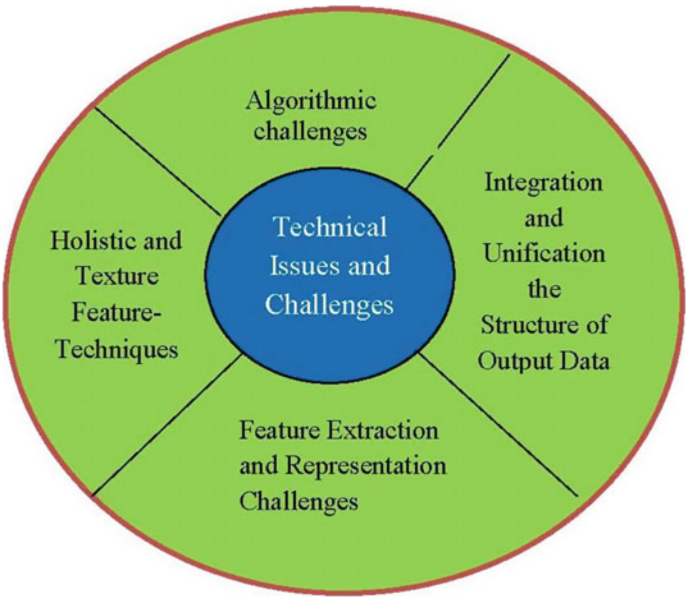

Fig. 2.15 Issues and challenges of animal biometrics

The availability of diverse approaches for animal identification often proscribes their transferability across different studies, which is one of the major objectives of animal biometrics.

The animal biometric systems that exist in the current state-of-the-art scenario use a broad spectrum of methods for acquisition, detection, representation, similarity matching, storage of database, and interfacing the outputs of various components of animal biometrics. This diversity of approaches frequently prevents their transferability across studies, which, ironically, is one of the goals of animal biometrics. Identifying general methods and advancing more modular system designs, customizable to individual studies, is a significant goal to make solutions more generic, and inexpensive to produce and maintain. Any move towards this objective can help to standardize the field and promote its more comprehensive applications and uses.

Particular algorithmic challenges rest in coping with unconstrained environments such as variable illumination, partial occlusion, complex organic deformation, and the requirement to annotate manually large image sets to train the recognition systems or models. Current advances in computer vision modeling, pattern recognition and machine learning promise to address these significant issues and challenges.

The effective feature extraction and representation are needed to uniquely identify individual animal. The existing image acquisition and transformation suffer due to their integration of different modules. The complete description of different scale transformation and image transformation techniques is illustrated in Fig. 2.16.

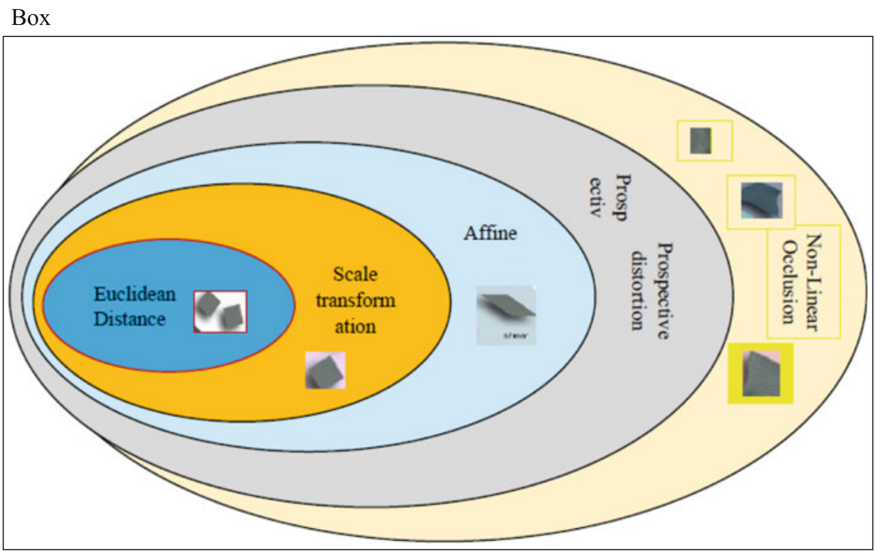

Fig. 2.16 Hierarchy of image transformation and feature extraction techniques

The Euclidian distance-based similarity matching technique is used to represent the extracted features. However, it needs better matching between training and testing models. The models also require different scale transformation, and affine and prospective image transformation for better representation of the feature in the feature space. These image transformation techniques take different input image from various unconstrained environments.

Most organic bodies are flexible entities that change their shape of body surface together with morphological image and phenotypic appearance feature of species or individual animal.

2.7.2 Integration and Unification Structure of Output Data

The requirement of structure for storing the output data is also a critical problem because it is the key interface between the animal biometric system and the researcher. The requirement of efficient structure and memory is needed to keep all the records and output data. The stored output data can be stored in the cloud.

Standardization of output structure can help multidisciplinary researchers, newcomers, and research committees to utilize animal biometric systems more quickly. It can also promote the system comparability and interaction among researchers as well as generate attractiveness, acceptance, and understanding of systems and frameworks for identification of species.

Although essential progress has been made in consolidating knowledge on misidentification error rates (false acceptance rates, false rejection rates) into biological and ecological data analysis, moreover intricate significant extensions to existing statistical methods and tools are needed to integrate animal biometric output fully [11, 12]. The statistical methods and models are required to integrate each output of animal biometric component [159, 173].

2.7.3 Feature Extraction and Representation Challenges

In animal biometrics, recognition and classification of species is a well-defined process based on their biometric features. Feature extraction and representation are preprocessing steps in the identification and matching of biometric features, detecting the phenotypic appearances, and morphological image pattern of animal. The main manifestation of feature extraction steps is to find unique representation of discriminatory set of extracted features in the feature space.

The representation of features depicts relevant information for identification and classification of groups of species or individual animal. The feature representation

Fig. 2.17 Extraction and representation of feature of different species [2]

can be found by maximizing a criterion or can be a predefined representation of features.

The representation of captured image of species is done by high-dimensional feature vector (e.g., feature vector size: $1 \times N$, where N is total number of extracted features) of pixel intensity values for image known as holistic feature-based representation. The feature extraction from images of species or individual animal is shown in Fig. 2.17.

2.7.4 Challenges of Feature Extraction and Representation of Species Using Holistic and Texture Feature-Based Techniques

The feature extraction and representation technique is most widely applied for identification of animal. In the computer vision and animal biometrics, various feature extractions and representations are available.

The feature extraction technique extracts the features from the phenotypic appearance of species, morphological image pattern, and biometric characteristics such as face, muzzle point image, spot point images, coat pattern, and other discriminatory images of species. The major problems of holistic and texture feature-based approaches for extraction and representation of features for identification of species or animals are illustrated as follows:

A. The representation of holistic extracted features is based on using the lexicographic ordering of raw pixel intensity values of an image to yield one vector per image.
B. The image of species can now be seen or visual features as a point in high-dimensional feature space. The dimensionality is defined as size of image in terms of pixel values. The problem of large dimensionality prohibits the use of machine learning and computer vision techniques to carry out in such high-dimensional feature space. This is known as curse of dimensional reduction. The dimensional reduction technique such as principal component analysis reduces the size of image.
C. In dimensionality reduction, those feature vectors are selected having more variances in the feature space, known as principal components. Remaining feature set are discarded. Therefore, minimal set of features are taken for identification of animal.
D. Holistic feature extraction and representation techniques may fail to provide the accurate representation of animal biometric features for identification of species in the unconstrained environment such as low illumination, poor image quality, and pose variations and occlusion (covering and non-covering of body of animals during vegetation). As holistic feature extraction and representation methods use global information of phenotypic appearances (faces and morphological image pattern), the disadvantage of the holistic approach is the variances captured may not be relevant features for identification of species in this constrained environment.
E. Holistic feature extraction and representation techniques fail to cater the compact representation of biometric features, morphological images, and visual feature of species in the unconstraint environment.
F. False acceptance rate, false rejection rate, and miss-identification error rate are high for recognition of species.

The brief description of working of holistic and texture feature-based descriptor techniques along with its major issues and challenges is depicted in Table 2.9.

The diversity of approaches of species deepens on better representation of the extracted biometric features and morphological features of species or animal. The machine learning-based representation approaches, mathematical modeling, software tools, and emerging technology often provide better opportunities and transferability of these techniques across different interdisciplinary researchers, population studies, paradoxically one of the primary objectives of animal biometrics-based systems, models, and frameworks [89, 87, 111–114, 174–190].

Table 2.9 Comparative study of holistic and texture feature-based feature extraction and representation techniques

Holistic feature extraction and representation	Standard algorithms/ techniques	Important description	Issues and Challenges
	Eigenvalue-based PCA approach [160]	– It finds a set of the most representative projection feature vectors so that the linearly projected samples retain most of the information about the original samples in the sense of the least mean squared reconstruction error	– Low illumination, poor image quality, and body pose variation
	Linear discriminant analysis (LDA) [161, 162]	It is a supervised classified method [161]	– Sensitivity of the local variations such as body dynamics and body pose, low illumination
	Independent component analysis [150]	ICA captures both second- and higher-order statistics and projects the input data onto the basis vectors that are as statistically independent as possible	– Sensitivity of the local variations such as body dynamics and body pose, low illumination – It loses the local discriminatory features by averaging – It covers the entire facial images
Texture feature-based descriptor techniques	Local binary pattern (LBP) [163]	– The texture description should be robust to conditions such as rotation or translation	– Sensitive to changes such as pose and illumination – It is inefficient to handle the noisy, artifacts, or constant gray-level flat areas of the face images of species or individual animal (such as chimpanzees, apes) – It happens due to the thresholding scheme of the operator
	Center symmetric local binary patterns (CS-LBP) [164]	– The CS-LBP feature descriptor is computationally simpler than the SIFT descriptor	Feature extraction
	Local ternary pattern (LTP) feature descriptor [191]	– It is used to add resistance to noise	– Sensitive to continuous changing of light and body pose of animal
	Four-patch LBP (FPLBP) feature descriptor [192]	– Feature descriptor-based feature extraction and representation technique	– Susceptible to the changes of illumination
	Three-patch LBP (TPLBP) Feature descriptor [174–176]	– TPLBP feature descriptor technique generates the binary codes. These codes are produced by comparing the values of three image patches	– Low accuracy – High-level feature extraction and representation are not possible due to less number of extracted set of features

2.8 Summary

This chapter has provided a comprehensive review of various state-of-the-art animal biometrics approaches. In addition to this, we have provided a brief introduction to the discipline of animal biometrics followed by the classification and identification techniques of species or individual animal in brief. Further, the potential challenges of existing techniques and research communities, tools, and data sharing are also discussed.

These techniques and data sharing provide a future perspective for the innovative research to new breed of scientists, researchers, biologically knowledgeable engineers, and technically potential biologists to solve major challenging problems during designing of animal biometrics-based recognition systems and frameworks. The computing research platform will also assist the cross-disciplinary engineers and scientists who have motivation to understand the major problems and provide efficient solutions for identification of target species and endangered species or animal in their habitat, as well as the technical and simulation tools that underpin practical engineering solutions for design and development of animal biometric systems.

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Chapter 3
Recognition of Cattle Using Face Images

Abstract In this chapter, a cattle recognition system is proposed. The proposed cattle recognition system uses the face image for identification of cattle using computer vision approaches. The major research contributions of this research are in three folds: (1) the preparations of a facial image database of cattle, (2) extraction of discriminatory set of features from the cattle's face image database and implementation of computer vision-based face recognition representation algorithms for recognizing individual cattle, and (3) finally, the experimental results and discussion of face recognition algorithms. Thus, this chapter presents a comprehensive review of the performances of various computer vision and pattern recognition approaches for the application of cattle face recognition.

Keywords Animal biometrics · Face recognition · Cattle identification Gaussian pyramid

3.1 Introduction

Toward successful operation of any farmhouse, effective livestock management of animals is essential for health management and tracking of the individual animal. Efficiency, affordability, and accuracy of livestock management framework-based systems play an indispensable role in the identification and verification of different animal in modern farming.

In the modern farming, the breeding association of animals also has severe problems in the livestock management-based frameworks and classical animal recognition-based systems. Animal biometrics has achieved recent more advances and better management paradigms and framework-based systems for management of livestock cattle.

Cattle identification is the well-defined procedure for registration and traceability of individual cattle using animal biometric techniques [1]. The registration process of individual cattle would prevent the efforts for manipulation, and verification and identification of swapped cattle. Registration process includes recognition systems

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and framework-based system for verification of false insurance claims of registered cattle. Cattle identification and traceability are also very crucial to control safety policies of animals and management of food production.

According to Wagyu Registry Association (WRA), the registration of individual cattle is required to be done at age of 4 months and over 14 months of cattle for proper breeding. They can be used for marketing purpose of cattle throughout the world [1, 2]. The recognition and traceability of cattle play significant roles in controlling safety policies of livestock animals and to provide better chain for management of food production [2].

Different international organizations (e.g., food security and world animal health) have fostered formally recognized the significant values of the design and development of the framework-based system and model using Internet of Things (IoT) for recognition and traceability of animals [3–5]. Many international organizations, e.g., food safety and world animal health, have formally comprehended the significant values of the development of the animal identification and traceability systems and they further actively encouraged for these systems.

The international organizations further actively promoted the livestock framework and recognition systems which are enabled IoT with sensing devices and equipment for the better monitoring and assessments of health management of individual cattle. The proper administration of animals is the first step toward reaching the objective of accurate livestock farming that helps animal welfare, registration, health management, and outbreak and control of critical diseases [6, 7]. Explicit recognition of individual livestock animals (especially cattle) is necessary to design better solutions for these problems and precise management of animals. Cattle identification system provides efficient solutions for the animals. It includes (a) controlling the widespread of the critical diseases of the animal by identifying and detecting infected animals, (b) reducing losses of livestock producers by controlling the diseases, and (c) reducing the government cost by the control, intervention, and elimination of the outbreak diseases.

3.2 Motivation Behind the Work

According to a survey of Cattle Today Online (http://www.cattletoday.com/), the total cattle population is 1.4 billion in the world. 30% of the total population of cattle are found in the Asian country and 20% in South America. The population of cattle in North and Central America, Africa are 14% and 15% respectively. Furthermore, the number of dairy cattle in Europe in 2017 attained at 23.5 million, a decrease of 0.2% from the year 2015 [8–10, 11, 12]. In available literature, Bovine Spongiform Encephalopathy (BSE) is the critical standard disease for livestock animals. It is a transmissible spongiform encephalopathy and fatal neurodegenerative disease in cattle that may be passed to humans who have eaten infected flesh. Therefore, especially after the discovery of the Bovine Spongiform Encephalopathy (BSE), advanced animal identification and livestock monitoring and tracking system systems were developed and deployed by big beef exporters and had been increasingly used by ranked beef importing countries.

Marchant et al. [1, 2, 13] reported that animal identification could be obtained using many different methods which could be classified as and biometrics, electronic, mechanical. The mechanical class includes techniques such as ear notching, ear tags, branding, and tattoos. The non-availability of biometric-based identification approaches, efficient, affordable, and scalable livestock management framework and recognition system for cattle has presently reported many fundamental problems of missed or swapped animals, registration and tracking of animal by identification process of livestock and controlling safety policies for livestock across the world [14–22].

Moreover, the electric and mechanical (non-biometrics-based techniques), cattle identification techniques, such as ear notching, freeze branding, and radio frequency identification (RFID)-based cattle identification techniques, provide low reliability, longevity, and minimum recognition rate to identify cattle [23]. The mechanical-based animal identification approaches such as ear notching and tipping and ear-tagging. These approaches suffer from many limitations. The ear notching and tipping method are not suitable for large-scale identification systems. The ear tag methods include metal clips and plastic tags. The ear tags are not expensive. However, they may cause animal infections. The freeze branding and tattoo systems are not achieving a relatively good accuracy as in one herd . All the artificial mechanical marking techniques can be duplicated for cattle identification easily.

For large hurds of animal, the traditional non-biometrics-based animal identification techniques have their own boundaries for identification of individual cattle. Therefore, these classical animal identification techniques do not provide a competent level of security to livestock cattle and making it open for missed, swapped, theft of cattle [12, 13, 23–28].

On the other hand, verification process of cattle under different government insurance claims has been a severe problem for cattle due to duplication of embedded or labeled tags number in the ear of cattle and the label can be lost. Moreover, the label of ear tags may also be eventually damaged, and the ear will gradually be corrupted because of the long-term usage. Therefore, classical animal identification systems and livestock framework-based systems also, do not provide accurate verification of false insurance of cattle based on the ear-tags-based numbers.

These classical verification systems do not have any efficient methodology to perform verification of registered and insurance cattle easily, without cutting the ear of cattle by verification officers. Therefore, it is still difficult to prevent the activities such as forgery, duplication, fraudulent, and manipulation of ear tags numbers of cattle in the classical animal identification system [25, 26]. These major challenging problems of cattle identification and verification cannot be ignored by biometric research communities, scientists, animal welfare society, veterinary researchers, professionals, experts, and different research communities of multidisciplinary to contribute valuable efforts for the design and development of robust, noninvasive and automatic recognition system for cattle.

Identification, monitoring, and tracking of cattle based on their physiological and behavior characteristics can supplement the better utilization of cattle recognition using animal biometrics-based cattle recognition systems. Therefore, the need for a robust cattle identification scheme has become desirable. Animal biometrics, a science that is recently applied to identify species or individual animals, is an emerging research in the cattle identification domain.

Animal biometrics has the broad range of applications and uses. It includes classifying cattle breeds, tracking the individual cattle, from their birth to the end of the food chain and understanding the trajectory of critical animal diseases, verification of false insurance claims, identification of missed or swapped cattle, and study of population pattern of cattle breeds.

In this chapter, the face image of cattle is considered as primary biometric characteristics for identification of individual cattle. Therefore, the proposed face recognition biometrics approach provides an affordable, non-invasive, efficient cattle recognition system for the cattle identification. An attempt has been made to solve the problem of missed or swapped animal, verification of false insurance claims and reallocation of livestock at slaughterhouses by using face recognition of cattle using computer vision and pattern recognition algorithms. The preparation and description of cattle face image database are given in the next subsections.

3.3 Preparation and Description of Face Database

The face image database of cattle is prepared for recognition of cattle and to validate the proposed computer vision framework-based system for identification of individual cattle. In the preparation of the face image database, a 20-megapixel digital camera has been used to capture the face image of cattle from Department of Animal Husbandry and Dairying, Institute of Agricultural Sciences (I.A.S), Banaras Hindu University (B.H.U), Varanasi, India-221005. The preparation of cattle database has taken more than seven months with the preparation of an adequate number of face image databases of cattle for validating the proposed cattle recognition system using training and testing phases.

The preparation of face image database is completed in two different sessions. The size of the cattle face image database is 5000 (e.g., 500 subjects (cattle) $\times$ 10 face images per subject). The sample face images of cattle are shown in Fig. 3.1 from face image database of cattle. Table 3.1 illustrates the composition of the face images for the experiments. The database is taken for four cattle races (e.g., Balinese cow, Hybrid Ongole cow, Holstein Friesian cow, and Crossbreed cow).

Face recognition is a well-studied problem in the field of computer vision, and many challenges have been well known by the researcher's incorporated pose, expression, illumination, aging, and disguise [26, 29]. The challenges of low illumination and pose due to the head movement and body dynamics and poor quality of images are manifested with face image database. However, pose and illumination are two relevant covariates in the cattle face image database. The covariates of cattle face images are captured during face database acquisition from the uncontrolled light of indoor and outdoor environment.

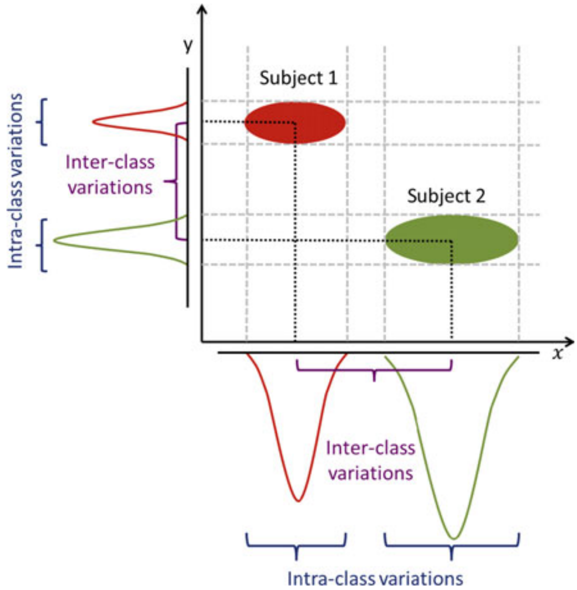
Fig. 3.1 Some face images of cattle from database

Table 3.1 Description of face image database of cattle

Types of cattle breeds (Races)	No. of subjects (cattle)	No. of face images
Balinese cow	150	$150 \times 10 = 1500$
Hybrid Ongole cow	150	$150 \times 10 = 1500$
Holstein Friesian cow	100	$100 \times 10 = 1000$
Crossbreed cow	100	$100 \times 10 = 1000$

In the data acquisition, many problems were due to the noncooperative behavior of cattle and the unconstrained environment. Moreover, the quality of captured face images is also affected by weather conditions during acquisition of face image. These are the major challenging problems during the preparation of face image database of cattle. In the preparation of face image database, various covariates of the face image of cattle have captured due to low illumination and increase the

Fig. 3.2 Inter-class and intra-class variations of face image of cattle



intra-class variability of face images of cattle. A covariate is defined as an effect that independently increases the intra-class variability or decreases the inter-class variability or both [26].

Figure 3.2 illustrates the intra-class and inter-class variability between face images of cattle from different subjects. It depicts the intraclass and inter-class variability between two subjects (cattle). Pose variations produce the covariates of face images due to head movement and body dynamics of cattle, low illumination, poor quality, and image blurriness in the unconstrained environment. It significantly affects the appearances of face images of cattle and their representations in the feature space. Variations due to body pose and low illumination hide /alter some of the features that make face images of cattle of different subjects appear more similar to each other than their actual faces, therefore decreasing the inter-class separation. The face recognition techniques for matching face images of cattle across pose variations can be broadly divided into two categories: (1) 2D methods, and (2) 3D methods.

In the 2D technique, several methods have been proposed to address pose variation due to head and body movement of species or animals. According to [20], these approaches can be categorized into three categories: 1) Pose tolerant feature ex traction, 2) View-based matching, and 3) 2D pose transformation. Pose tolerant feature extraction method constructs a classifier or finds a linear or non-linear mapping in image space that is insensitive to pose variations. Various methods based on extracting features from local facial regions have been employed for robust face recognition in any arbitrary pose. Local techniques such as Elastic Bunch Graph Matching [23] and Local Binary Patterns (LBP) [24], [25] have shown excellent performance across pose variation. Unlike holistic feature extraction and representation approaches (such as PCA, ICA, and LDA, Kernel-LDA, 2D-PCA), local methods are independent of pixel-wise correspondence between the gallery and probe images. These pixel-wise correspondences are adversely affected by pose variations due to the movement of the animal body.

In view-based matching methods, multiple gallery face images per cattle are obtained from different viewing angles to cover exhaustive range poses for each cattle. It is observed that the tolerance of a cattle face recognition system across pose variations increases with more gallery images per cattle because it improves the probability that the probe pose lies close to one of the gallery poses.

3D methods for pose-invariant face recognition of cattle can be studied as (1) generic shape-based methods, (2) feature based 3D reconstructions, and (3) image-based 3D reconstruction. Generic shape models are the most straightforward and quite efficient methods based on the cylindrical face shape. Arbitrary face images of cattle are mapped onto a generic cylindrical face shape, and frontal views are reconstructed. Feature-based 3D reconstruction of face estimate face shapes from the 2D locations of facial features. The facial components include eyes, muzzle point (nose), etc. and image features such as edges or corners.

Image-based reconstructions depend on the pixel-wise appearance of face images of cattle and are capable of generating more detailed face structures. Currently, the extensive researches have been developed algorithms to solve these major problems that can efficiently address these covariates for the accurate recognition of individual cattle. Apart from these challenges, face recognition of human with aging and disguise variations have also been studied, and several techniques have been proposed to solve these problems.

The covariates of illumination, blurriness, and pose of face image due to body dynamics of cattle are shown in Fig. 3.3.

Moreover, there are challenges in the acquisition and preparation of a cattle's face database, and one of them is the disapproval of an insurance officer of the cattle regarding information privacy and lack of support from the dairy stuff. It was tough to control the pose and body deformation of livestock's body and structure

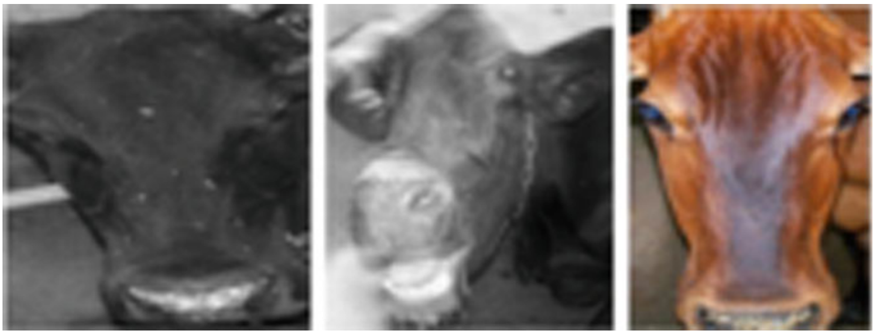


Fig. 3.3 Some challenging face images of cattle from the database

variation. It took about 25–30 min to organize a real environment with the help of dairy staff member for capturing face images of cattle as raw biometric data.

Cattle breeds also exhibit different poses and movement due to body dynamics if cattle breeds feel uncomfortable while being photographed (during acquisition process). If animals are nervous due to hunger or medical illness, they stand and do not keep the frontal face in standing position and ceaselessly movement of cattle heads. Therefore, body deformations of cattle in the whole body (shape and structure) are also a major challenge in the database preparation of cattle.

The major issues in the acquisition of cattle face database are generally actively deformation in the body of cattle and body surface reflects differently under different light luminescence (lighting condition). Therefore, cattle breeds are frequently have seen partially hidden by vegetation. Cattle are highly noncooperative with identification. It is a big challenge to capture the images of frontal face for cattle with pose and illumination problems.

3.4 Proposed Cattle Recognition System

This chapter explores the effectiveness of a novel computer vision and pattern recognition framework-based cattle recognition system (CRS) for identification of individual cattle using face images. The proposed recognition-based CRS system is a pattern recognition-based system. Pattern recognition is a well-defined process of classifying input image (data) into different objects or classes based on the extracted set of discriminatory features of objects.

The pattern recognition-based systems apply supervised and unsupervised machine learning algorithms for classification and identification and segmentation of objects from given data. The proposed cattle recognition system uses supervised learning technique for extracting and matching the face feature of cattle.

The cattle recognition system consists of several steps. The steps involved in the proposed cattle recognition system are illustrated with several components (modules). The modules of cattle recognition system are namely (1) sensor module (data acquisition phase), (2) preprocessing and enhancement of face images, (3) feature extraction module, (4) similarity matching module, (5) decision module based on matching scores of the face images of cattle and defined threshold value for identification of cattle.

The recognition system captures face images of cattle using a 20-megapixel camera. The block diagram of proposed recognition system of cattle is shown in Fig. 3.4. The pseudocode for recognition of cattle based on face image of cattle is illustrated in Algorithm 3.1.

The primary objective of the proposed approach for cattle recognition is that to first validate the prepared face image database of cattle by applying the pattern recognition algorithms and computer vision techniques. The pattern recognition methods and computer vision techniques are handcrafted texture feature-based descriptor techniques and appearance-based feature extraction and representation

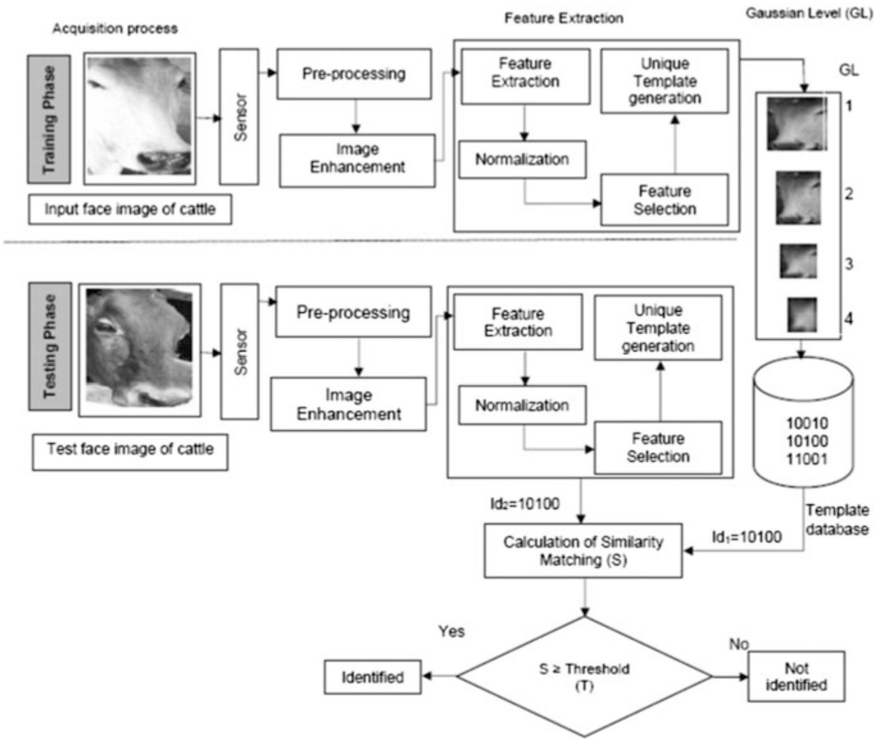


Fig. 3.4 Proposed block diagram of cattle recognition system

techniques, similarity matching-based technique for recognition and matching face image of individual cattle in the feature space.

3.4.1 Sensor Module (Data Acquisition Phase)

The proposed cattle recognition system consists of two phases: (1) the training phase, and (2) testing phase. During the training phase, the cattle recognition system creates a database of the face image of cattle and stores these captured images and valuable biometric information in the database. The face images of cattle are obtained by using sensors (e.g., camera or smart devices) in the proposed recognition system for cattle. The recognition system assigns a unique identification number to each cattle.

In the testing phase, captured face image as the query (test) image is matched with stored face image database for the recognition of cattle.

3.4.2 Preprocessing and Enhancement Phase

The face images of cattle are captured in the unconstrained environment. The face images can be defective, poor quality, contrast, and blurred. The proposed cattle recognition system performs the preprocessing to mitigate and filter the noise and specific artifacts from the captured face images of cattle using Gaussian pyramid-based low-pass filtering technique and increases the image quality of cattle's face image [30, 31]. The contrast limited adaptive histogram equalization (CLAHE) image processing-based enhancement technique is applied to enhance the contrast of the face images of cattle [32, 33].

The primary objective of the preprocessing step in the proposed approach for recognition of cattle is to mitigate the specific degradation such as noise reduction and enhance the contrast of face images of cattle. The face images of cattle are captured from the unconstrained environment (e.g., poor illumination, and blurriness). These captured images can be defective and deficient in some respect, such as poor image quality, contrast, and blurred. The database of face images of cattle needs to be improved through the process of image enhancement, filtration of noises which increases the image quality by the contrast between the foreground (objects of interest) and background of face images of cattle. Therefore, contrast limited adaptive histogram equalization (CLAHE) technique [33] is applied for enhancement of face images of cattle database.

In Algorithm 3.1, it illustrates the pseudocode for recognition of cattle based on their face images. It depicts the representation of face image of cattle in the feature space after extraction of facial features of cattle database. It also measures the mean and variance of cattle face images and computation of the discriminatory set of features using covariance matrix based on eigenface of individual cattle images.

3.4.2.1 Algorithm of Face Recognition of Cattle

Algorithm 3.1 illustrates the number of steps for recognition of individual cattle based on their face the biometric image features. It depicts the representation of face image for cattle in the feature space after the extraction of the facial features of individual cattle from the database. It also measures the mean and variance of extracted the set of face biometric features from the cattle face image database. The computation of the discriminatory set of facial features produces the eigenface feature vectors of individual cattle using the covariance matrix. In the testing phase, the generated Eigen-face feature vectors are matched with stored feature templates identification and classification of individual cattle. The computation of Eigen-feature vectors, generation of the discriminatory feature vectors and testing of cattle face image are given as follows:

Keeping Components and Generating the Feature Vector

After the computation of eigenvectors of the face image, the eigenface is reconstructed from the eigenvector values to achieve the eigenface of cattle. It is estimated from the stored covariance feature matrix of cattle face image database. After that, it is to order them by selecting the eigenvalue, highest to lowest, the principal component analysis method is used to analyze the feature values of face images. This procedure gives the discriminant feature components in order of significance set of prominent principal components for identification of individual cattle. The eigenvector with the largest eigenvalue is known as the Principle component. The principal components of eigenfaces are achieved by applying the principal component analysis (PCA) method. It is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of distinct principal components is equal to the smaller of the number of original variables or the number of observations minus one. The principal component-based transformation is established in such a way that the first principal component. The principal components have the highest possible variance (that is, accounts for as much of the variability in the data as possible), and each following component, in turn, has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal component analysis method is sensitive to the relative scaling of the original extracted features component of the face image database. The feature vectors are generated from the highest eigenvalue of cattle face image.

Testing of the New Face Dataset of Cattle

Once chosen the eigenvectors from test face images that keep the features (data) and formed a feature vector. It takes the transpose of the feature vectors and multiplies it on the left of the original face image data set, transposed.

The Euclidean distance-based matching technique is applied to calculate the distance between the mean adjusted input face image of cattle and the projection onto face space. The value of eigenvectors indicates that there are a face image and display the face image of cattle.

3.4.3 Challenges of Face Recognition in Cattle

Face recognition is a long-studied problem. It includes several major challenges have been identified by the biometrics research groups, computer science researchers and scientists including body pose, facial expression, low illumination, aging, and disguise for human recognition. With cattle, the major challenges are: How to identify individual cattle based on their biometric characteristics, such face image and muzzle point image pattern (nose pattern)? There is no such availability of face and muzzle point image database in the public domain for cattle identification. These challenges are not manifested in the emerging field of animal biometrics. Automatic face recognition system in the computer vision has several covariates for face recognition which have been distinguished such as pose, expression, illumination, and aging. Performance of current face recognition systems is affected by covariates. In cattle identification, body pose and poor image quality due to low-illumination are major covariates in the face image database. This chapter focuses on designing algorithms to mitigate the effect of covariates in face recognition of individual cattle.

Many applications of cattle recognition may require face images of cattle to be captured outdoors where the lighting conditions are unpredictable, the subjects may not be cooperative, the body poses may vary, or the angles and distances from the camera may not be normal. The animals can be considered as uncooperative users of face recognition. They may also exhibit different body poses and body reflectance during different lighting condition, especially if animals become uncomfortable while photographing. Some of these bodies pose due to body dynamics that affect the performance of cattle face recognition. Therefore, the performance of current face recognition systems significantly deteriorates for such imperfect and challenging cases. Apart from these covariates, the different challenge for face recognition algorithms is the computational time required for training and updating of parameters as new data which is included in the database. The most state-of-the-art animal biometric method utilizes training for parameter estimation and learning the decision boundary with domain-specific knowledge.

Furthermore, the excessive movements of animal can cause motion blur in the captured face images. Moreover, it is difficult to restrict the body pose and body dynamics and variations of cattle, implying that holistic feature extraction and representation algorithms may not provide good experimental results. On the other hand, local texture feature-based descriptor algorithm may yield good results because that face images of cattle have rich skin texture and distinct facial features.

Algorithm 3.1: Recognition algorithm for cattle face

1. **Benign Procedure** (face recognition) ((F_1), (F_2)).
2. **Initialization:** Input face images $[X] = (X_{1,}\ X_2\ \ldots.X_N)$ with $m \times n$ (where the value of m and n = 200 pixel).
3. **Preprocessing and Enhancement:** The face images of cattle are preprocessed and quality of face images are improved by using contrast limited adaptive histogram equalization (CLAHE) image processing-based enhancement technique.
4. **Feature extraction:** Facial feature (pixel intensity values) is extracted using texture feature and appearance-based feature extraction and representation technique from the preprocessed and enhanced face image of cattle database.
5. **Compute the mean**: The mean (μ) value is calculated for extracted feature of cattle face image database as follows (shown in Eqs. (3.1) and (3.2), respectively).

$$\mu = \frac{\sum_{i=1}^{N} X_i}{N} \tag{3.1}$$

6. **Compute the covariance** feature Matrix (S) of cattle face images:

$$S = \frac{1}{N_i} \sum_{i=1}^{N} (X_i - \mu) \times (X_i - \mu)^{\mathrm{T}} \tag{3.2}$$

7. **Compute the eigenvalues** λ_i and the eigenvectors of S (shown in Eq. (3.3):

$$SV_i = \lambda_i V_i, \quad \text{where}(\mathrm{i} = 1, 2, 3 \ldots N) \tag{3.3}$$

8. Equation (3.3) provides the solution V that contains the most discriminant projection directions.
9. Principal components are the eigenvectors corresponding to the largest eigenvalues.
10. The K-principal components of the observed vector are then given by [shown in Eq. (3.4)]:

$$Y = W^{\mathrm{T}}(X - \mu) \quad \text{where } W = \left(W_1, W_{2,} W_{3,} \ldots W_n\right) \tag{3.4}$$

11. The reconstruction from the principal component analysis-based eigen basis features is given by [shown in Eq. (3.5)].

$$X = Wy + \mu \tag{3.5}$$

12. Eigenvalue decomposition: Decomposition of eigenvalue is given as follows [shown in Eq. (3.6)]:

$$SS = X^{\mathrm{T}} X V_i = \lambda_i V_i \tag{3.6}$$

13. **Obtained original eigenvectors**: The original eigenface is computed [shown in Eq. (3.7)]

$$XX^{\mathrm{T}}(XV_i) = \lambda_i(XV_i) \tag{3.7}$$

14. **Return**: Original face image of cattle using PCA-based eigenfaces of cattle
15. **End Procedure**.

3.5 Feature Extraction and Matching Phase

Feature extraction is an essential step in the preprocessing phase. The classification is a method to assign an object to categories or classes based on an extracted set of feature vector information. The proposed cattle recognition system is motivated by observing that face images have rich skin texture information and distinct facial features. The salient and discriminatory features are extracted from the face image database of cattle using appearance-based (holistic) feature extraction and representation techniques.

The holistic (appearance-based) feature extraction and representation techniques are namely principal component analysis (PCA) [34], linear discriminant analysis (LDA) [35–37], independent component analysis (ICA) [37–40] and modified version of appearance-based face recognition representation algorithms (e.g., batch-candid covariance-free incremental-PCA (CCIPCA) [41, 42] independent-candid covariance-free incremental-PCA (IND-CCIPCA) [42] incremental-linear discriminant analysis (ILDA) [42–44] for the recognition of cattle using face image of cattle.

In this chapter, library package of the Support Vector Machine classification model (LiBSVM) [45] and Incremental-Support Vector Machine (I-SVM) [46–48] are adapted to classifying the sets of facial features of cattle database with techniques (e.g., PCA-LiBSVM, LDA-LiBSVM, ICA-LiBSVM, Incremental-SVM and Incremental-Local Discriminant Analysis-SVM (ILDA-SVM).

The primary motivation to apply the classifier models using Incremental Support Vector Machine (I-SVM) [43] is those classification models can be successively used to update several histories of the image of cattle and replenish new face image achieved lately. Moreover, the face image database is updated periodically to change the variation of pixel intensity in the salient sets of prominent features of cattle face image database. One of the advantages of I-SVM classification model [44] is to train the proposed cattle recognition system using the small training set of the face image of cattle quickly to classify the extracted features for identification of cattle in the fast and less consumption of memory as compared to traditional support vector machine-based classification and recognition models [42].

The appearance-based (holistic) face recognition and representation approaches have been applied to cater better identification accuracy due to rich, dense skin texture (information), and facial features [42–44]. Moreover, face images of classes in the cattle database are affected from the two major covariates, such as poor

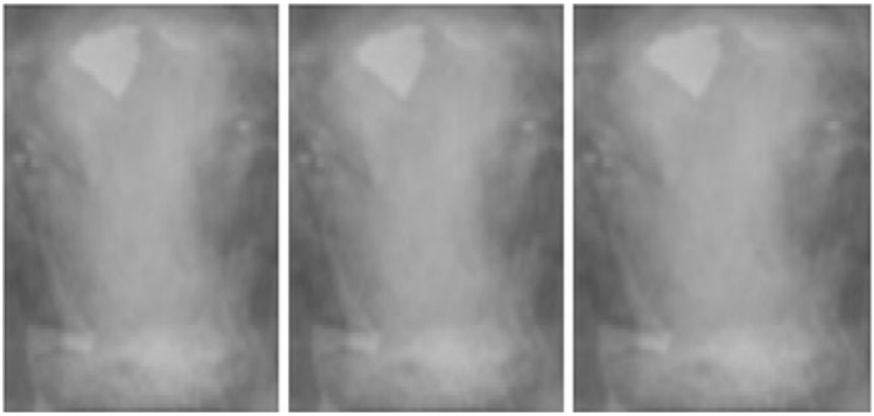


Fig. 3.5 Computation of mean of face images of cattle

illumination and pose due to body dynamics and head movement during data acquisition (shown in Fig. 3.5). However, body pose and low illumination are two essential covariates. Since it is difficult to make the cattle sit still and provide good frontal face images, animals can be distinguished as uncooperative for face recognition.

The covariates of face images of cattle have major problems in the feature representation of cattle by applying the holistic feature extraction and representation techniques. Therefore, the performance of face recognition of cattle using holistic methods is affected by such non-ideal and challenging cases. Therefore, holistic face recognition algorithms may not yield good results for cattle identification.

On the other hand, local feature extraction and representation based descriptor algorithm may provide excellent results. The hypothesis is that for cattle, the information content present in the face image changes with the pose, poor image quality, and variations due to light illumination. Therefore, texture feature-based descriptor techniques are used to extract the texture features of the face image of cattle. Using texture feature-based descriptors, a compact vector representation of a local neighborhood of covariates face images of cattle enables to handle scale changes due to poor illumination, occlusion, and rotation. Therefore, local feature extraction techniques are applied to provide the better improvement on the covariates of the face images of cattle.

Face recognition and representation algorithms utilize face images for feature extraction and matching process to identify and verify the individual. The face covariates affect the performance of face recognition algorithms for identifying the individual face of cattle. In the available literature, there are six covariates for which multiple research studies summarized effects on face recognition performance. These covariates are the age of the person, the elapsed time between images, the gender of the individual, the facial expression, the poor image quality of the face images, and the race of the individual. To achieve higher resilience toward face covariates of cattle such as low illumination, poor image quality, body pose due to head movement and blurriness, the low pass filtering technique is used for smoothing process. It is applied to mitigate the covariates effects from the low illumination, blurred and body pose of cattle. It also enhances the contrast of the background of images using the Gaussian pyramid smoothing technique. It is a low-pass filtering technique used to reduce the noise and specific types of artifacts from the face image database of cattle at four reduction levels for recognition of cattle [39–42].

3.6 Experimental Result and Discussion

This section provides details about the experimental protocols and obtained results. Furthermore, the results are analyzed and compared with those other techniques implementing computer vision methods. The simulations and testing of the proposed framework were performed on Intel (R) Core 2 Duo and 1.7 GHz computer with 20 GB of random access memory (RAM). The AdaBoost-based face detection technique [49] is applied to detect the face image of cattle.

The face was detected by implementation using AdaBoost-based face detection technique [49]. Face detection of cattle is used in conjunction with many other types of machine learning algorithms to improve performance.The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. However, the eyes of cattle are one of the significant features of AdaBoost detection technique. During detection, eyes of the cattle are hidden due to their heads being downward in standing position in the image of the cattle face database.

Additionally, several face images were captured with non-frontal face images produces high number of false detection in the process of cattle's face recognition.

A face image database of 500 cattle (subjects) is prepared by capturing the face image of individual cattle using a low-cost camera (20-megapixel camera), from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U.), Varanasi–221005, India.

The prepared face image database of cattle is shared with the research community to promote further research in this animal biometrics and computer vision research area. Detailed experimental protocols along with train–test splits are shared to encourage other researchers to report comparative results. Thus, we conclude that face recognition of the cattle can be done in a friendlier, cost-effective, and non-invasive way if the performances of automatic best face recognition and matching algorithms are satisfied.

3.6.1 Performance Evaluation

For evaluating the performance of the proposed framework, experiments were conducted on face image database of cattle. The face image database was divided into two parts: (i) training (gallery) part and (ii) testing (probe) part. This database was selected for validation of proposed framework for recognition of cattle and contains the high quality of face images.

For evaluating the recognition accuracy, six face images of each subject (cattle) were randomly selected for training the proposed framework (e.g., 500 × 6 face images from a total of 500 subjects (cattle) × 10 images per subjects). The rest face images of cattle were used for testing of query face image of cattle. The training and testing partitioning were tested to perform five times cross-validation and to compute the rank-1 recognition accuracy.

The performance evaluation of cattle face database was done by applying computer vision techniques, such as holistic for the recognition of cattle's face. In this chapter, the Support Vector Machine classification models (LiBSVM) and Incremental-Support Vector Machine (I-SVM) are used to classify the sets of facial features of cattle database with techniques (e.g., PCA-LiBSVM, LDA-LiBSVM, ICA-LiBSVM Incremental-SVM, and Incremental-local discriminant analysis-SVM (ILDA-SVM) using the customized version of available source code.

The appearance-based face recognition and representation algorithms have been applied for comparison the experimental results. The holistic face recognition and representation techniques are illustrated as follows:

1. Principal component analysis (PCA) [34–36]
2. Linear discriminant analysis (LDA) [37–39]
3. Independent component analysis (ICA) [40–44]
4. Candid covariance-free incremental-PCA
5. Incremental-linear discriminant analysis [48]
6. Batch-candid covariance-free incremental-PCA (CCIPCA)
7. Principal component analysis (PCA)-LiBSVM
8. Independent-candid covariance-free incremental-PCA (CCIPCA)
9. Incremental-support vector machine (iSVM)
10. Linear discriminant analysis (LDA)- LiBSVM
11. Batch–linear discriminant analysis (LDA)
12. Candid covariance-free incremental-PCA-LiBSVM
13. Independent component analysis (ICA)-LiBSVM
14. Incremental-LDA (iLDA)
15. Linear discriminant analysis (LDA)-LiBSVM

Linear discriminant analysis (LDA) is applied the Fisher discrimination criterion-based strategy to maximize the ratio of the scatter feature matrix to find the determinant of between-class (S_B) and within-class (S_W). The classes (S_B) and (S_W) are defined as follows (shown in Eqs. 3.8 and 3.9):

$$(S_B) = \sum_{i=1}^{c} n_i \times (m_i - m) \times (m_i - m)^T \tag{3.8}$$

$$S_{\mathrm{W}} = \sum_{i=1}^{c} \sum_{X_j \in X_i} n_i (m_i - m) \times (m_i - m)^{\mathrm{T}} \tag{3.9}$$

The ratio of Fisher discriminant is defined by maximizing the ratio of the determinant of between-class (S_{B}), and within-class (S_{W}) shown in Eqs. (10) and (11) as follows:

$$\text{Fisher\_}W_{\mathrm{OPT}} = \arg\max_{\mathrm{w}} \frac{W^{\mathrm{T}} S_{\mathrm{B}} W}{W^{\mathrm{T}} S_{\mathrm{W}} W} \tag{3.10}$$

$$\mu = \frac{1}{n} \sum_{i=1}^{c} \sum_{x_j \in X_i} N_i \times X_j \tag{3.11}$$

Figure 3.5 illustrates the mean face of cattle. The mean value of cattle face images is computed using PCA statistical face recognition and representation technique for recognition. The brief description of cattle face recognition algorithm using face image of cattle is shown in Algorithm 3.1. The computation of eigenvectors of cattle faces images and reconstruction of original face images of cattle using PCA technique are shown in Figs. 3.5 and 3.6, respectively.

The overlapping and maximum class separability of extracted feature of between-class (S_{B}) and within-class S_{W} of face images of cattle are shown in Fig. 3.7.

Fisher discriminant technique has been applied to compute the projection weight matrix (W) in the feature space for optimization of separated the different classes of face images of cattle. The ratio of Fisher discriminant between-class (S_{B}), and within-class (S_{W}) is denoted by Fisher (W_{OPT}) (Fig. 3.8).

3.7 Experimental Protocol and Analysis

In this section, experimental protocol and brief analysis are presented. The performance evaluation of proposed framework-based cattle recognition system is evaluated to identify the individual cattle based on their face image database (Fig. 3.9).

For performance evaluation, the face image database of cattle was partitioned into two parts: (1) training/gallery part and (2) probe part. Four face images of each cattle breed were randomly chosen for training/gallery database (total of 2000 = 500 $\times$ 4 images), and the remaining 30,000 = 500 $\times$ 6 images were used as probe/testing the proposed cattle recognition system. The training and testing partitioning of the given database were performed by using five times cross-validation testing protocol and rank-1 average identification accuracies were computed from the levels (1, 2, 3, and 4) of Gaussian smoothed face images of cattle (Fig. 3.10).

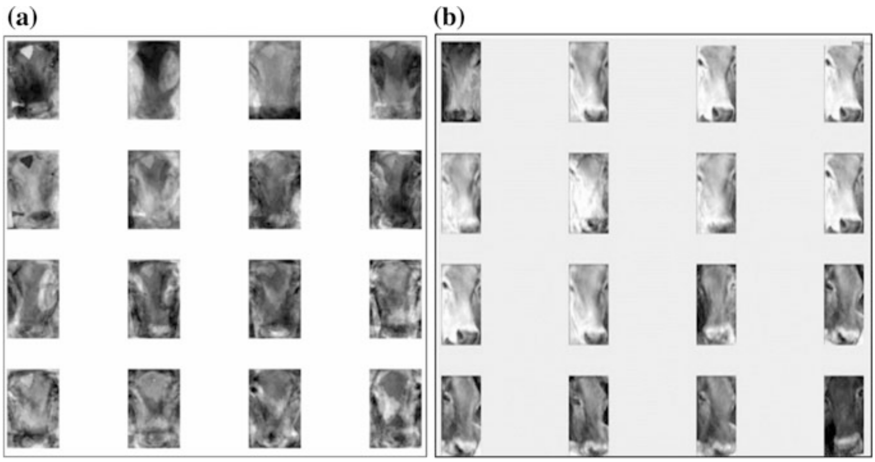


Fig. 3.6 Computation eigenfaces of face of cattle on (**a**) and (**b**) and reconstruction of original face images using eigenvectors

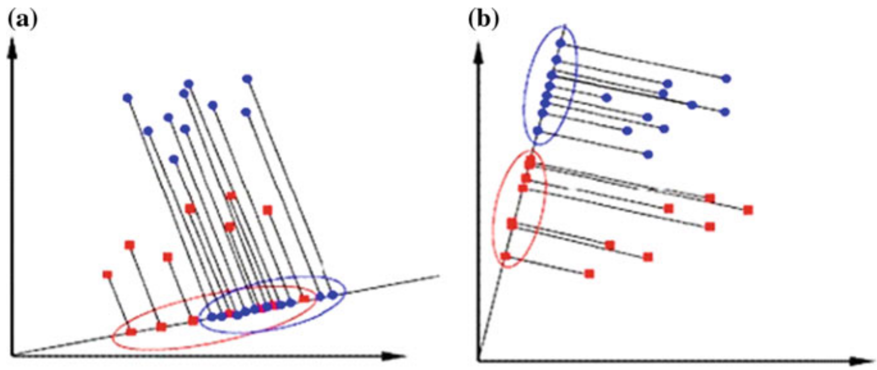


Fig. 3.7 Between-class and within-class feature scatters in the feature space

The identification accuracies of cattle identification are reported and summarized in the given Tables 3.2, 3.3, and 3.4, respectively. Tables 3.2, 3.3, and 3.4 depict the average identification accuracy for cattle identification which is achieved from the different levels of Gaussian smoothed face images of cattle database.

Figure 3.12 demonstrates CMC curve for identification accuracy of cattle face image based on Table 3.4 evaluation. It illustrates that the Incremental Support Vector Machine (ISVM) [33] algorithm yields identification accuracy of 95.87% with respect to others. The identification accuracy of batch-Independent Candid Covariance Incremental-PCA (batch IND-CCIPCA) [50] increases slowly with increasing the Gaussian level because number of selected Eigen faces decreases at each Gaussian level. PCA-LiBSVM [37, 38, 47, 49] recognition approach achieved

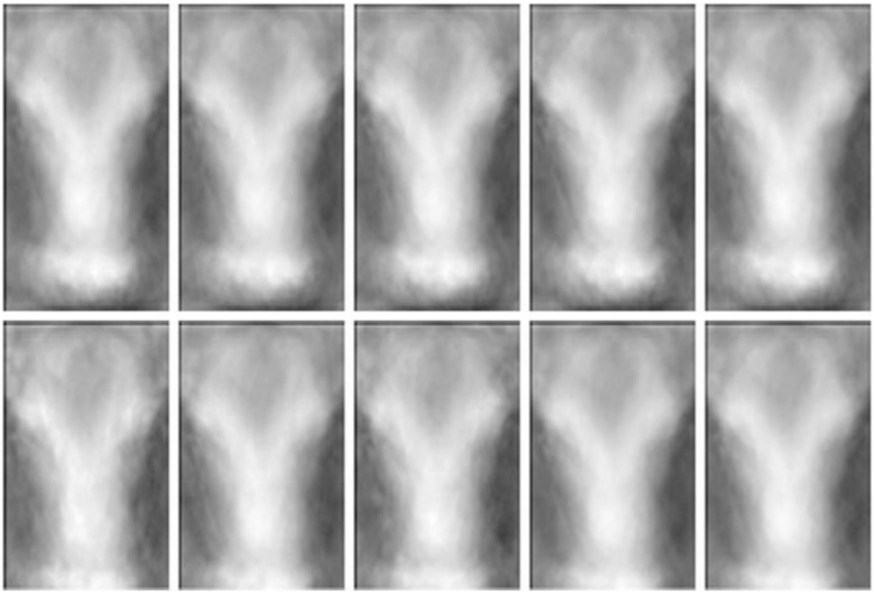


Fig. 3.8 Reconstruction of face image of cattle using LDA technique

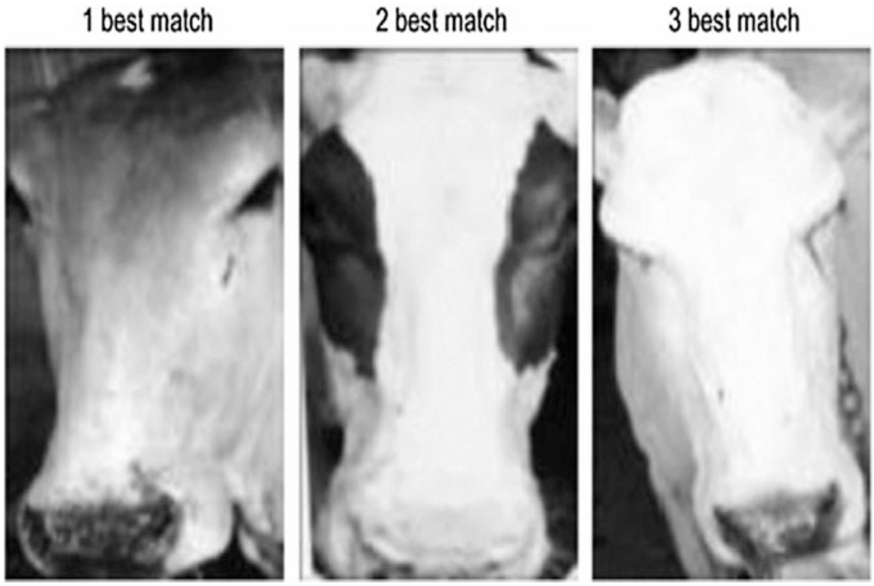


Fig. 3.9 Identification of face image of cattle using linear discriminant-based similarity matching techniques

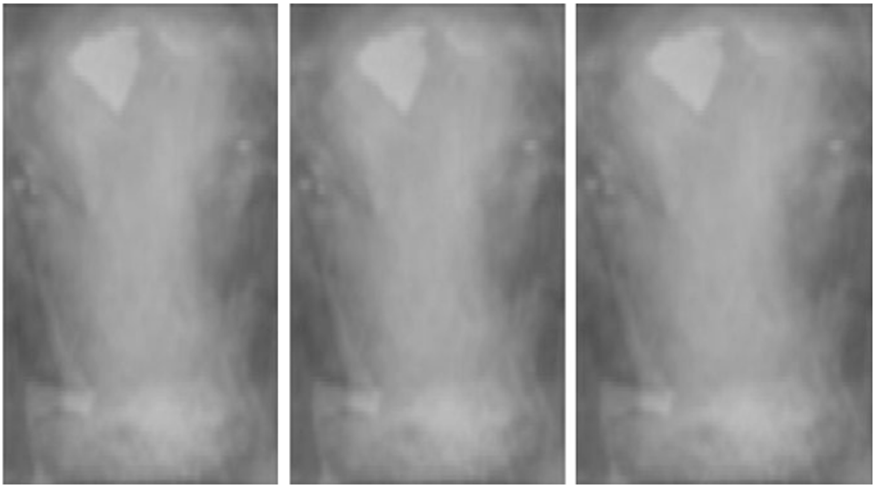


Fig. 3.10 Representation of extracted facial feature of face image of cattle using linear discriminant analysis technique and eigenvector method

the higher recognition accuracy as compared to PCA approach due to the prediction of maximum variance of Eigenfaces of test face images. Similarly, LDA-LiBSVM [40, 41, 48, 49] recognition approach provides relatively higher recognition accuracy (93.91%) than LDA [40, 41] techniques at each levels of Gaussian pyramid [11, 27]. While Independent Component Analysis (ICA) yields recognition accuracy of 89.75% for cattle identification.

All the experimental results are presented in the form of Cumulative Match Characteristic (CMC) [11] curves for analysis of identification accuracy of individual cattle. The CMC curve has been applied to compute the rank-1 identification accuracy for the identification of cattle. The CMC curves are shown in Figs. 3.11, 3.12, and 3.13, respectively.

The CMC measures to how well an identification system (1: *m*) ranks the identities of individuals in the enrolled database of face image with respect to unknown probe face image of cattle. The performance evaluation of the face identification of cattle has been done with feature extraction techniques which are mentioned previously.

The performance of the proposed framework-based cattle recognition system has been evaluated by applying three appearance-based face recognition algorithms (such as PCA, LDA, and ICA face recognition algorithms) using our modified version of the publically available source code. The appearance-based face algorithms are used for comparison of experimental results for the identification of cattle.

Table 3.2 illustrates that in the appearance face recognition algorithms (such as PCA, LDA, and modified algorithms), Independent Component Analysis

Table 3.2 Identification accuracy (%) of face images of cattle using PCA, LDA, and ICA approaches

Gaussian level	PCA	LDA	ICA
1.	74.39	75.57	79.75
2.	79.81	80.64	82.95
3.	81.89	84.19	84.90
4.	83.86	85.95	86.95

GL Gaussian Level, *Batch-CC* Batch-Candid Covariance-free Incremental-PCA (CCIPCA), *PCA-L* PCA-LiBSVM, *Ind-C* Independent-CCIPCA

Table 3.3 Identification accuracy (%) of face images of cattle using batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms

Gaussian level	Batch-ILDA	CCIPCA LiBSVM	ICA-LiBSVM	ILDA	ILD-LiBSVM
1.	74.40	79.50	80.70	77.75	78.93
2.	80.25	81.90	82.42	79.49	80.90
3.	85.50	83.95	88.50	82.85	83.25
4.	94.40	86.79	95.87	88.10	94.44

(ICA) recognition method yields the recognition accuracy of 86.95% at the fourth level of Gaussian smoothing face images using sum rule fusing techniques.

ICA method accounts the more variations (e.g., low illumination, pose image due to body dynamics and blurred face images of cattle) in the input cattle's face images of cattle database as compared to PCA and LDA classification techniques. The performances of PCA, LDA, and ICA algorithms are amplified by increasing the level of Gaussian smoothing image of cattle database. The performance analysis of PCA, LDA, and ICA algorithms is illustrated in Fig. 3.11.

Figure 3.11 demonstrates the perform analysis using CMC curve for identification accuracy of cattle face image. The identification accuracy is also summarized in Table 3.2. Figure 3.11 illustrates that the Incremental-Support Vector Machine (I-SVM)-based classification algorithm yields the identification accuracy of 95.87% with respect to other classification and identification algorithms.

Identification accuracy of Independent-Candid Covariance Incremental-PCA (IND-CCIPCA) technique increases slowly with increasing the smoothed level of Gaussian pyramid-based face images. It happens due to the number of chosen eigenfaces of face image of cattle database decreases at each level of smoothed Gaussian pyramid.

The CMC curve of recognition accuracy of PCA, LDA [37, 38], and ICA [39–41] face recognition algorithms for cattle are shown in Fig. 3.11. The recognition accuracies of PCA, LDA, and ICA recognition technique are amplified by increasing the level of Gaussian smoothing levels of face images of cattle.

Table 3.3 illustrates the identification accuracy of face images of cattle using the Batch-CCIPCA, ICA, Ind-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM face recognition approaches. The Incremental Support Vector

Table 3.4 Identification accuracy of batch-CCIPCA, ICA, Ind-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA and PCA-LiBSVM

Gaussian	Identification Accuracy (%)							
Level	Batch-CCIPCA	ICA	Ind-CCIPCA	ISVM	LDA	LDA-LiBSVM	PCA	PCA-LiBSVM
1	78.39	78.75	46.95	82.48	77.29	70.33	75.95	78.57
2	83.90	80.29	47.32	88.68	80.95	75.79	83.50	85.67
3	85.90	86.34	50.95	93.87	85.59	84.90	86.70	92.75
4	93.37	89.75	52.25	96.87	92.87	93.91	90.38	95.62

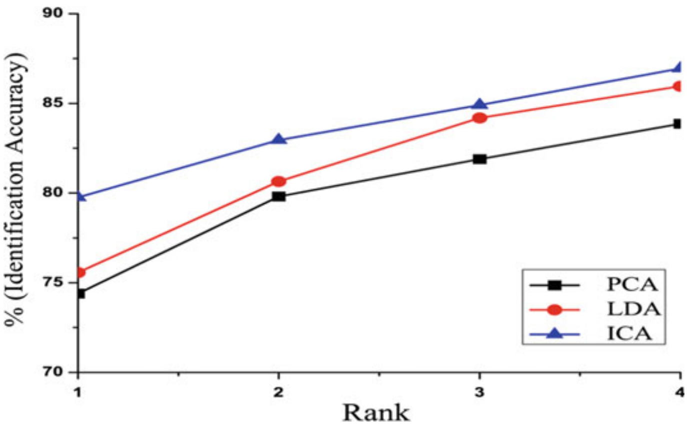


Fig. 3.11 Identification accuracy of PCA, LDA, and ICA technique

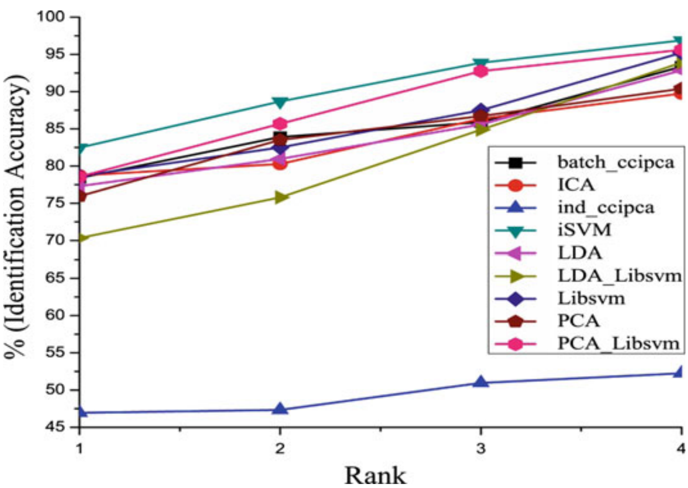


Fig. 3.12 To show identification accuracy of batch-LDA, CCIPCA-LiBSVM, ICA-LiBSVM, incremental-LDA (iLDA), and LDA-LiBSVM for cattle face (based on Table 3.4)

Machine (ISVM) classification algorithm yields the 96.87% identification accuracy for classifying the individual cattle based on the extracted facial features of cattle database.

The identification accuracy of batch–batch-candid covariance-free incremental-PCA (Batch-CCIPCA) face recognition algorithm increases slowly with increasing the Gaussian levels of smoothed images of cattle because of the number of selected eigenfaces increases at each Gaussian Level (GL). Therefore, batch-CCIPCA faces recognition algorithm gives 93.37% identification accuracy for identification of cattle.

On the other hand, the principal component analysis (PCA) and PCA-LiBSVM-based recognition methods are also tested to achieve the identification accuracy by classifying the extracted features of face images of cattle. The PCA-LiBSVM classification accuracy makes the higher identification accuracy as compared to traditional PCA face recognition approach based on eigenfaces due to the correct prediction of maximum variance of extracting eigenfaces of test images of cattle face database.

The linear discriminant analysis (LDA) and LDA-LiBSVM recognition methods are also utilized for the recognition of facial image of animals (cattle) based on training and testing images. LDA-LiBSVM techniques provide relatively higher identification accuracy (93.91% accuracy) than LDA recognition approach (92.87% accuracy) by classifying the extracted set of salient features of cattle face images at each smoothed level of the Gaussian pyramid. However, Independent Component Analysis (ICA) technique does not need the orthonormalization of eigenfaces of cattle, which allows higher-order dependencies in face image pixels to be exploited. Therefore, Independent Component Analysis (ICA) technique yields the identification accuracy of 89.75% of individual cattle.

Moreover, in this experiment, 10 eigenfaces have not taken into consideration for cattle face recognition due to the minimum variance of facial features (pixel intensity of cattle face). ICA technique improves the accuracy of straight PCA unsupervised learning-based method by significantly increasing the computation times and memory requirements. However, when discarding the top 10 eigenfaces of cattle face images for each algorithm, the PCA-LiBSVM, and PCA techniques perform better, perhaps because the top PCA eigenfaces encode illumination variations in the face image of cattle due to the unconstrained environment.

While, Independent-Candid-Covariance-free Incremental-PCA (IND-CCIPCA) technique provides 52.25% identification accuracy at the fourth level of Gaussian smooth images. Because, by processing one face image of cattle at a time, CCIPCA method incrementally estimates the eigenvectors of the covariance matrix from each level of Gaussian smoothed face images that would usually be determined from few face images of cattle.

Moreover, the extracted sets of the feature are not getting any update in the covariance matrix during training and testing phase. Therefore, the Independent-Candid Covariance-free Incremental-PCA (Ind-CCIPCA) technique provides 52.25% (shown in Table 3.3 and Fig. 3.12).

Table 3.4 illustrates the identification accuracy of cattle recognition based on face images using the batch-incremental linear discriminant analysis (batch-ILDA), candid covariance-free incremental-PCA (CCIPCA-LiBSVM), independent component analysis-LiBSVM (ICA-LiBSVM), incremental-LDA (ILDA), and incremental-LDA-LiBSVM (ILDA-LiBSVM) face recognition and classification algorithms. It can be observed that independent component analysis-LiBSVM (ICA-LiBSVM) face recognition technique yields 95.87% identification accuracy.

ICA technique does not need to compute the orthonormalization of feature vectors of the face image of cattle. It finds the higher-order dependencies in the extracted pixel intensity of face recognition. The first-order statistic (mean value) of the extracting pixel value of face image is mitigated from the face image database of cattle using the PCA dimensional reduction method.

ICA selects the discriminatory set of features by removing the first- and second-order statistics using “sphering” the data. Therefore, Independent Component Analysis-LiBSVM (ICA-LiBSVM) provides higher accuracy as compared to other face recognition approaches.

The incremental-ILDA-LiBSVM technique provides the identification accuracy 94.44%. The incremental LDA method caters the better identification accuracy on the small face image datasets. Since LDA approach is infeasible on a large system, we applied the training and testing of the database in the batch-mode and incremental learning-based approaches to achieve the better identification accuracy for cattle recognition.

The incremental-ILDA and ILDA-LiBSVM methods are used to identify the cattle based on face images. The identification accuracy (94.44%) of ILDA-LiBSVM technique is slightly greater ILDA technique (88.10%). On the other hand, the identification accuracy (94.40%) of batch-ILDA-based incremental learning method is slightly lower than ILDA-LiBSVM (94.44%). It is also shown that the ILDA-LiBSVM method achieves more identification accuracy than PCA and ICA technique.

The candid covariance-free incremental-PCA-LiBSVM (CCIPCA-LiBSVM) yields average identification accuracy at the different level of Gaussian smoothed images of cattle. It achieves 86.79% identification accuracy at fourth level of Gaussian smoothed level. The CCIPCA technique incrementally estimates the eigenvectors of the covariance matrix from each level of Gaussian smoothed face images. It takes one face image of cattle at a time in the training and testing phases that would usually be determined from few gorgeous texture-based face images of cattle for feature extraction and representation in the feature space (shown in Fig. 3.13).

In this experiment, the eigenface is calculated by applying the PCA technique. PCA is an unsupervised learning method. It separates pairwise linear dependencies between the pixel values of cattle face images. The objective to apply the PCA technique is to perform the computation of the covariance matrix of the extracted pixel intensity values of cattle face image database.

If pixel intensity-based features of cattle face image are not aligned or standardized properly, then the variance of one pixel can be high because it corresponds to different positions in the defined feature space. Therefore, PCA technique has been used to find the linear projection of the inputs (features) that captures the most variance in the feature sets. Therefore, it minimizes the reconstruction error of the input face images using least-squares approach.

Hence, eigen-based PCA face recognition technique has been applied to generate new dimensions (e.g., eigenvectors) that can be combined linearly to form good representations of input cattle face images. It is usually the case that combinations of rather few eigenvalues which have maximum variance are sufficient to produce a reasonable reconstruction for recognition of face image of individual cattle.

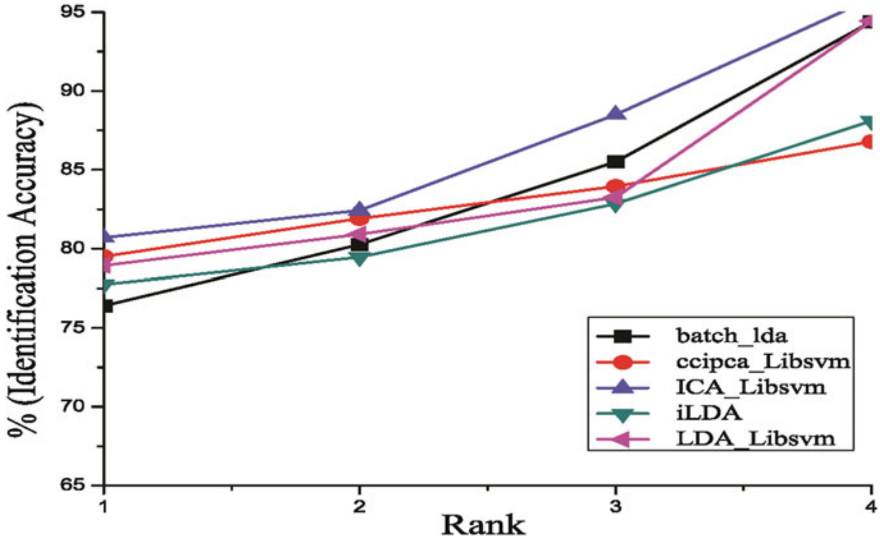


Fig. 3.13 CMC to show recognition accuracy of cattle face image based on Table 3.3

In this experiment, 10 eigenvalues are not considered in the representation of face image-based feature in the feature space because these eigenvectors have minimum variance in the extracted features. Therefore, PCA machine learning technique yields the identification accuracy of 83.86% for face recognition of individual cattle. PCA-LiBSVM technique achieved the higher recognition accuracy compared to PCA technique.

PCA-LiBSVM technique selects the maximal principal components of the extracted features based on the maximum variance of eigenface values of the cattle face images similarly, the LDA-LiBSVM classification technique has provided the relatively better recognition rate of 93.91% which is higher than LDA face recognition technique at each smoothed levels of Gaussian pyramid of cattle face database [12, 27, 28, 51–53].

3.8 Summary

In this chapter, the face image of cattle is considered as primary biometric characteristics for identification of cattle. Because the face image of cattle consists of rich skin texture information and distinct facial features.

Moreover, the primary biometric characteristic of face image-based feature includes mainly universality, distinctness, and permanence. The salient sets of features (e.g., pixel intensity) are selected for identification of individual cattle based on the discriminatory features of the face image of cattle. Therefore, the proposed approach provides an affordable, noninvasive, efficient cattle recognition system for the cattle identification.

An attempt has been made to solve the problem of missed or swapped animal, verification of false insurance claims and reallocation of livestock at slaughter-houses by using face recognition of cattle using computer vision and pattern recognition algorithms.

This research demonstrated a current state-of-the-art approach for recognition of individual cattle based on face image database in the emerging research field of animal biometrics and computer vision. The appearance (holistic)-based face recognition approaches, independent component analysis (ICA) [39] algorithm provided identification accuracy of 86.95% at the starting smoothed level of the Gaussian pyramid of cattle face image database. The PCA-LiBSVM [34, 40, 50] and ICA-LiBSVM [41, 42] recognition approaches provided the recognition accuracy of 95.62 and 95.87%, respectively. Experimental results on cattle face database of 5000 face images (e.g., 500 subjects (cattle) $\times$ 10 images of each subject) illustrate that face recognition for cattle is feasible.

A face image database of 500 cattle has been prepared with 20-megapixel camera from the Department of Dairy and Husbandry, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U.), Varanasi–221005, India, shared with the research community to promote further research in this animal biometrics and computer vision research area.

A detailed experimental protocol along with train–test splits are also planning to share to encourage other researchers to report comparative results. Thus, we conclude that face recognition of the cattle can be done in a friendlier, cost-effective, and noninvasive way if the performances of automatic face recognition, representation matching algorithms are satisfactory.

Contrary to popular belief that all cattle look similar, this chapter presents a current state-of-the-art approach and study in the field of animal biometrics-based cattle recognition system for identification of individual cattle which provides important insight in the identification of cattle based on their face image.

The face image database of cattle has been validated by proposed computer vision-based framework for recognition of cattle face and yielded the better possible results. It plays vital importance to initiate proper research in this direction of animal biometrics to provide the better platform to multidisciplinary researchers, scientists, biologists, and several biometric communities for design and development of the recognition systems to solve the major problems related to the recognition of different species or individual animal throughout the world. Finally, we conclude that face recognition of the cattle can be done in a friendlier, cost-effective, and noninvasive way if the performances of automatic best matching algorithms are satisfactory.

The future will demonstrate whether animal biometrics can carry out on its promise of revolutionizing the way we look at the different primary characteristics of phenotype, morphological image pattern and soft biometric characteristics traits.

In the future, the research the animal biometrics can be achieved extensive range proliferation due to the variety of uses and its application in the monitoring of livestock animal or species using frameworks. Nearly two-thirds of primate species face the threat of extinction primarily as a result of human actions that kill animals directly and destroy habitats, according to a new review from more than 50 leading primatologists. The overall range of primate species stretches across 90 countries. However, interdisciplinary researchers and communities have recognized four—Brazil, Madagascar, Indonesia and the Democratic Republic of the Cong. These are home to 2/3 of primate species. Those four represent a reasonable starting point for policy measures aimed at stopping primate extinction using animal biometrics-based systems [54–56]. These systems can be used for animal registration, identification, and tracking of individual animals. Further, this research can be enhanced keeping in view the following areas:

- Size of face database biometrics images can be utilized to be enhanced the identification of individual animal at large scale of database in the different conditions such as low illumination, pose, and poor image quality. These conditions may be considered while the acquisition of animal face image for each subject (animals) including the pose variation, distance variation and illumination variation, occlusion, and covering, non-covering variation. Therefore, it should focus on designing and developing pose and illumination invariant algorithms to recognize animals.
- Illumination, pose, and image quality are major covariates in the acquisition of face image database of cattle. Therefore, multimodel-based fusion techniques can be developed as cattle's covariates and to be estimated from the pair of images being compared.
- After performance evaluation of different face recognition algorithms with different covariates, we hereby conclude that algorithm developers, scientist, different researchers have yet to explore the depths of the process of cow face recognition

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Chapter 4
Muzzle Point Pattern-Based Techniques for Individual Cattle Identification

Abstract Animal biometrics-based recognition systems are gradually gaining more proliferation due to their diversity of application and uses. The recognition system is applied for representation, recognition of generic visual features and classification of different species based on their phenotype appearances, the morphological image pattern, and biometric characteristics. The muzzle point image pattern is a primary animal biometric characteristic for the recognition of individual cattle. It is similar to the identification of minutiae points in human fingerprints. This chapter presents an automatic recognition algorithm of muzzle point image pattern of cattle for the identification of individual cattle, verification of false insurance claims, registration, and traceability process. The proposed recognition algorithm uses the texture feature descriptors, such as speeded up robust feature and local binary pattern for the extraction of features from the muzzle point images at different smoothed levels of Gaussian pyramid. The feature descriptors acquired at each Gaussian smoothed level are combined using fusion weighted sum rule method. With a muzzle point image pattern database of 500 cattle, the proposed algorithm yields the desired level of identification accuracy. Moreover, the comparative analysis of experimental results for proposed work and appearance-based face recognition algorithms has been done at each level. The proposed work, therefore, can be a potential approach for the recognition of individual cattle using muzzle point image pattern.

Keywords Animal biometrics · Cattle recognition · Muzzle point
Computer vision · Pattern recognition · PCA · LDA · ICA · LBP
SURF · Fusion · Texture descriptor

4.1 Introduction

Cattle identification is a severe problem in the livestock management [1, 2]. The registration and traceability of livestock animals using cattle identification can provide the better platform for livestock management using animal biometrics [3]. Animal biometric recognition system stops the efforts for manipulation, swapping

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of animals using matching of biometric features of animals. It also traces and follows food, feed, food-producing animal and substance that are supposed to be or expected to be incorporated into a food or feed throughout all stages of production, process, and their distribution [4, 5]. Hence, animal biometrics-based cattle recognition system is essential for design and development of effective and efficient livestock management in modern farming throughout world.

Efficient animal biometrics-based recognition system also provides to control safety policies of animals. It also provides a better management for the food production. Moreover, traceability process of livestock also provides identification of parentage or ownership of animals using animal biometrics [6–11].

In the current state-of-the-art-based methods, identification of cattle has become extensively used for various applications ranging from the animal registration, traceability, tracking, outbreak, and control of severe disease to behaviors analysis using computer vision and machine learning approaches [12, 13, 9]. However, recognition of cattle has been serious problems for breeding associations in the traditional animal recognition systems throughout the world [14, 4, 6–10].

In Indonesia, the ear-tagging-based techniques suited the extremely expedient for the recognition and verification of different livestock animals [11]. Moreover, in the various countries similar to USA, Australia, Europe, Canada, and Great Britain, embedded RFID in the ear-tags is also applying for the registration, traceability, and recognition of livestock animals [15, 16]. The traditional animal recognition methodologies (such as ear-tags, RFID, embedding of microchips and hot iron-based marking system) have their boundaries and limitations for recognition of cattle. Therefore, it is a requirement to design and develop an automatic, noninvasive, cost-effective, and robust animal biometric-based- recognition system for identifying individual cattle using muzzle point image pattern.

Besides that, all traditional animal recognition techniques, the artificial marking methods (e.g., ear-tips and ear-notches, freeze branding (hot iron), embedded microchips, and RFID) can also be duplicated, fraudulent, and unable to verify the false insurance claims, swapped, and cattle manipulation [11, 16–18]. Due to major significant limitations and failures of the traditional animal recognition based methodologies and livestock based framework, animal biometrics explored the better alternative means of cattle recognition based on their biometric feature characteristics such as face and muzzle point images of cattle. In order to achieve registration and traceability purposes, face and muzzle point image-based cattle recognition system provide accurate and robust identification of individual livestock animals.

Muzzle point image-based identification of individual cattle is suitable and unique solution in the available literature. It is also shown and reported in the dermatoglyphics study of cattle. The dermatoglyphics study illustrates the muzzle point image consists of ridge, granule, and vibrissae. These are unique structure of muzzle point image. This structure is different for each cattle breed. Therefore, the muzzle point image pattern of cattle is a suitable and first animal biometric identifier for the recognition of livestock (especially for cattle).

In this current study, it is also claimed that the recognition of muzzle point pattern is similar to identification of minutiae points in human fingerprint [7–11, 15–21]. Only a few researches have been done so far for identification of cattle in animal biometrics. In this chapter, muzzle point algorithm-based animal biometrics-based cattle recognition system is proposed for identification of individual cattle. It gives better solutions to solve the major problems of classical cattle identification [22].

4.1.1 Motivation Behind the Work

The classical animal recognition approaches include ear tattoos, the embedded microchip, and freeze branding, hot irons, ear-tags [23, 24], RFID, marking, and sketching pattern on their hides. The classical animal recognition approaches have been applied to identification and verification of individual animals for numerous of years.

In the literature of animal recognition and classification, there are no such animal biometrics-based cattle recognition systems available in the traditional livestock framework to prevent the manipulation and swapping of cattle. Classical cattle identification and tracking methods such as ear tags, branding, tattooing, and electrical techniques have long been in use; although, their performance is restrained due to their vulnerability to losses, duplications, fraud, false insurance claims of animals and security challenges. Such significant challenging problems of recognition cannot ignore by scientists, experts, ecologists, diverse research communities, and multidisciplinary researchers. Therefore, it needs to contribute valuable efforts for the design and development of robust, non-invasive, and automatic recognition system for identification, tracking, and monitoring for animals or species.

In this chapter, muzzle point pattern recognition system is proposed for recognizing individual cattle. The proposed muzzle point recognition system is noninvasive, cost-effective, robust primary biometric marker, easy to acquire, accurate, and also humane.

The cattle recognition system provides the efficient solutions to solve these problems of cattle recognition. The muzzle point image pattern of cattle is taken as primary and suitable animal biometric feature for the identification of individual cattle. In this chapter, a novel cattle recognition system is proposed. The proposed recognition system extracts the discriminatory set of salient textures features of muzzle point image database. The extracted set of texture feature of muzzle point image is considered for generation of biometric feature template during enrollment process.

Moreover, the primary motivations of the research for cattle recognition using muzzle point image are: (1) To provide significant contributions by designing and developing a cattle recognition system with the help of interdisciplinary researchers, veterinary professionals computer scientists, and engineers using the animal biometric techniques. The system can cater efficient solution for registration and monitoring of livestock animals (2) There is the need for validation and testing of the designed, and the developed cattle recognition system based on the face image database of cattle. However, there is no such face image database is available in public domain for testing and validation of designed system on the different identification settings. (3) therefore, a 5000 muzzle point image database of cattle is prepared by the 20-megapixel camera from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S), Banaras Hindu University (B.H.U), Varanasi, India. (4) The detailed experimental design and standard identification protocols along with train-test splits are shared to encourage other multidisciplinary researchers to report comparative results and depth analysis of preliminary results.

In this chapter, the extracted feature extraction algorithm is novel for identification of individual cattle because it is motivated by observing that the muzzle point (nose print) image pattern consists of texture feature. It also has distinct beads and ridge features, known as muzzle point features. The silent sets of extracted texture muzzle point features are more discriminate, accurate to recognize the cattle. The major research contributions of this chapter are given in next subsection.

4.1.2 Major Contributions of the Research Work

To the best of our knowledge, this is the first work for the automatic recognition of cattle using muzzle point image pattern database. Along with this, the major contributions of our research are as follows:

1. The covariates of muzzle point images of cattle are available due to poor illumination, pose, and poor quality images. These are significant challenges for the recognition of individual cattle. The proposed muzzle point recognition algorithm mitigates the artifacts from these covariate image using texture descriptor-based algorithms and Gaussian pyramid filtering technique. The Gaussian pyramid filtering is a low-pass filter used for smoothing the captured images up to four levels of the Gaussian pyramid levels of muzzle point image database.
2. The proposed recognition algorithm extracts the salient texture features from the muzzle point images using the texture descriptors-based recognition algorithms, such as speeded up robust feature (SURF) and local binary pattern (LBP) at various levels of Gaussian pyramid. The feature descriptors acquired are combined using fusion weighted sum rule method at each Gaussian level.
3. In this chapter, the comparative study of experimental results of appearance-based face recognition approaches, texture-based algorithms, and proposed muzzle point recognition algorithms are done for identifying individual cattle.
4. The database of muzzle point image pattern of 500 cattle (subjects) is prepared with 20 megapixel camera from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U.), Varanasi, India-221005.

The rest of the chapter is organized as follows: Section 4.2 illustrates the descriptions of proposed muzzle point image pattern recognition system of cattle. Section 4.3 depicts the proposed system for cattle identification based muzzle point image of cattle. It also presents the matching technique for cattle identification. Section 4.4 presents the experimental results and discussion along with identification setting to validate the experimental results and evaluate the performance evaluation with their detailed analysis. Finally, Sect. 4.5 summarizes and concludes our work and provides future directions.

4.2 Biometric Characteristics of Muzzle Point Images

According to Baranov et al. and Mishra et al. [4], muzzle dermatoglyphics (i.e., ridges, granola, and vibrissae) from various races is mostly differences. The recognition of minutiae point in muzzle image is similar to human fingerprint recognition [22–25]. The artifact of muzzle point image pattern of cattle grouped into two distinctive attributes of a muzzle point image known as beads and ridges [22–27].

The bead attributes consist of irregular structures, and their shape is similar to the islands, whereas the structures of ridges attributes are similar to minutiae points in human fingerprint and shaped similar to rivers, and it separates the beads structures from the ridges. The muzzle points image pattern shown in Fig. 4.1.

4.3 Proposed System

In this section, the muzzle point image pattern-based recognition system is proposed for identification of individual cattle. In the proposed system, the muzzle point image pattern of cattle has been considered as biometric characteristic for individual identification of cattle.

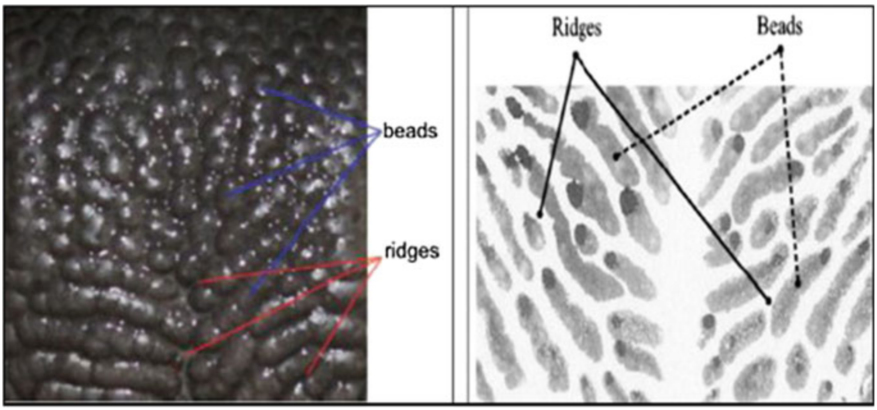

Fig. 4.1 Beads and ridges features of the muzzle point image pattern of cattle from the database

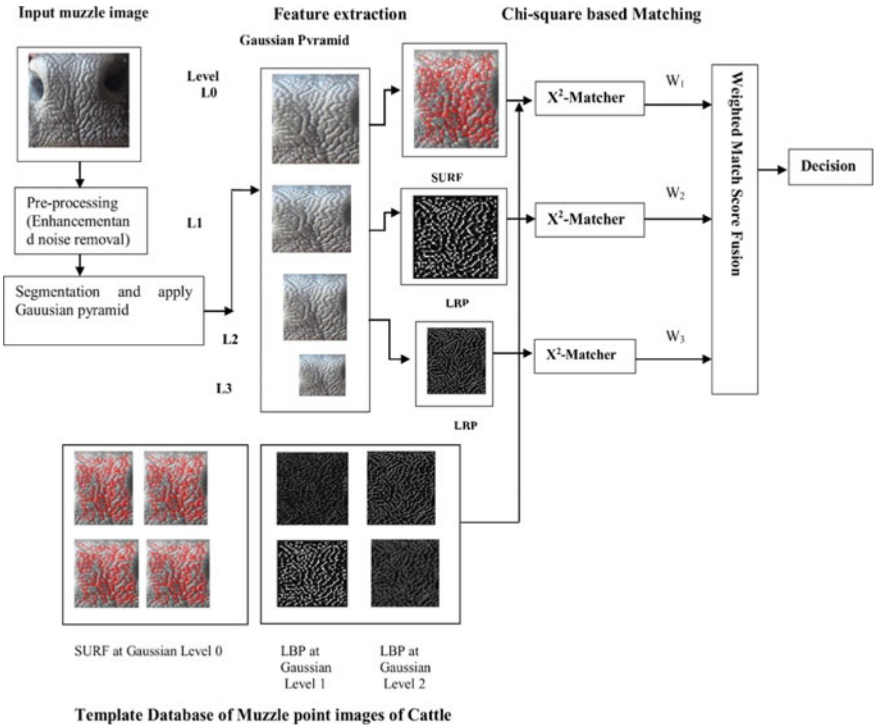

Fig. 4.2 Steps involved in the muzzle point pattern recognition algorithm of cattle

Figure 4.2 illustrates the working flow diagram for preprocessing of captured muzzle point image. The blurred muzzle point images of cattle are preprocessed using various filtering techniques. The artifacts of muzzle point images are removed by using filtering technique.

In the proposed recognition system, muzzle point feature-based biometric template is generated from the dense texture feature of bead and ridge pattern of muzzle point image. A biometric feature-based template is a digital coding or reference of distinguishing characteristics that have been extracted from the captured data and templates that are stored in the database. In the recognition process, the recognition system performs a one-to-one or one-to-many comparison of the captured biometric feature of query image with the stored biometric template in the biometric database to ascertain in the correct individual animal or species [28, 29].

The muzzle point image pattern of cattle has rich texture information and distinct features in the form of beads and ridge feature pattern. The proposed cattle recognition system is an animal biometrics-based pattern recognition system. The recognition system mainly focuses on the cattle recognition using the discriminatory set of patterns, features, and regularities in captured image data. The input muzzle point image database is captured by the proposed cattle recognition system using sensor (e.g., digital camera, smart phones, or other devices).

After the acquisition of muzzle point image database of cattle, the preprocessing and enhancement of images are done for removal of various kind of artifacts and noises from the images. The working of proposed cattle recognition system consists of following steps to recognize the individual cattle. These steps are namely (1) preprocessing, (2) segmentation of muzzle point images, (3) exaction of features (bead and ridge features) from the segmented muzzle point images.

In the feature extraction step, the bead and ridges pattern features of muzzle point images are extracted using local texture descriptor-based techniques and appearance-based feature extraction and representation approaches at various Gaussian pyramid levels [30, 31] (i.e., L0, L1, L2, and L3), (4) chi-square distance-based matching technique is applied to compute the dissimilarity scores between corresponding levels of the Gaussian smoothed test muzzle point images and stored muzzle point images.

Finally, the weighted sum rule fusion technique is applied to compute the final similarity score of muzzle point features for identification of individual cattle. The brief description of each stage of the proposed system is given in next subsections.

4.3.1 Preprocessing and Enhanced of Muzzle Point Image Pattern

The muzzle point image is preprocessed using the image processing techniques and computer vision methods for the feature extraction and matching. The preprocessing step in the proposed algorithm has been applied to alleviate a specific degradation such as noises.

The muzzle point images were captured from the unconstrained environments (i.e., poor illumination, pose, and movement variation of the head and blurred muzzle images) that may be defective and deficient in some respect such as poor image quality, low contrast, and blurred muzzle point images.

4.3.2 Image Enhancement Using CLAHE Technique

After that the quality of the muzzle point images is needed to be improve through the process of image enhancement techniques for achieving the better contrast between the foreground (objects of interest) and background [32]. Therefore, the contrast limited adaptive histogram equalization (CLAHE) image enhancement technique has been used for the enhancement of muzzle point image in the proposed recognition algorithm of muzzle point image for recognizing of cattle.

After that, the preprocessing the muzzle point image using CLAHE technique, there is the requirement to extract features and to find the number of beads and ridge regions from the muzzle point images. The image enhancement of muzzle point image of cattle is shown in Fig. 4.3. Figure 4.3 illustrates preprocessing, image

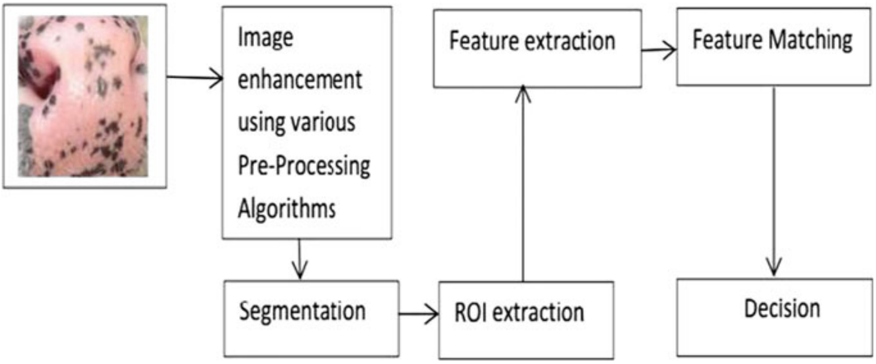

Fig. 4.3 Preprocessing and image enhancement process of muzzle point image

enhancement, segmentation process to find the region of interest (ROI), feature extraction and matching steps based on the decision strategy for identification of cattle based on muzzle point features. It shows the filtration process of overlapping region of muzzle point images between beads and ridges in the muzzle point images.

The muzzle point is enhanced in contrast and richness using various image enrichment methods, and later, it founded out which algorithm will be best suited for image enhancement in real-time cattle recognition system.

The images of muzzle point pattern of cattle after undergoing image enhancement using various methods are shown below in Fig. 4.4.

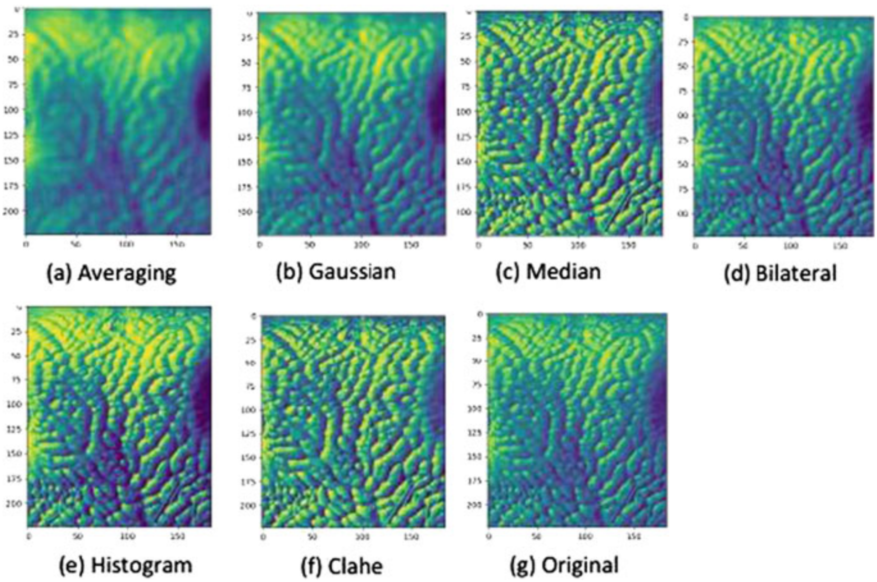

Fig. 4.4 Preprocessing of muzzle point image of cattle

In order to achieve the better quality of cattle recognition system, different image processing methods are used to pre-process the captured muzzle point image pattern of cattle. These methods are averaging filtering, Gaussian pyramid, a low-pass filtering technique, median filter, bilateral filter, histogram-based image quality enhancement technique. Moreover, contrast limited adaptive histogram equalization (CLAHE) method is applied to enhancement the images.

The image processing techniques are used to improve the quality of muzzle point image of cattle by mitigation of noises and other artifacts from captured images for the recognition of individual cattle. Based on overall observation, CLAHE image enhancement technique provides the better quality of muzzle point image during preprocessing and enhancement phase.

Figure 4.4 depicted the preprocessing of muzzle point images using (a) average filtering technique, (b) Gaussian filtering techniques, (c) median filter, (d) bilateral filter (e) histogram-based technique, (f) contrast limited adaptive histogram equalization (CLAHE), (g) original muzzle point image pattern of cattle.

After the preprocessing, texture segmentation algorithm is applied to partition the muzzle point image pattern into different region of interest (ROI) to extract the discriminatory features. The segmentation of muzzle point images using texture segmentation algorithm is shown in Fig. 4.5.

Figure 4.5 illustrates (a) original muzzle point images and (b–c) illustrates the extraction and selection of discriminatory features of beads and ridges pattern from ROI of segmented muzzle images using texture segmentation algorithm.

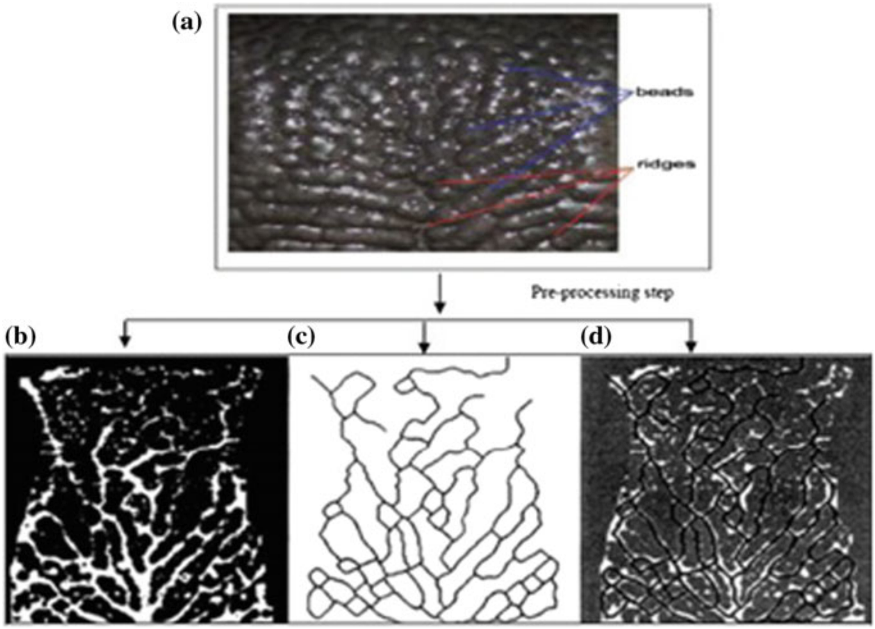

Fig. 4.5 Illustrates the preprocessing and extraction of bead and ridge feature from the muzzle point image of cattle

4.3.3 Segmentation and Feature Extraction

In computer vision and digital image processing, image segmentation is the process of partitioning a digital image into multiple segments. The multiple segments include sets of pixel values, also known as super-pixels. The objective of image segmentation process is to simplify and improve the representation of the image into more meaningful and more straightforward to analyze the images. For image analysis, feature plays a vital role in providing accurate and non-redundant information about the image. The feature extraction based algorithms provide a way to decode a given image pattern into a set of measurable discriminatory features for facilitating the subsequent learning and generalization steps for identification and classification of different objects, and in some cases leading to better human interpretations images. The final target of feature extraction and representation step is to articulate a feature vector for every muzzle point image pattern for cattle identification.

In the feature extraction, the quality of muzzle point images is first assessed to determine its suitability for further processing. After the quality improvement of muzzle point images using the CLAHE technique [24–28, 30–34], the discriminatory set of muzzle point image features (i.e., pixel intensity and texture feature) are extracted and represented by appearance-based feature extraction and representation algorithms and texture features-based descriptor algorithms, respectively. The segmentation is process to divide the input into different partition for the analysis of individual objects (beads and ridge features) of muzzle point image of cattle.

The main motivation to apply the segmentation is to find the accurate the region of interest (ROI) of segmented muzzle point image pattern of cattle. After that, discriminatory set of muzzle point feature is extracted from the segmented muzzle point images. The segmentation and feature extraction of muzzle point image are shown in Fig. 4.6.

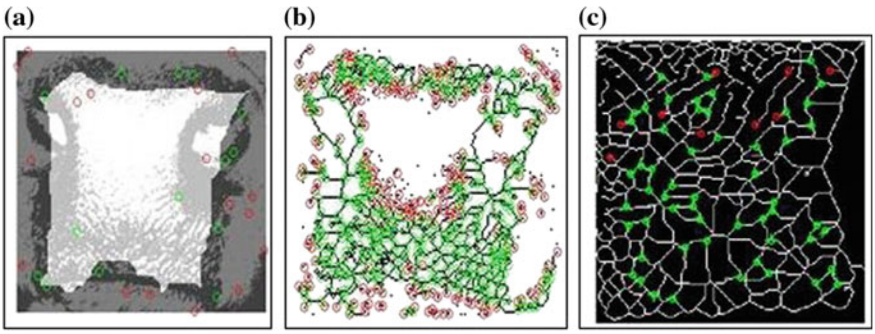

Fig. 4.6 Illustration of segmentation and feature extraction process for muzzle point images pattern of cattle

The selection of the region of interest (ROI) of muzzle image pattern is made by removal of foreground and background of muzzle point pattern. In particular, the binary regions generated by simple thresholding method which are deteriorated by noise and texture. Therefore, morphological image processing techniques are used for removing these imperfections by accounting for the form and structure of the greyscale images of muzzle point pattern. It also applied to find the number of minutiae points in muzzle image by using fundamental operations (Erosion and Dilation). It processes images based on shapes of muzzle point.

Dilation operation adds pixel values to the boundaries of the objects in an image, while erosion operation removes pixel values on object boundaries. The number of pixel values included or excluded from the objects in the muzzle point image that depends on the size and shape of the structuring element such as ridge and bead feature used to find the number ridge bifurcation and termination points in the muzzle point of the cattle. The ridge endings and bifurcations form the minutiae point feature in the muzzle image of animals. Minutiae points are discriminatory feature points in a muzzle image. These feature points are used for identification and verification of species or animals. Figure 4.6a presents the selected region from the original muzzle point image, and Fig. 4.6b–c illustrates the extraction and selection of discriminatory features of beads and ridge biocuration and termination pattern from the ROI of segmented muzzle images using texture segmentation algorithm.

The minutiae point is collection of ridge termination and ridge bifurcation feature points of muzzle point image pattern of cattle. The recognition of cattle based on muzzle point image pattern is similar to recognition of minutiae point in the human fingerprint. The ridge termination feature points of muzzle point are shown in red dotted points as a visual representation in the feature space. The number of ridge bifurcation feature point is shown in green color (shown in Fig. 4.6a–c). The extraction of beads and ridges features from the selected ROI regions and Fig. 4.6c depicts the section of discriminatory features of muzzle point images for recognition of cattle.

4.3.4 *Matching of Muzzle Point Image Using Chi-Square-Based Matching Technique*

For recognition of cattle, initially, template matching-based technique is applied for similarity matching of muzzle point image pattern. In training phase, the local binary pattern (LBP) [34–45] histograms of muzzle point images, and speeded up robust feature (SURF) [46] are computed from given class of cattle database. After that, average LBP histogram is evaluated to generate a histogram template for given class of muzzle point images [44, 47].

In this experiment, nearest-neighbor (NN) [47] classification technique is applied for matching and classify the histogram of muzzle point feature for recognition of individual cattle.

The LBP histogram and SURF texture feature vectors of the input muzzle point image are matched with the closest template of muzzle point image in the stored database of cattle.

In order to evaluate the histogram values of muzzle point features, chi-square (X^2) as the dissimilarity measure is applied to find the match score values from each smooth level of Gaussian pyramid muzzle point image [45, 47]. A chi-square (X^2) statistical analysis-based method is used to study whether distributions of categorical feature values differ from one another. It is observed that muzzle point features are contained highly rich texture information. This information mainly lies in some regions of beads and ridges pattern of muzzle point images.

These texture patterns provide more discriminatory information for classification and identification of cattle. Therefore, a weight can be set for each region of muzzle point images based on the discriminatory information of the (beads and ridges). The weighted chi-square (X^2) dissimilarity measure is defined as follows (shown in Eq. 4.1)

$$X_W^2(S_1, S_2) = \sum_{i,j} W(i,j)\frac{(S_1(i,j) - S_2(i,j))}{S_1(i,j) + S_2(i,j)} \tag{4.1}$$

In above Eq. (4.1), (S_1) and (S_2) are two histogram values of the local binary muzzle point feature pattern on smooth level L1 and L2 of Gaussian pyramid and W_j is defined as the weight for region (j) of muzzle point image pattern.

The primary objective of weighted sum rule fusion algorithm for recognition and classification of cattle is given into two folds:

- To improve the discriminatory between distinct classes of muzzle point database of cattle.
- To alleviate the redundancy of feature, via dimensionality reduction [31–33].
- Furthermore, in this chapter, the experimental results of the proposed approach are compared with appearance-based face recognition methods and existing standard texture feature-based descriptor technique for recognizing individual cattle based on muzzle point image. The proposed algorithm is facilitated by Algorithm 4.1.

In proposed approach, the weighted sum rule-based fusion technique is applied to compute the fusion scores corresponding to each smoothed level of Gaussian Pyramid. The scores are evaluated using SURF and LBP feature descriptor-based technique. The fused *Sfused* similarity score is used for final decision to identify individual cattle based on muzzle point image pattern.

In the experiments, $W1 = 0.90$, $W2 = 0.05$, and $W3 = 0.05$ weight parameters are chosen to fuse the similarity matching scores and computed average match scores for identification of cattle. Based on overall observation, the weight parameters selected as optimum to yield the better accuracy of cattle identification. Muzzle point algorithm using weight sum rule fusion technique is shown in Algorithm 4.1.

Algorithm 4.1: Muzzle point recognition algorithm

Procedure FUSION (($S1$, $S2$, $S3$), ($W1$, $W2$, $W3$)) /* procedure function*\
1. **Initialization step:** input muzzle point images (N) with $m \times n$ (where m and n = 400 pixel value of muzzle point image pattern of cattle).
2. Initialize the weights ($W1$ = 0.9, $W2$ = 0.05 and $W3$ = 0.05) and fused score S(fused).
3. **Pre-processing step:** The muzzle point images are convolved using the Gaussian pyramid.
4. **Database preparation step:** Store the pre-processed and convolved muzzle point images into database.
5. **Feature extraction step:** texture feature descriptor technique SURF feature is applied to extract the texture feature from smoothed level (L0) images.
6. **Texture feature extraction technique:** LBP texture feature based descriptor technique is applied to extract the feature from smoothed level L1 and L2 of muzzle point images.
7. **Combination of feature histogram:** Combine the LBP texture features histogram from Gaussian smoothed pyramid levels L1 and L2.
8. **Matching technique**: Chi-square distance measure technique is used to compute the dissimilarity scores of muzzle point images of cattle.
9. **Normalization process:** The similarity matching scores $S1$, $S2$ and $S3$ are normalized using the min-max technique.
10. **Sum rule:** Weighted sum rule fusion method is applied to fuse the scores $S1$, $S2$ and $S3$ [48].
11. **Computation Fused score:** The fused score (Sfused) is computed (shown in Eq. 4.2).
Sfused $= W1 \times S1 + W2 \times S2 + W3 \times S3$ (4.2)
12. Return Sfused.
End procedure

4.4 Experimental Results and Discussion

In this section, we have performed the experiments on Intel core-2 duo, 1.35 GHz computer with 20 GB of primary random access memory. The muzzle point image of the database is cropped from the frontal face images of cattle and re-sized into 400×400 pixels. After the preprocessing and enhancement and segmentation of muzzle point images quality, features are extracted from the muzzle point image pattern database.

4.4.1 Database Preparation and Description

To the best of our knowledge, there is no publicly available muzzle point image pattern database of cattle that can be applied to evaluate the current recognition and classification algorithms or develop new algorithms for recognizing the muzzle point image pattern of cattle. However, to conduct a scientific experimental study on extracted set of muzzle point features. Moreover, the local (texture features) and global (appearance-based features) features of covariates of muzzle images are also used to analysis for biometric feature of individual cattle. It is imperative to collect muzzle point images for the cattle registration. It is very important for analysis of breeding, production, and distribution of the livestock animals.

The database of muzzle point image pattern of cattle is prepared using a 20-megapixel camera from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S.), Bananas Hindu University (B.H.U.), Varanasi, India-221005. The sample images of muzzle point pattern of cattle is shown in Fig. 4.7.

The prepared database of muzzle point image contains few images of muzzle point in the form of various covariates of muzzle images due to low illumination, poor image quality, pose variation, and blurred muzzle images because of head movement and body dynamics of cattle.

In the database, some muzzle point images of cattle are suffered from the low illumination, poor image quality, and blurred image of muzzle point of cattle. Figure 4.8 shows sample images of muzzle point due to low illumination in (b) and (c), blurred point muzzle images in (a) and (d), and pose variation and blurred images in (e) and (f), respectively.

From these muzzle point images, we manually filtered the images along with blurred and low illumination muzzle images. In total, muzzle point image pattern database of cattle therefore consists of 5000 muzzle point images pertaining to 500 subjects (cattle) and 10 muzzle images of each cattle.

Fig. 4.7 Sample image of muzzle point pattern of cattle from database

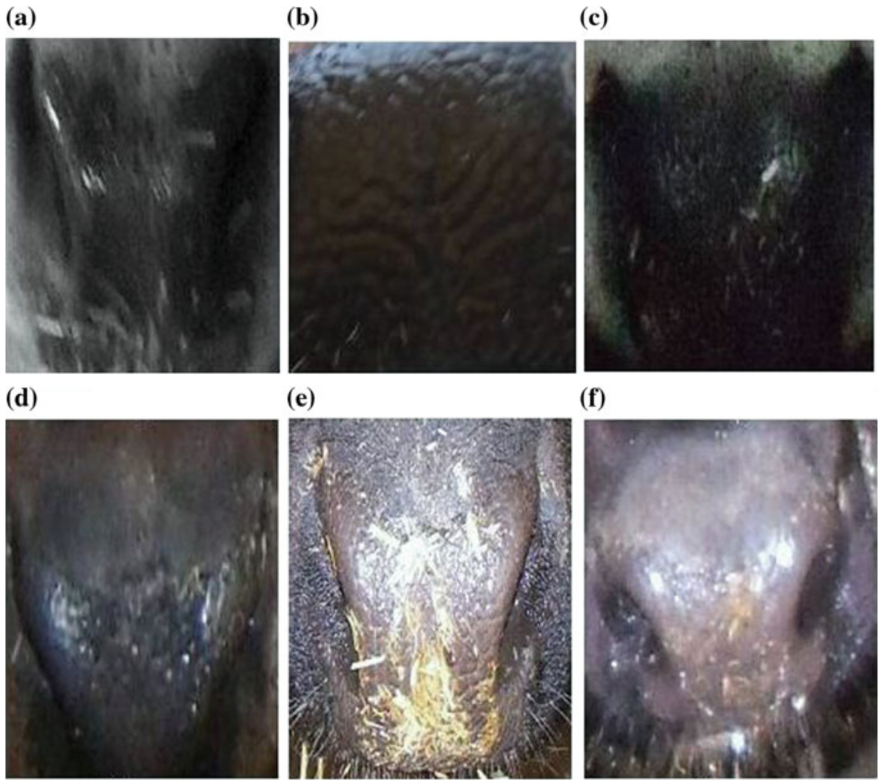

Fig. 4.8 Some challenging images from the cattle database

Table 4.1 Details of the muzzle point image pattern database of cattle

Name of cattle breeds	No. of subjects (cattle)	No. of images
Balinese cow	150	$150 \times 10 = 1500$
Hybrid Ongole cow	150	$150 \times 10 = 1500$
Holstein Friesian cow	100	$100 \times 10 = 1000$
Cross breed cow	100	$100 \times 10 = 1000$

Table 4.1 illustrates the composition of the muzzle point pattern images from various races of cattle for the experiment scenario.

4.4.2 Performance Evaluations of Proposed Algorithm

In order to evaluate the performance, appearance-based face recognition and representation algorithms and existing standard texture feature-based descriptor techniques are applied to extract the feature of muzzle point images and computation of the performance of proposed cattle recognition system. The brief description of appearance-based face recognition and representation algorithms and texture feature-based descriptor techniques are given in next subsection as follows:

4.4.2.1 Appearance-Based Feature Extraction and Representation Technique

In this subsection, the appearance-based feature extraction, and representation techniques are used to identify the individual cattle based on extracted features of muzzle point image database.

For the evaluation of performance, the combination of well-known appearance-based feature extraction and representations algorithms is first evaluated. The appearance-based feature extraction and representation algorithms are; namely Eigen faces [e.g., principal component analysis (PCA)] [35], linear discriminant analysis (LDA) [8, 19–21, 33, 34, 37], independent component analysis (ICA) [39]. Furthermore, we have also customized the batch and incremental-based face recognition and representation algorithms (e.g., batch-CCIPCA candid covariance-free incremental-PCA algorithm: CCIPCA [40], LDA-LiBSVM [36–38, 41], PCA-LiBSVM [41, 42], batch-incremental-LDA [43], and incremental-LDA-LiBSVM [43] with support vector machine (SVM) [41] for classification of the extracted discriminatory set of features of muzzle point images.

The primary motivations behind to apply the PCA and LDA classification and representation algorithm are to provide the optimal reconstruction of the sample images of muzzle point and dimensionality reduction. The most descriptive linear for the objects (beads and ridge patterns in muzzle point images) is achieved by Eigen feature space decomposition techniques and extracts discriminatory features (pixel intensity) for better representation in the feature space.

Linear Discriminant Analysis (LDA) is a supervised classification technique. The primary objective to apply the LDA classiifcation algorithm is to classify the extracted set of muzzle point features based on labelled classes of muzzle images for discriminating the different classes of muzzle point images for accurate identification of individual cattle. Therefore, LDA supervised algorithm is more efficient for the recognition and classification problems than the PCA algorithm. The LDA algorithm uses Fisher discrimination criterion by maximizing the ratio of the determinant of between-class (S_{b}) and within-class (S_{w}). The (S_{b}) and (S_{w}) classes are defined as follows [shown in Eqs. (4.3)–(4.6)]:

$$S_{\mathrm{b}} = \sum_{i=1}^{c} (n_i(m_i - m)(\sum_{i=1}^{c} (m_i - m))^T \tag{4.3}$$

$$S_{\mathrm{w}} = \sum_{i=1}^{c} \sum_{x_j \in X_i} ((n_i(m_i - m)(m_i - m))^T \tag{4.4}$$

The linear discriminant analysis algorithm is defined by following mathematical formulation for an optimization problem. The mathematical equations are shown in the Eqs. 4.5 and 4.6, respectively.

$$W_{\mathrm{OPT}} = \arg\max_{w} \frac{w^T S_{\mathrm{b}} w}{w^T S_{\mathrm{w}} w} \tag{4.5}$$

$$m = \frac{1}{n} \sum_{i=1}^{c} \sum_{x_j \in X_i} (n_i x_j) \tag{4.6}$$

where (m) and (c) are defined as defined as mean of database and number of classes of sample images. While the primary objective of LDA algorithm is to build the feature subspace that discriminates the various classes of muzzle point images. Therefore, LDA algorithm is more efficient for the recognition and classification problems than the PCA algorithm [22, 23]. The LDA algorithm uses Fisher discrimination criterion to maximize the ratio of the determinant of between-class (S_{b}) and within-class (S_{w}).

4.4.2.2 Texture Feature-Based Descriptor Algorithms

The proposed muzzle point recognition algorithm is motivated by the observation that muzzle point images of cattle have rich texture and distinct features in the form of bead and ridge pattern. Moreover, it is very difficult to restrict pose and body dynamics of cattle due to head movement and illumination variations, implying that appearance-based (holistic) face recognition and representation algorithms cannot provide better results. On the other hand, texture feature-based descriptor algorithms can yield good results.

High discriminating power of local texture-based LBP descriptor technique exploits the capability of local region-based feature of muzzle point image for better representation. Hence, it is fast to compute and robust to pose, illumination, and pose variations.

The effect of artifacts such as low illumination, poor image quality, and blurred of muzzle images can be mitigated by applying the Gaussian smoothing techniques. In the Gaussian pyramid, subsequent muzzle point images are weighted down using a Gaussian average known as Gaussian blur and scaled down. Each pixel value is comprising a local average that compares to a pixel neighborhood on a lower level of the pyramid for removing the noise and specific artifacts from the muzzle point images of cattle. Therefore, two levels of Gaussian smoothing pyramid levels are used to ensure that low illumination, blurred and poor image quality due to head movement of cattle's images is satisfactorily filtered while keep discriminating information of muzzle point images of cattle.

The texture feature of muzzle point images is extracted using local binary pattern (LBP) [45, 46] and speeded up robust feature (SURF) [47] for the recognition and representation of muzzle point images in the feature space, respectively. Therefore, texture feature-based descriptor algorithms have been applied to extract the texture features from the muzzle point images for better recognition of individual of cattle.

To extract muzzle point features from the original muzzle image database and two Gaussian smoothed images, texture feature extraction SURF and LBP techniques are applied. LBP features are extracted from low levels (L0 and L1) of smoothed muzzle point images while texture features of muzzle point images are extracted from higher smoothed level (L2) of muzzle point of cattle.

4.4.3 Experimental Evaluation

For evaluating the results, first, the prepared database of muzzle point image pattern was segmented into two parts—(1) train (gallery) and (2) test (probe) part. The six muzzle point images of each cattle were randomly chosen for training phase (e.g., total number of 500 cattle × 6 muzzle point images per subjects (cattle)), and remaining muzzle point images were selected as test images (probe) in this experiment.

The non-overlapping train–test partitioning is repeated ten times, and recognition performances are evaluated regarding identification accuracy of cattle. The Cumulative Matching Curves (CMC) is generated by computing the identification accuracy over these trials for top five ranks. The cumulative match score curve is the rank n versus the percentage of correct identification of muzzle point images, where rank n is defined as the number of top similarity scores which are reported during the recognition process. Experimental results are also summarized in Tables 4.2, 4.3, and 4.4, respectively.

The experimental results in Tables 4.2, 4.3, and 4.4 show the rank-1 identification accuracy of proposed algorithm which is reported in Table 4.2. In general, LDA algorithm performed better than the PCA algorithm. The top recognition accuracy of the LDA and PCA algorithms are 84.19 and 81.89%.

Table 4.2 shows the performances of recognition algorithms, such as PCA, LDA, ICA, SURF, LBP, and proposed algorithms for the recognition of muzzle point image pattern of cattle; the identification accuracy is amplified by increasing the levels of the Gaussian pyramid which decreases the resolution of the muzzle point image of cattle. As shown in Table 4.2, appearance-based face recognition-based independent component analysis algorithm yields the better identification accuracy of 86:97% at the starting level of the Gaussian pyramid.

In this experiment, texture feature-based SURF descriptor algorithm yields the maximum identification accuracy at level L0, while for LBP algorithm, it was noticed that the performance of LBP algorithm increases with increasing the respective levels of Gaussian pyramid (smoothing level) which is shown in Table 4.2, respectively. Therefore, local feature-based descriptor technique, such as LBP, yields better identification accuracy based on smooth muzzle point images by Gaussian pyramid technique.

The correlation values of SURF features on Gaussian level L0 and LBP features at Gaussian level–1 showed a very low recognition rate for cattle identification. Therefore, it validates that SURF texture features on level–L0 and LBP features at level–L1 and level–L2 at Gaussian levels used for recognizing the muzzle point image of cattle in the proposed approach.

In this experiment, the performance of the proposed algorithm is evaluated with five-time random cross-validation on the muzzle point pattern database of cattle. The average rank-1 identification accuracy of proposed approach is observed to be 93.87% with a standard deviation is equal 3.17. The identification accuracy of proposed approaches and other descriptor recognition techniques is shown in Tables 4.3 and 4.4, respectively.

Table 4.3 illustrates the identification accuracies of Batch-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM algorithms for recognition of cattle using muzzle point image pattern of cattle. The incremental-support vector machine (ISVM) technique yields identification accuracy of 86.98% in comparison of other feature extraction representation algorithms.

The identification accuracy of the PCA-LiBSVM algorithm is higher than PCA algorithms because PCA-LiBSVM selects the maximum variance-based Eigen-features (principal component) of muzzle images. Therefore, it classifies the Eigen-features of muzzle point images for identification of individual cattle.

Table 4.2 Identification accuracies of PCA, LDA, ICA, SURF, LBP, and proposed approaches for cattle recognition

Gaussian smoothed level	Algorithms	Identification accuracy (%) (Rank-1)
Level 0	PCA	74.39
Level 1		79.81
Level 2		81.89
Level 0	LDA	75.57
Level 1		80.64
Level 2		75.57
Level 0	ICA	86.97
Level 1		75.95
Level 2		78.97
Level 0	SURF	83.40
Level 1		62.10
Level 2		60.95
Level 0	LBP	78.68
Level 1		82.20
Level 2		85.92
Level 0	Proposed approach	93.87
Level 1		
Level 2		

Table 4.3 Performance of modified appearance-based recognition algorithms such as, Batch-CCIPCA, ICA, IND-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM

Gaussian smoothed level	Algorithms	Identification accuracy (%) (Rank-1)
Level 0	Batch-CCIPC	66.67
Level 1		70.49
Level 2		74.95
Level 0	ICA	82.75
Level 1		84.29
Level 2		86.34
Level 0	IND-CCIPCA	50.95
Level 1		54.32
Level 2		58.95
Level 0	Incremental-SVM	82.40
Level 1		87.68
Level 2		90.98
Level 0	LDA-LiBSVM	74.29
Level 1		79.95
Level 2		87.59
Level 0	PCA	60.25
Level 1		63.75
Level 2		66.85
Level 0	PCA-LiBSVM	64.78
Level 1		68.82
Level 2		71.86

On the other hand, identification accuracy of LDA-LiBSVM technique is relatively higher than LDA technique at each Gaussian pyramid level. The LDA-LiBSVM algorithm finds the more discriminating features of muzzle point images.

The LDA-LiBSVM selects the discriminating features of muzzle images by maximizing the inter-class variation and minimizing the intra-class variation (i.e., between-class scatter matrix (S_{b}) and the within-class scatter matrix (S_{w}) by maximizing the (S_{b}) and minimizing (S_{w})) of muzzle point of cattle database. Therefore, LDA classifies all samples of classes of muzzle point images correctly.

Independent component analysis (ICA)-LiBSVM algorithm yields 88.87% of identification accuracy for muzzle point pattern recognition, which is higher than Batch-ILDA, CCIPCA-LiBSVM, and ILDA and ILDA-LiBSVM recognition algorithms. The identification accuracies of CCIPCA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms increase with increasing the number of selected Eigen-muzzle images decreases in levels of Gaussian pyramid.

The identification accuracies of ICA and ICA-LiBSVM algorithms are higher than PCA, PCA-LiBSVM, LDA, and LDA-LiBSVM because the important features of muzzle image pattern which are contained in the high-order relationships

Table 4.4 Identification accuracies of Batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms

Gaussian smoothed level	Algorithms	Identification accuracy (%) (Rank-1)
Level 0	Batch-ILDA	74.40
Level 1		79.25
Level 2		85.50
Level 0	CCIPCA-LiBSVM	79.50
Level 1		81.90
Level 2		83.95
Level 0	ICA-LiBSVM	80.70
Level 1		82.42
Level 2		88.50
Level 0	Incremental-LDA	77.75
Level 1		79.49
Level 2		82.85
Level 0	ILDA-LiBSVM	78.93
Level 1		80.92
Level 2		83.25

between the muzzle images (pixel intensity) that can be used for the better representation of muzzle images in feature space. Therefore, we have applied independent component analysis algorithms for muzzle pattern recognition of cattle, which finds a better representation of basis images (muzzle point images) which is sensitive to high-order statistics for basis image representation. The identification accuracies of above algorithms are shown in Table 4.4.

4.5 Summary and Future Directions

In this chapter, a muzzle point pattern recognition-based system is proposed for recognition of cattle. The proposed system identifies cattle based on their muzzle point image pattern. The recognition of cattle based muzzle point image is similar to minutiae point recognition in human fingerprint.

The proposed recognition extracts set of salient features using texture descriptor-based techniques such as SURF, LBP and appearance-based feature extraction and representation algorithms from the muzzle point images at various levels of Gaussian pyramid-based low-pass filtering technique. The average filter and bilateral filtering techniques are used to remove the noises from the captured muzzle point image database of cattle.

The texture features descriptors obtained at each Gaussian smoothed level are combined using weighted fusion sum rule method. The experimental results on a database of 5000 muzzle point image pattern (500 individual cattle $\times$ 10 images of each subject) illustrate that automatic muzzle recognition algorithm is feasible for recognizing cattle.

Moreover, this chapter presents the current state-of-the-art-based approach for recognition of cattle using texture feature descriptors and similarity matching techniques for the matching of query (test) muzzle point image with stored muzzle point image.

In this experiment, the performance evaluation of the proposed algorithm is computed with five-time random cross-validation of the muzzle point pattern database of cattle. The average rank-1 identification accuracy is observed to be 93:87%.

After experimental performance evaluations of feature texture descriptors [49–53] and appearance based face recognition, representations algorithms are used based on their muzzle point images. Animal biometrics provides powerful tools and computer vision based frameworks to obtain significant impact for registration and identification of individual cattle [54–57]. Therefore, animal biometrics-based recognition system are gaining proliferation and huge applicability for monitoring and recognition of endangered spaecis and individual animal

The proposed recognition system can be used to solve the problems of registration, insurance claims, health management of livestock animals and their traceability. In future, it can be planned to do further research keeping in view the following areas:

- The size of the muzzle point pattern database is to be enhanced, and different conditions can be considered while capturing of cattle muzzle image for each subject, including pose variation and poor illumination as covariates in the database.
- The multimodal-based animal biometric system can be developed for the robust and enhancement of recognition accuracy of cattle and other species muzzle point images and their visual generic features as primary animal biometric characteristics.
- In the current scenario, real-time animal biometric-based recognition systems are needed to be developed for the registration, identification, tracking, and health monitoring of different species or individual using advanced and efficient pattern recognition and computer vision algorithms.

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Chapter 5
Identification of Cattle Based on Muzzle Point Pattern: A Hybrid Feature Extraction Paradigm

Abstract This chapter presents a novel cattle recognition system using hybrid texture feature of muzzle point pattern for identification and classification of cattle breeds. The major contributions of this research are (1) preparation of muzzle point image database, (2) extraction of hybrid texture features of muzzle point images of cattle dataset, (3) classification of cattle using classification models such as K-nearest neighbor (K-NN), Fuzzy-K-NN, Decision Tree (DT), Gaussian Mixture Model (GMM), Probabilistic Neural Network (PNN), Multilayer Perceptron(MLP), and Naive Bays. In addition, the proposed approach is validated by achieving the state-of-the-art accuracy on muzzle point image database of cattle with standard identification settings.

Keywords Animal biometrics · Muzzle pattern · Cattle recognition
Features extraction · Classification

5.1 Introduction

Due to the biodiversity crisis, numerous species or individual animal including the whale shark, great apes, leopard, African elephant, Rothschild's giraffe, and chimpanzees are on the verge of extinction [1]. Over 50% of the total population of species is determined to be at risk of extinction throughout the world. Consequently, there is an essential requirement to protect the surviving populations of endangered species and individual animals.

For example, in Africa more than 500 endangered species or individual animals are found in the dangerous regions due to critical health problems [2]. There is a requirement to overcome the catastrophic problems of monitoring and identification of species and individual animal by applying animal biometrics recogition systems. It will require integration of methodologies among the scientific disciplines involved. Therefore, ecologists, biologists, scientists, engineers, research communities, and multidisciplinary researchers recently have started to design and develop the animal biometrics-based recognition systems for endangered species. Animal biometrics can also benefit a wide range of disciplines, including biogeography, population ecology,

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and behavioral research [1–3]. The designed automatic animal biometrics-based recognition systems can also used for identification, monitoring and tracking of the rare and endangered species or individual. The designed and developed systems can be needed to train each modules of system with unbiased and accurate information on their life history for producing computerized systems for phenotypic measurement and interpretation [4].

These animal recognition systems can provide the better support for data analysis and study of animal population. The monitoring endangered species and individual animal are an essential and critical step in their conservation. Animal biometrics-based recognition system is a pattern recognition-based image retrieval system. It acquires the biometric data from captured images of individual animal [3, 5].

The recognition system extracts the most important sets of biometric features from the captured image dataset of animals, compares biometric feature set against the feature(s) which are stored in the database [4, 5]. After that, system executes an action based on the similarity matching result for comparison of biometric train and test images to identify individual animal [3–6].

The identification of animal is a well-defined procedure. It includes various steps such as processing of captured data, extraction of salient biometric feature, and similarity matching of biometric features for animals [7, 8].

The monitoring of endangered species using animal biometrics-based recognition system provides a well-defined process to keep track by recognizing the species based on their discriminatory morphological image pattern and biometric features of animals [9]. It also monitors the species based on their gait characteristics or movements pattern [10].

To achieve higher resilience toward traditional identification approaches of cattle, the proposed recognition approach introduces muzzle point recognition algorithms for identifying cattle [9–11]. Due to the limitations of the traditional animal identification methodologies, this chapter introduces a novel muzzle point image-based approach for identification of cattle. It is similar to the recognition of human fingerprint. The muzzle point pattern-based identification is a suitable and noninvasive approach for identification of cattle.

The authors of [12, 13] have studied muzzle point dermatoglyphics of individual cattle. In their study, the authors include ridges, granula, and vibrissae of muzzle point images of cattle from various cattle breeds (races). Based on their study, they concluded that the muzzle patterns of cattle are not similar to other breeds.

Furthermore, based on the available literature [11, 12], the recognition of cattle based on muzzle point image pattern is very similar to recognition of human's fingerprint. Because minutiae points in the muzzle point image pattern of cattle include the most important features such as ridge bifurcations and termination and angle which are similar to minutiae points of human's fingerprint [11]. The salient set of features in muzzle point image is known as bead and ridge features. The features form the minutiae points in the muzzle point images which are able to recognize individual cattle. The beads are irregular structures and its shape is similar to islands, while ridges have structure which is shaped similar to a river [12, 13]. It separates the beads. Therefore, muzzle point pattern of cattle is a suitable

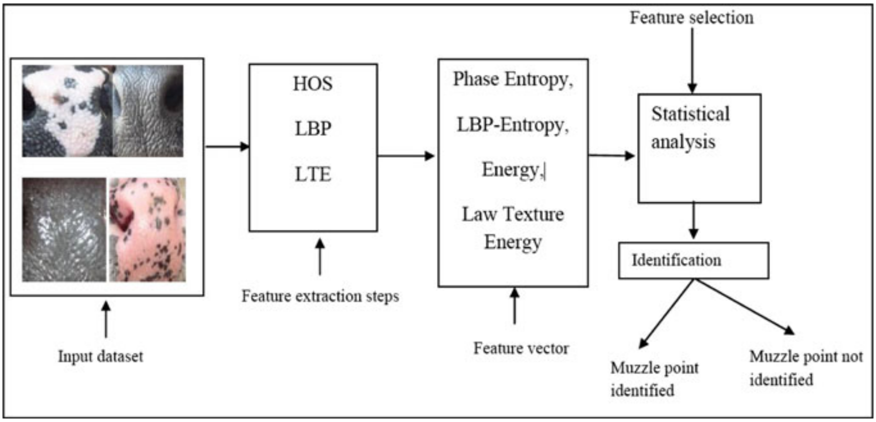

Fig. 5.1 Block diagram of the proposed automated identification system of cattle based on muzzle pattern

biometric identifier for identifying cattle [14]. The few sample images of the muzzle point pattern of cattle from the database are shown in Fig. 5.1.

Only few researches have been done so far and proven that muzzle point image pattern is used for cattle identification. The muzzle point image-based cattle identification approach can provide better solutions to major problems in traditional cattle recognition framework by applying the images muzzle point of cattle [13].

The advantages of muzzle point pattern-based recognition system are noninvasive, robust, fraud-proof, robust, easy to acquire, cost-effective, and accurate compared to previous animal identification systems which are mentioned previously [13, 14]. It can provide an improvement to previous identification animal systems for registration of false insurance claims, health management, missed, identification and traceability [15], prevent the fraudulent and duplication of various ear-tagging systems [16–18].

The muzzle point pattern of cattle has been considered as fundamental biometric characteristics for identification of the cattle in this chapter. The feature extraction algorithms are motivated by observing that images of muzzle point of cattle have rich skin texture and distinct features such as breads and ridges [15, 19–21].

The salient set of features is more accurate to identify the cattle based on muzzle point image pattern. Current methods for individual identification of many animals include capture and tagging techniques and researcher knowledge of natural variation in different phenotypes. These methods can be costly, time-consuming, and may be impractical for larger-scale, population-level studies. The salient set of biometric features of animals is more accurate to identify the cattle based on muzzle point image pattern. Therefore, the fundamental objective of this chapter is to design and develop a fully automated animal biometrics recognition based systems for cattle animals (livestock/cattle). The cattle recognition systems are not yet available in the literature. Therefore, animal biometrics can also improve the performance of systems by applying human-machine interfaces systems that yield low-cost computation and less time for pre-processing steps.

In these approaches, the animal-based recognition algorithms can mitigate human effort and the human feedback can improve the performances of animal biometric-based recognition system. Together, such valuable efforts can generate extensible, scalable, and effective large-scale deployments [16, 17, 22]. Within the realm of animal biometrics, a cattle recognition system appears to be the first such operational system for recognition of cattle based on muzzle point image pattern.

5.1.1 Major Contribution of the Work

The cattle identification plays significant role in vaccination management, controlling disease and outbreak and production management, assignment of ownership, registration and traceability of cattle. It can also solve the problems of animals being missed, swapped, forgotten, prevent the efforts of duplication and forgery of ear tags, border transfer and being falsely claimed for insurance and relocation at slaughterhouses. The major key contributions of this research are:

- A proposed approach is used for recognition and classification of cattle based on texture pattern of muzzle point images.
- The texture features of the muzzle point images of cattle are extracted using the hybrid texture feature extraction techniques (i.e., Haralick texture features techniques, morphology and shape-based features, histogram of oriented gradient (HOG), wavelet feature, color feature, Tamura's feature, Law's texture energy (LTE), speeded up robust features (SURFs), local binary pattern (LBP) and Fuzzy-local linary pattern (Fuzzy-LBP)) from the images of muzzle pattern database.
- The muzzle point image pattern database of 500 cattle (subjects) is prepared with 20 megapixel camera from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U), Varanasi, India.
- The motivation behind this research is to provide a better platform for emerging research prospective of animal biometrics to multidisciplinary researchers, communities, and scientists. Therefore, we provide a muzzle point pattern image database of cattle in the public domain for research purpose because there is no availability of such important database in the public domain. A detailed experimental protocol along with train–test splits is also shared to encourage other researchers to report comparative results.

5.2 Materials and Methods

This section deals with the details of the database of muzzle point pattern of cattle used for layout of the proposed approach. The complete description about prepared database of muzzle point image of cattle is provided in Chap. 4 (Sect. 4.4.1 Database Preparation and Description). It depicts total number of cattle and cattle breeds and total number of captured muzzle point images. The working model of cattle recognition system is illustrated in the next subsection.

5.3 Proposed Cattle Recognition System

In this section, proposed cattle recognition system using hybrid texture feature is illustrated. The schematic description of proposed approach for cattle identification and classification is shown in Fig. 5.1. Various steps of proposed recognition for cattle recognition in the proposed approach are namely, (1) preprocessing and enhancement of muzzle point images, (2) segmentation of images (find out region of interest (ROI)), (3) features extraction and finally the classification and recognition of muzzle point pattern of cattle.

In the proposed approach, the motivation of preprocessing step is to enhance the low-quality images and reduce noises from the captured database of muzzle point images; therefore, we have applied the contrast limited adaptive histogram equalization (CLAHE) [23–25] technique for the enhancement process.

After enhancement process, color K-means segmentation algorithm [26–28] is applied to find out the region of interest (ROI) from input muzzle point image pattern. After segmentation of muzzle point images, texture features of muzzle pattern (rich and distinct texture features such as beads and ridges) are extracted using texture feature approaches such as Haralick texture feature techniques [29–31], morphology and shape-based features [32, 33], histogram of oriented gradient (HOG) [34], wavelet feature [35], color features [36, 37], Tamura's feature [38], Law's texture energy (LTE) [39, 40], and Fuzzy-local binary pattern (Fuzzy-LBP) [41–43] features from the database of muzzle point image of cattle.

The texture feature extraction approach sees an image texture as a quantitative measure of the arrangement of pixel intensities in a region. The texture feature extraction-based approaches encoded and decoded the texture features of muzzle images of cattle and stored in the feature matrix with [M*N], where M and N are the numbers of rows and columns. Finally, the K-nearest neighborhood (K-NN) [44], Fuzzy-K-NN [45–47], Radial Basis Probability Network (RBPN) [48], Probabilistic Neural Network (PNN) [49, 50], Decision Tree (DT) [51], Gaussian Mixture Model (GMM) [52, 53], Multilayer Perceptron (MLP) [54], and Naive Bays [55, 56] classifier models are used for classification and recognition of cattle based on stored feature matrix. The various stages involved in the proposed approach are discussed in the next subsections.

5.3.1 Preprocessing and Enhancement Process of Muzzle Point of Cattle

The preprocessing step is an initial process in the proposed approach for recognition of cattle using muzzle point image pattern. The wiener filter-based approach has

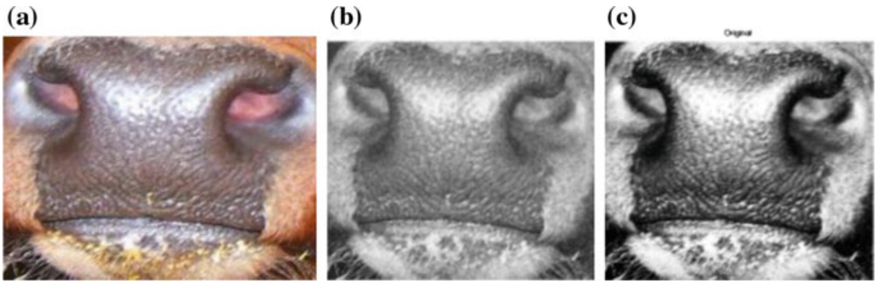

Fig. 5.2 Preprocessing: **a** Original image, **b** blurred image, **c** enhanced muzzle point images

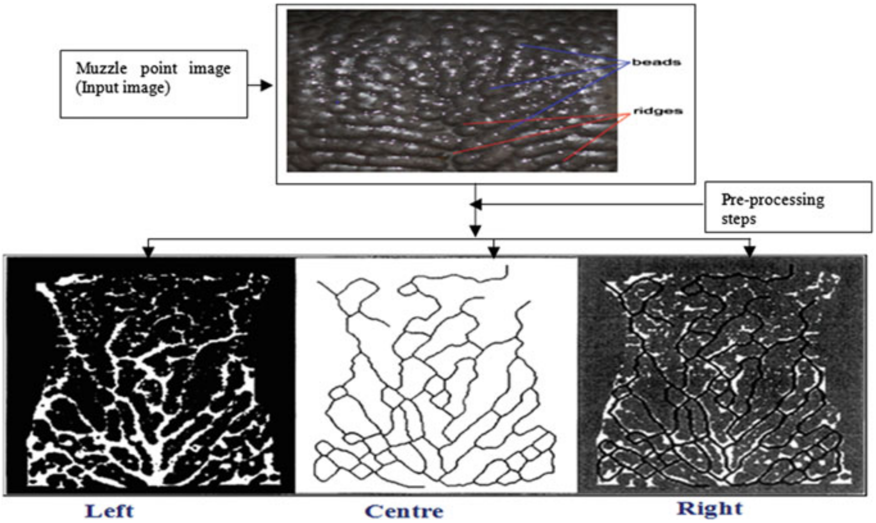

Fig. 5.3 Preprocessing of muzzle point image of cattle

been used for the noise removal and shading correction (e.g., shading occurs due to non-uniform illumination) to get the better quality muzzle image pattern.

The existence of noises in the muzzle image pattern occurred due to the presence of poor illumination, blurriness, and pose variation of their body, and these are manifested in the acquisition of muzzle point image pattern database. After that, contrast limited adaptive histogram equalization (CLAHE) [23] technique is used to mitigate the noises and enhancement of muzzle point image pattern database. Figure 5.2 illustrates the preprocessing process of muzzle point image pattern database. The preprocessing of muzzle point image pattern and extraction of beads and ridges as relevant texture features are shown in Figs. 5.2 and 5.3, respectively.

The color muzzle image pattern (e.g., combination of RGB color) is converted to Lab (La*b) color space, and luminance channel (L) is subjected to (a) Wiener filtering [57] using a 5 × 5 size filter (b) gray level shading correction using low-pass filtering (c) contrast enhancement of muzzle point image pattern using contrast limited adaptive histogram equalization (CLAHE) [30] image enhancement technique. The processed L channel is then combined with the chrominance channels (a and b) and converted back to red, green, and blue (RGB) color space.

It demonstrates the filtering of noises and other artifacts from the beads and ridge features of original muzzle point images using Wiener filtering technique [57] with 5×5 filter size.

For analysis of muzzle point image in the unconstrained environment. The blurred muzzle point image is preprocessed and enhanced using the Weiner filtering and CLAHE [23] image enhancement technique. After the enhancement and preprocessing, the feature is extracted from the processed image of muzzle point of cattle using texture feature extraction techniques. The obtained set of features includes the number of ridge bifurcations and ridge termination points of muzzle images. The ridges and beads are unique and immutable biometric feature for classifying individual cattle.

Figure 5.3 illustrates the filtration process using Wiener filtering technique with 5×5 filter size to find out the overlapped region of interest (ROI) between beads and ridge features.

5.3.2 Segmentation of Muzzle Point Image

The segmentation algorithms generally partition the input images into multiple segments and find out region of interest (ROI) from each segmented images. However, segmentation algorithms generally depend on the type of the required discriminating features to be preserved and extraction of discriminatory information from particular ROI of segmented muzzle point image pattern.

The motivation behind to select the K-means clustering [28] segmentation algorithms is that K-means clustering approach preserves the distinct information from muzzle point image pattern database. The segmented muzzle point image pattern is shown in Fig. 5.4.

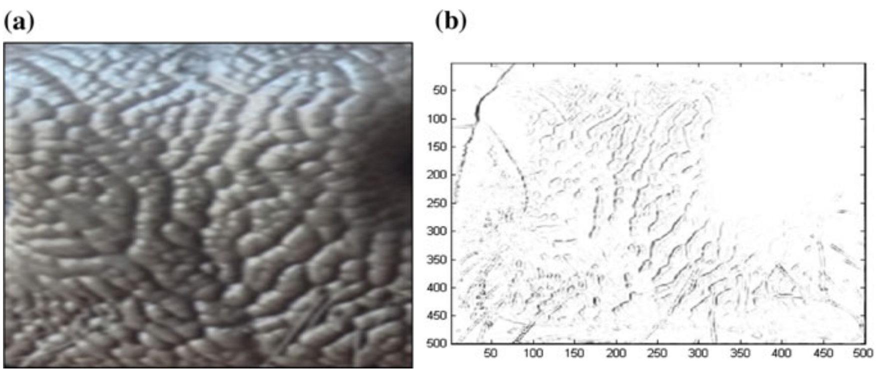

Fig. 5.4 **a** Original image and **b** segmented image of muzzle image pattern

After segmentation of muzzle point image pattern, the feature extraction approaches are used to find out useful texture features for the recognition and classification of muzzle point image pattern. In this chapter, texture feature-based segmentation, color-based image segmentation, and watershed segmentation techniques are used to segment the captured muzzle point images into multiple segments or region of interest (ROI). The main manifestation to apply these image segmentation techniques is (1) simply change the feature representation of a muzzle point image, (2) discriminatory visualization and easily understand the meaningful feature (information), and (3) easier to analyze of region of interest information of muzzle point image pattern of cattle.

However, the segmentation algorithms depend on the type of essential discriminating features to be preserved and extraction of discriminatory information from particular ROI of segmented muzzle point image pattern. The brief descriptions of texture feature-based segmentation, color-based image segmentation, and watershed segmentation techniques are illustrated in the next subsections.

5.3.2.1 Texture-Based Segmentation and Color-Based Segmentation

The main motive to apply the texture-based segmentation and color-based segmentation algorithms is to preserve relevant and discriminatory information of muzzle feature sets for the recognition and classification process of cattle. Moreover, K-means color clustering and texture feature-based segmentation algorithms are also applied to analyze the segmented muzzle point images of cattle by dividing into distinct region of interest (ROI) [58].

Fig. 5.5 **a** Original muzzle point image pattern, **b** segmented muzzle image with color K-means-based segmentation approach

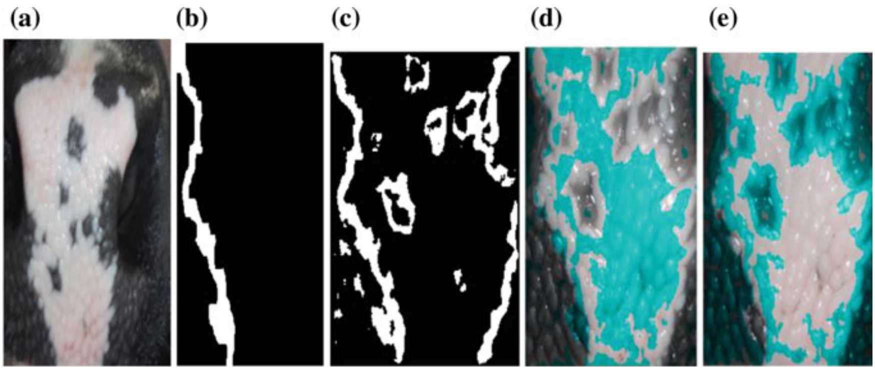

Fig. 5.6 Segmentation of muzzle point image pattern: **a** Original muzzle images, ground truth, and **b–e** found out ROI using texture segmentation algorithm

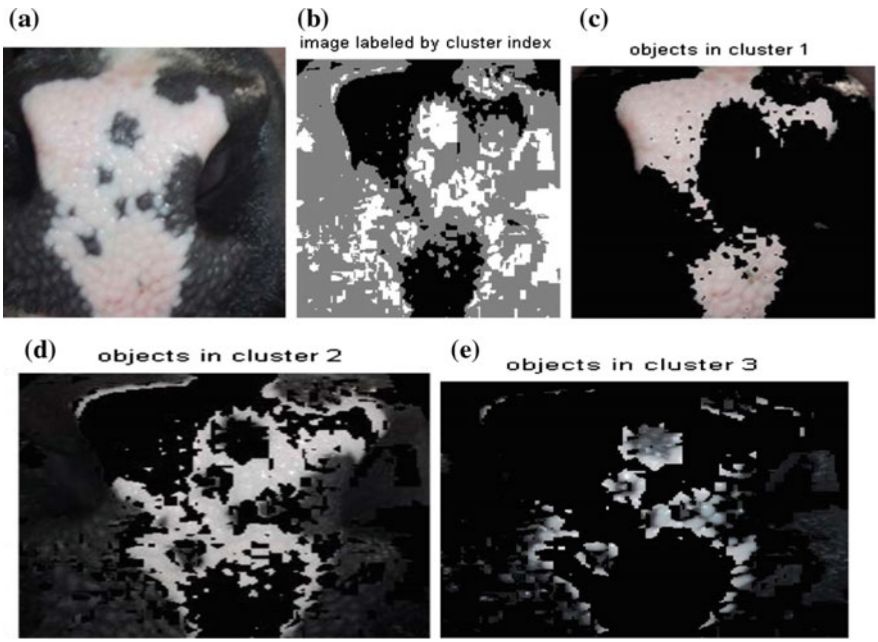

Fig. 5.7 Segmentation of muzzle point image pattern using K-means color cluster algorithm

From each ROI, texture feature and color feature are extracted using these techniques from the muzzle point image database of cattle. The segmented muzzle point image pattern of cattle using color K-means technique is shown in Figs. 5.5 and 5.6, respectively. Figure 5.7 depicts the segmentation of muzzle point image pattern using K-means color cluster algorithm.

Figure 5.7a–e illustrates the different color segmentation of muzzle point image. The segmentations of muzzle point images for clusters n = 3 (cluster-1, cluster-2, and cluster-3, respectively) are taken into consideration to preserve the muzzle point features for cattle identification. In this research work, number of cluster n = 3 keeps the meaningful information into different region of interest.

5.3.2.2 Minima Selection and Region Merging Using Watershed Segmentation Technique

The watershed segmentation algorithms are applied to partition into regions of the object in given image. The major disadvantages of watershed algorithm are mainly (1) it begins from the initialization of every minimum of the gradient of the image and (2) it always excessively performs oversegmentation [59, 60]. To reduce the problem of over-segmentation and minimum gradient of the images the dynamic algorithm is applied. The dynamic algorithm performs the segmentation of texture feature of the muzzle point images for the selection of the discriminatory set of features. The selection of discriminatory features is done on the minimum feature using suppression of irrelevant gradient feature selection methods. It preserves the rest texture feature of muzzle point image for unique discrimination of cattle using different classification models.

These values are used to initialize the markers for the selection of watershed region (e.g., region of interest) from muzzle point images. The dynamic algorithm mitigates the oversegmentation problem by reducing the insufficient minima of partitioned ROIs of muzzle images pattern into different classes [59]. The unsupervised watershed segmentation algorithm provides an efficient method for merging process of local minima values for better segmentation of muzzle point images. Finally, merging the neighboring regions of different classes of muzzle image is applied to merge the local minima values of the region of interest and it is processed as follows:

A. In the merging procedure, it applies a strategy for combining the smaller regions of segmented image (applicable on RGB color values of muzzle point images). The values of RGB color produce the regions keeping areas of regions which are significant to evaluation statistically as well as textural parameters.
B. In the second case, it merges into bigger regions of segmented images using defined stopping criteria (e.g., difference between of pixel intensities, textural and histogram differences). The segmented muzzle point images using watershed segmentation algorithm are shown in Fig. 5.8.

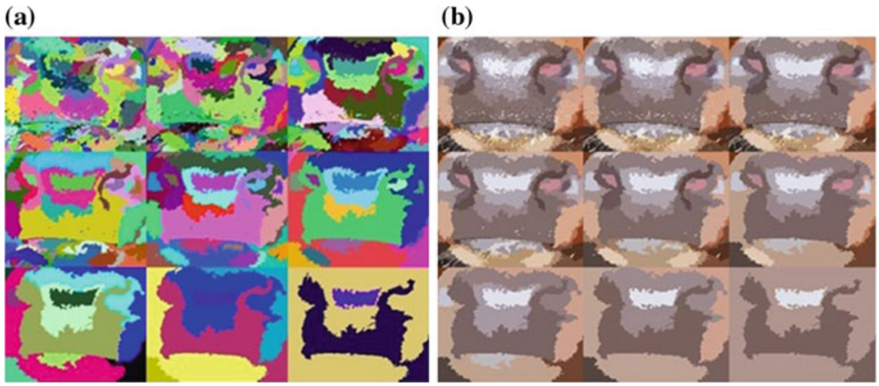

Fig. 5.8 Watershed-based segmentation of muzzle point image: **a**–**b** Selection of region of interest (ROI) from muzzle point image pattern database

5.4 Feature Extraction and Matching

The feature of any object is an important characteristic to encode the given image pattern into set of discriminatory measurable information or values. The feature extraction is a preprocessing process in the proposed approach, which is responsible for texture analysis and classification of muzzle image pattern based on discriminating sets of muzzle texture features. The eventual objective of this section is to articulate extraction of feature vector from each image of muzzle point pattern database of cattle.

The features of muzzle point image pattern are calculated with help of the eight types of texture features from the muzzle image pattern database. These features are namely, Haralick texture features techniques [29–31], morphology and shape-based features [32, 33], histogram of oriented gradient (HOG) [34], wavelet feature [35], color features [36, 37], Tamura's feature [38], Law's texture energy (LTE) [39, 40], and Fuzzy-local binary pattern (Fuzzy-LBP) [41–43] features from the database of muzzle point image of cattle. The ranges of extracted sets of texture feature are shown in Table 5.2.

After segmentation, texture features are extracted from the muzzle point image pattern database. To capture the discriminating shape and structure information of muzzle image pattern, the region-based and contour-based shape feature extraction descriptor techniques are used for the extraction of beads and ridge as rich texture pattern features (information) of muzzle image pattern. The shape is an essential fundamental feature for describing the muzzle point image pattern. Due to the presence of the noise, occlusion, distortion, the form of the muzzle is often corrupted. The shape representation-based descriptor methods perform the recognition of object based on shape features which are either based on the shape boundary information or boundary plus interior content of input image. One of the fundamental characteristics of the shape descriptor is low computation and fast method.

Table 5.1 Illustration of various texture features extracted from the muzzle point image pattern and their ranges

Name of features	Number of features	Range F1–F186
1. Haralick texture features [29–31]	22	F1–F22
2. Morphology and shape feature [32, 33]	10	F23–F32
3. Histogram of oriented gradient (HOG) [34]	36	F33–F69
4. Wavelet feature [35]	32	F70–F102
5. Color features [36, 37]	6	F103–F109
6. Tamuras's feature [38]	3	F110–F112
7. Law's texture features [39, 40]	16	F113–F129
8. Fuzzy-local binary pattern (F-LBP) [41–43]	56	F130–F186

By involving the discriminatory feature properties of the image in the recognition process, the computation of feature sets can be minimized and lower computation complexity achieved.

Therefore, we have used shape-based features which are manifested in feature extraction and discriminating capability of muzzle point image pattern of cattle based on these set of texture features. Table 5.1 illustrates the distribution of name of the feature type, and the number of features is chosen for the identification and classification of muzzle point image pattern of cattle.

5.5 Experimental Results Performance Evaluation

The texture features extracted from the muzzle pattern database of cattle were subjected to the statistical test such as Analysis of Variance (ANOVA) [61]. The performance evaluation has been performed after the computations of variation between feature sets of inter-class (within-class) and intra-classes (between classes) of database.

When the variation between classes of muzzle point pattern was produced to be relatively high as compared to the variation of within-class, then the test was taken under the consideration statistically significant. It indicates that the higher value of (F) or low value of (p) has been calculated from extracted feature [61]. The p-value is universally used in statistical hypothesis testing, especially in null hypothesis significance testing. In this method, as part of the experimental design, before experimenting, one first chooses a model (the null hypothesis) and a threshold value for p, called the significance level of the test, traditionally 5% or 1% and denoted as (α).

The 'F' and 'p' parameters are statistical parameters for evaluating the discriminatory of extracted set of muzzle point features for classification and identification of cattle based on between-class and within-class variation of muzzle point features of cattle. If the p-value is less than the chosen significance level (α), that intimates that the observed feature (data) is adequately inconsistent with the null hypothesis that the null hypothesis may be rejected. However, that does not prove that the tested hypothesis is true. When the p-value is estimated correctly, this test guarantees that the Type-I error rate is at most (α). The parameters (F) and (p) are defined as follows:

A. ***F*-Statistics parameter**: F parameter is defined as a ratio of two quantities that are expected to be equal under the defined null hypothesis.
In other way, F-statistics is a ratio of two variances of extracted set of salient muzzle point features. The variances are measure of dispersion of feature sets. It also measures how far the extracted features (bead pattern and ridge pattern information in the muzzle point images) are scattered from the mean value of extracted features [shown in Eq. (5.1)].

$$F = \frac{\text{Between} \ - \text{class} - \text{variation}}{\text{Within} - \text{class} - \text{variation}} \tag{5.1}$$

or

$$F = \frac{\text{Variation} - \text{Between} - \text{class} - \text{features}}{\text{Variation} - \text{within} - \text{class} - \text{features}}$$

The calculation of variation for between-class (S_{B}) and within-class (S_{W}) of extracted set of muzzle point image features is given as follows [shown in Eqs. (5.2–5.3)]:

$$\text{Variation} - \text{Between} - \text{class} - \text{features} = \sum_{i=1}^{K} N_i \frac{(\mu_i^- - \mu)}{(K-1)} \tag{5.2}$$

$$\text{Variation} - \text{within} - \text{class} - \text{features} = \sum_{\mathrm{i}=1}^{K} \sum_{j=1}^{Ni} \frac{\mu_{(i,j)} - \mu_i)}{(N-K)} \tag{5.3}$$

where $\left(\mu_i^-\right)$, (N_i), and (μ) are defined as sample mean of extracted feature set of ith group/class of cattle [shown in Eq. (5.1)], total number of the muzzle point images of cattle database, and overall mean of cattle muzzle point image database, respectively. $\left(\mu_{i,j}^-\right)$ depicts the jth observation in the ith out of K class of extracted set of muzzle point feature of cattle database.

A. **(*p*)-statistics-based parameter**: (p)-statistics-based parameter is defined as to determine whether any of the differences between the means are statistically significant and compare p-statistics-based parameter [0,1] to evaluate the significance of the extracted set of muzzle point features of cattle database based on the defined null hypothesis. The defined significance level (α=*0.0.5*) to validate the classification and identification of cattle based on extracted features.

1. If p value $\leq \alpha$, indicates strong evidence against the null hypothesis, so you reject the null hypothesis. There is no all of the classes of extracted feature set of muzzle point images are equal.
2. If the p value is larger than the significant level (α), indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis, then enough evidence is available to reject the defined null hypothesis and the mean of overall database of cattle muzzle point images is equal.

In this chapter, 186 texture features are extracted from the database of muzzle image pattern for recognition and classification of cattle and few samples of extracted texture features from muzzle point are resulted in a p value which is less than 0.0001. It indicates the extracted features are statistically more significance for classification and recognition of cattle based on extracted texture features.

The texture features of muzzle point images pattern have been divided into three classes, known as A, B, and C labeled classes. The set A and set B dataset consist of 2000 muzzle images each (e.g., 200 subject $\times$ 10 images of each subject) and set C consists of 1000 images of muzzle point pattern (e.g., 100 subject $\times$ 10 images of each subject) with size 200 $\times$ 200 pixels.

The characteristic of subset A muzzle images is manifested with poor illumination of 2000 muzzle pattern images pattern, set B holds blurriness and pose variation-based covariates muzzle images pattern of 2000 images (e.g., 200 subjects $\times$ 10 images) and finally, images of set C corresponding to each individual which are highly diversified by varying with various illumination, blurriness, and occlusions (shown in Fig. 5.9, respectively).

The muzzle point image database is divided into three classes for analysis and computation of more discriminatory sets of features of muzzle point image from each classes for classification and identifcation of cattle. The extracted sets of muzzle point feature from three classes are listed in Table 5.2. The division of database of muzzle point image pattern into three sets are such as A, B and C. The pictorial representation of sets A, B and C are illustrated in the form of Venn diagram (shown in Fig. 5.9).

Fig. 5.9 Distribution of muzzle point image database

5.6 Performance Analysis

The experimental results in this chapter have been conducted using computer with Intel® Core™ i5-4210U CPU running at 2.40 GHz and 50 GB of RAM. In the classification scenario, A, B and C groups of cattle each with 2000, 2000, and 1000 different muzzle images pattern of cattle are used in training and testing purpose to evaluate the recognition accuracy of cattle using different classification techniques. Table 5.5 illustrates the performance of different classifiers and comparative accuracy of experimental results.

In Table 5.3, the next three columns (1–3) present the recognition rate of cattle based on different cases of class-A muzzle point image pattern. The columns (4–6) and columns (7–9) present different recognition rate of classes or groups B and C, respectively. It is also evident from the experimental results that the K-NN classifier performed better than other used classifiers.

The K-NN classifier achieved the classification accuracy of 95.82%. The Fuzzy-K-NN, Decision Tree (DT), GMM, PNN, Multilayer Perceptron(MLP), and Naïve Bays classifiers yield the 94.85%, 75.54% (from group A), 79.45% accuracy from Group B and 85.76% accuracy from C groups; GMM classifier provides performance measures 77.63, 85.67, and 88.47% from the group A, B and C of muzzle point image pattern, respectively. Moreover, PNN classifier yields the classification rate of 94.56, 94.88, and 79.68% for recognizing cattle from the group A, B, and C of muzzle image pattern database, respectively.

While, MLP classifiers achieved the classification rates of 67.84, 77.93, 74.43% for groups A, B, and C, respectively, and Naive Bays classifier yields 77.32, 73.84, 71.84% classification rate of muzzle images pattern for recognizing the cattle. The classification accuracy of K-NN classifier among all the classifiers such as fuzzy K-NN, RBF, Decision Tree (DT), Gaussian Mixture Model (GMM), and Probabilistic Neural Network (PNN) yields the maximum classification accuracy of 96.74%. Therefore, K-NN classifier also has been chosen for the cattle recognition and classification using muzzle point image pattern in our work.

The Fuzzy-K-NN classifier has performed better recognition of cattle by classifying the feature vectors of muzzle images pattern as compared to remaining classification approaches. For Fuzzy-K-NN classifier strategy, we have selected fuzzy inference system (FIS) for classification, where the clusters were fixed using radii. The radii defined as a vector that indicates a cluster centers range of inference in each of the data dimensions, supposing that features (data) fall within a unit hyper box.

The range of small radii values of each cluster mostly belongs to 0.2–0.5 where $0.2 \leq \text{radii} \leq 0.5$. The range of clusters play a significant role in finding few large clusters of extracted set of features (data) from muzzle image pattern. In this work, we have chosen radii values of cluster are equal to 0.50 for the analysis and classification of extracted features of muzzle image pattern. In this experiment, for Fuzzy-K-NN-based classifier, the input membership function is Gaussian and

Table 5.2 Summary statistics (mean ± standard deviation) of few extracted texture features of muzzle pattern of set A, B, and C groups

Features	Set A	Set B	Set C	*F*-value	*P* value
Haralick features	7.1133e + 018 ± 9.7511e + 018	1.8778e + 019 ± 2.2334e + 019	2.1482e + 019 ± 2.7006e + 019	10.4606	<0.0001
LTE1	1.9634e + 009 ± 1.1345e +009	1.6626e + 009 ± 6.1147e +008	3.2373e +009 ± 1.7594e + 009	16.2052	<0.0001
LTE2	1.0628e + 009 ± 6.0847e +008	1.1165e + 009 ± 4.9497e +008	1.3241e + 009 ± 7.1588e + 008	1.9141	<0.0001
LTE3	2.4890e + 009 ± 1.4208e +009	1.2204e + 009 ± 6.7234e + 008	3.3821e + 009 ± 1.5850e + 009	24.5293	<0.0001
LTE4	1.6038e + 008 ± 8.1916e +007	1.0689e + 008 ± 4.2658e + 007	2.0546e + 008 ± 1.0112e + 008	13.8461	<0.0001
LTE5	1.5785e + 008 ± 7.7265e +007	1.2408e + 008 ± 4.8826e +007	1.7115e +008 ± 8.5985e + 007	4.3046	<0.0001
LTE6	1.4530e + 009 ± 8.9512e + 008	7.9325e + 008 ± 5.5436e + 008	1.5152e +009 ± 6.7139e + 008	11.4587	<0.0001
LBP1, 8 entropy	2.0290 ± 0.4720	1.1916 ± 0.3442	2.1978 ± 0.5986	55.7414	<0.0001
LBP1, 8 energy	0.3992 ± 0.1506	0.6764 ± 0.1066	0.3630 ± 0.1817	59.3935	<0.0001
LBP2, 16 entropy	2.3655 ± 0.5837	1.2949 ± 0.3692	0.4472 ± 0.6627	60.6534	<0.0001
LBP2, 16 energy	0.3826 ± 0.1564	0.6722 ± 0.1064	0.3612 ± 0.1777	60.5802	<0.0001
LBP3, 24 entropy	2.5046 ± 0.6359	1.3285 ± 0.3789	2.5079 ± 0.6736	62.1876	<0.0001
LBP3, 24 energy	0.3855 ± 0.1542	0.6719 ± 0.1053	0.3726 ± 0.1696	60.8724	<0.0001
Fuzzy-LBP	2.5146 ± 0.6369	1.3285 ± 0.3799	2.5079 ± 0.6756	62.1376	<0.0001
HOG feature	2.4956 ± 0.6459	1.3385 ± 0.3889	2.5079 ± 0.6936	63.1876	<0.0001

LBP Local binary pattern, *LTE* Law's texture energy, Fuzzy-LBP

Table 5.3 Classification of cattle based on muzzle point images classes (A, B, and C), each group has different size of muzzle point images

Classification group	Group A (200 subjects)			Group B (200 subjects)			Group C (100 subjects)		
Classification model/cases	50 cases (%)	50 cases (%)	100 cases (%)	100 cases (%)	50 cases (%)	50 cases (%)	20 cases (%)	30 cases (%)	50 cases (%)
K-NN	95.82	93.82	96.74	96.34	91.72	92.85	85.62	85.83	89.95
Fuzzy-K-NN	92.75	92.75	94.56	86.25	83.25	90.73	74.35	75.45	76.26
RBF	88.75	86.26	88.25	74.36	73.36	76.65	85.27	87.98	87.98
DT	78.47	73.23	75.54	70.41	72.45	79.45	81.47	82.68	85.76
GMM	70.25	73.25	77.63	82.74	82.25	85.67	72.74	79.65	84.47
PNN	92.63	92.63	94.56	90.42	90.42	94.88	78.42	79.62	79.68
MLP	62.63	62.47	67.84	72.33	71.37	77.93	68.73	70.92	74.43
Naive Bayes	63.21	63.21	77.32	64.67	75.65	73.84	63.92	74.83	71.84

output membership function. It is used for linear study of extracted set of muzzle point features.

In this chapter, PNN classification technique is tested on muzzle point features. In the PNN classifier, all biases in radial basis layer were set to $\sqrt{\ln(0.50)/s}$ where s denotes the spread constant of PNN. In this experiment, the better performance measure is achieved for $s = 0.50$. Furthermore, in the case of K-NN classifier technique, value of K-nearest neighbor varied from 2 to 6 in this experiment. However, at nearest neighbor $K = 2$, K-NN classifier provides the maximum accuracy in the recognition of muzzle point image pattern and distance is calculated using Euclidean distance-based technique [60–64].

In this experiment, majority rule has been applied for classifying the features of muzzle image pattern, that is, sample point is assigned to the class; the majority vote rule is an aggregation technique to generate one final prediction. In K-nearest neighbor classification models make local predictions based on nearest neighbour values. After that nearest neighbour values are collected and combined using a weighted majority rule to output the final prediction for cattle. In the case of GMM-based classification technique, the centers of clusters are initialized to five for all the respective groups of muzzle point pattern database. While, in Decision Tree (DT) classifier, the parent and leaf node values must be tuned for image classification. The parent and leaf node values are initialized to 10 and 1, respectively.

Naïve Bays classifier Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features. The motivation to apply the Naïve Bays classifier technique in this research is the extracted features sets of muzzle point from the within-class and between-class database are not discriminatory to analysis. The dimensionality of the input feature is high. Naive Bayes reduces input feature sets to a one-dimensional kernel density estimation for finding the discriminatory set of feature of muzzle point image of cattle. The kernel estimator includes the

Table 5.4 Classification rate for classes (A, B, and C) groups of muzzle point pattern, each group has different cases (muzzle point images of cattle)

Classification Group	Group A (200 subjects)			Group B (200 subjects)			Group C (100 subjects)		
Classification models/image	25 cases (%)	40 cases (%)	135 cases (%)	60 cases (%)	60 cases (%)	80 cases (%)	20 cases (%)	30 cases (%)	50 cases (%)
K-NN	75.32	76.63	78.84	66.47	73.89	75.59	74.43	79.93	82.25
Fuzzy-K-NN	79.85	85.93	93.88	83.95	85.75	87.68	72.89	74.93	77.96
RBF	64.25	68.78	72.65	69.96	71.46	72.95	78.84	74.68	87.68
DT	69.76	72.67	78.64	75.45	76.35	78.75	82.87	83.58	84.86
GMM	70.75	72.43	74.45	69.72	72.56	78.86	72.43	79.65	84.47
PNN	56.73	58.76	62.95	66.97	70.82	73.68	63.72	65.84	69.96
MLP	51.37	57.67	63.84	65.33	69.87	72.93	64.73	67.92	72.84
Naive Bayes	60.35	64.78	68.82	70.47	72.55	73.94	66.92	68.83	70.84

small number of parameters which are needed to be estimated for classifying the muzzle point pattern with small estimator variance (e.g., one-dimensional kernel density estimation with Gaussian distribution). The recognition rate of muzzle point pattern of cattle from different classes is shown in Table 5.4. In Table 5.4, recognition rate of groups (A, B, and C) has been considered in different cases of muzzle images pattern database and their recognition accuracies are illustrated in Table 5.4.

5.7 Recognition of Muzzle Point Image Under Different Rotations

In this section, the performance evaluation of experimental results based on muzzle point image pattern using different orientations is done. The query muzzle images of cattle are tested against different orientations in testing phase. The muzzle images patterns are rotated in the following angles: angles (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°). The images of muzzle point pattern and classification rate are shown in Fig. 5.10 and Table 5.5, respectively.

5.8 Recognition of Muzzle Image Pattern Under Different Occlusion Conditions

In this section, the experimental results and analysis have been also performed on the muzzle images database which is partially occluded (e.g., percentage (%) of occluded part of muzzle image pattern) [60–62, 65–71].

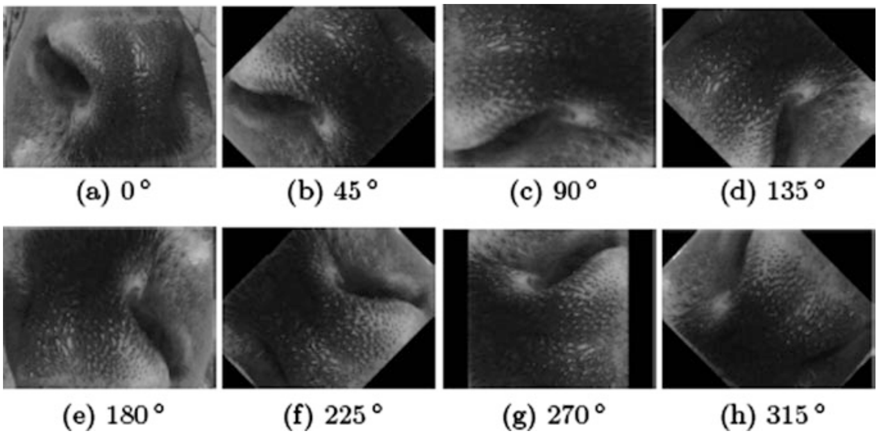

Fig. 5.10 Sample images of muzzle point pattern are rotated with different angles (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°)

Table 5.5 Recognition rate for (A, B, and C) groups of muzzle point pattern, each group has different cases (muzzle point images of cattle)

Classification group	Group A (200 subjects)			Group B (200 subjects)			Group C (100 subjects)		
Classification models/angles (in degree)/ images	0°	15°	45°	90°	135°	180°	225°	270°	315°
	50 cases (%)	50 cases (%)	100 cases (%)	50 cases (%)	50 cases (%)	100 cases (%)	20 cases (%)	40 cases (%)	40 cases (%)
K-NN	95.82	93.87	90.74	92.34	90.72	92.85	83.62	85.83	89.95
Fuzzy-K-NN	85.75	85.75	89.56	84.25	83.75	82.73	74.35	72.67	76.26
RBF	78.83	73.23	79.54	71.65	72.45	79.45	81.47	85.68	85.76
DT	69.76	72.67	78.64	75.45	76.35	78.75	82.87	83.58	84.86
GMM	69.75	70.25	71.63	73.42	76.25	78.47	68.74	70.65	72.47
PNN	90.73	92.89	94.56	89.42	91.72	92.88	78.42	79.42	80.68
MLP	62.73	64.47	67.84	72.33	73.97	75.93	68.73	70.92	71.84
Naive Bayes	65.87	67.58	70.45	74.39	76.55	78.94	70.72	70.72	74.82

The occluded muzzle images are considered to investigate whether proposed system using texture feature extraction is robust against the occluded of muzzle point images pattern while classifying the muzzle texture features for recognition of individual cattle. In this experiment, we have used 60% of the total database images of muzzle point for training process and remaining images for testing process which are occluded in different occluded percentage of its sizes as shown in Fig. 5.11.

After that, we used the occluded testing images to identify the cattle. The result of this experiment is shown in Table 5.6. The current state-of-the-art-based cattle identification approaches are illustrated, and performance of existing methods for

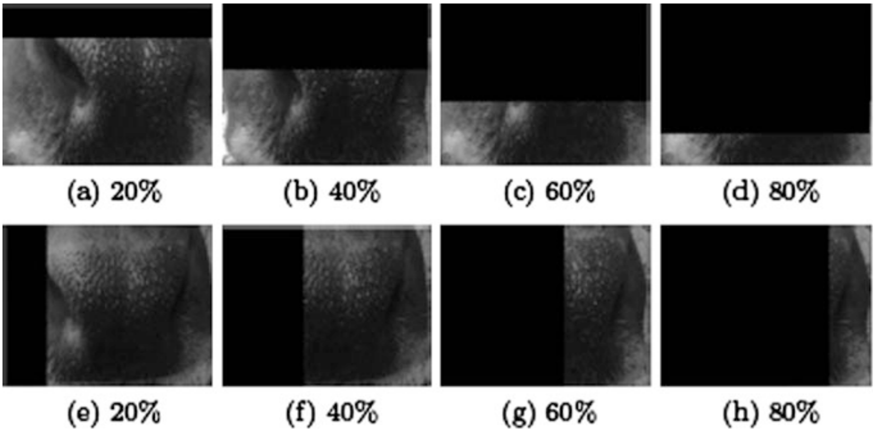

Fig. 5.11 Samples of occluded muzzle images, top row **a–d** represents bottom (horizontal) occlusion, and bottom row **e–h** represents top (vertical) occlusion

Table 5.6 Classification accuracy rate (%) for muzzle point image classes (A, B, and C) under occlusion (%)

Classification group	Group A (200 subjects)				Group B (200 subjects) + Group C (100 subjects)				
Classification model/occluded muzzle point image (%)	Occluded muzzle images (Bottom portion)				Occluded muzzle images (Top portion)				
	20%	40%	60%	80%	10%	20%	40%	60%	80%
	50 cases (%)	50 cases (%)	50 cases (%)	50 cases (%)	40 cases (%)	50 cases (%)	60 cases (%)	70 cases (%)	140 cases (%)
K-NN	92.78	94.87	96.84	97.34	98.85	96.65	85.82	88.65	91.82
Naive Bays	95.85	97.75	98.56	88.95	89.25	94.73	74.35	72.89	76.26
PNN	97.86	97.45	89.39	94.55	99.94	89.72	91.43	94.72	95.56

cattle identification and classification is compared with the proposed approach. The comparisons are depicted in Table 5.7, respectively.

5.9 Summary

In this chapter, a cattle recognition system is proposed using hybrid texture feature extraction and representation approach. The proposed hybrid approach identifies the individual cattle based on extracted texture feature of muzzle point image pattern. The proposed approach operates on the texture feature vectors obtained from 5000 images of muzzle image pattern using texture Haralick texture feature approaches

Table 5.7 Summary of cattle identification and classification techniques based on muzzle image pattern used in the literatures and experimental results of proposed approach

Authors	Images used for study	Features	Classifiers/ recognition approach	Accuracy (%)
Tharawat et al. [62]	217 muzzle print image	LBP	LDA, SVM	89
Awad et al. [63]	72 muzzle print image	SIFT	SVM	90
Minagawa et al. [64]	43 muzzle print image	Beads features of muzzle print image	PCA	40
Noviyanto et al. [72]	15 muzzle print image	SURF	Eigenvalues-PCA techniques	90
Barry et al. [73]	100 muzzle print image	Beads features of muzzle print image	Euclidean distance	45
Proposed approach	5000 muzzle point image	Hybrid texture features of muzzle point image	K-NN, RBNF, PNN, Fuzzy-K-NN, Naïve Bayes, MLP	94.74

and local texture feature approaches such as local binary pattern (LBP), Fuzzy-LBP descriptor techniques. From the achieved experimental results on a database of 5000 muzzle point pattern images (e.g., 500 individuals (subjects) $\times$ 10 images of each subject) and their qualitative and quantitative analysis, it can be concluded that the proposed hybrid texture feature-based method is performing better in comparison to other cattle recognition methods and illustrates that automatic recognition of cattle based on muzzle point image pattern is feasible [65].

As well as it is also capable of alleviating the problems associated with covariates of muzzle image pattern due to low illumination, poor image quality, blurriness. After performance evaluations of different classification algorithms on muzzle image pattern database, we hereby conclude that developers, scientist, different researchers have yet to explore the depths of the process of cattle recognition.

In future, it can be planned to do further research keeping in view the following areas:

- Size of muzzle point pattern datasets is to be enhanced and different conditions can be considered while capturing of cattle image for each subject: pose variation and poor illumination as covariates in the database.
- Covariate-based fusion techniques can be developed for cattle recognition as cattle covariates are to be estimated from the pair of images being compared.
- Multimodality-based recognition approaches can be developed to improve the recognition accuracy of cattle by using muzzle point pattern and face as biometric traits.
- Real-time biometric system for cattle recognition can be designed and developed using advanced algorithms.

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Chapter 6
Deep Learning Framework for Recognition of Cattle Using Muzzle Point Image Pattern

Abstract Recently, deep learning approaches have achieved more attention for recognition of species or individual animal using visual features. In this chapter, the deep learning-based recognition system is proposed for identification of different cattle based on their primary muzzle point (nose pattern) image pattern characteristics to solve major problem of missed or swapped animal and false insurance claims. The major contributions of the research work are as follows: (1) preparation of muzzle point image database, which are not publically available; (2) extraction of the salient set of texture features and representation of muzzle point image of cattle using the deep learning-based convolution neural network and deep belief neural network proposed approaches. The stacked denoising auto-encoder technique is applied to encode the extracted feature of muzzle point images; and (3) experimental results and analysis of proposed approach. Extensive experimental results illustrate that the proposed deep learning approach outperforms state-of-the-art methods for recognition of cattle on muzzle point image database. The efficacy of the proposed deep learning approach is computed under different identification settings. With multiple test galleries, rank-1 identification accuracy of 98.99% is achieved.

Keywords Cattle recognition · Muzzle point image · Deep learning
Convolution neural network · DBN · SDAE · Verification · Computer vision
LBP · SURF · PCA · VLAD · LDA

6.1 Introduction

Animal biometrics is an emerging research field of computer vision, wildlife science, and pattern recognition [1]. Animal biometrics-based recognition system develops quantified and efficient recognition methodologies for representing extracted visual features and detecting discriminatory features for identifying the phenotypic appearance of species or analysis of individual animal's behaviors based on its morphological image pattern and animal biometric characteristics.

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The phenotypic presentations consist of the composite of an organism's observable morphological features [1, 2].

The animal biometrics-based recognition system is a pattern recognition system. The recognition system extracts the prominent animal biometric features from the morphological image, biometric characteristics, and phenotypic appearances of different species or individual animal. In animal biometrics, identification of cattle based on biometric features has been one of the current and future research frontiers in the modern livestock for registration, tracking, and breed associations of animals [1–3].

Based on available literature, animal identification methodologies can be categorized into following groups: (1) permanent recognition method, (2) semipermanent recognition method, and (3) sketch pattern-based marking recognition approach [1, 2, 4–8].

6.1.1 Motivation Behind the Work

Toward successful operation of any farm, an effective animal identification and traceability play a vital role. In the livestock management, identification of cattle and traceability are also the very crucial well-defined process to provide the control safety mechanism and suitable policies for verification of animals, health management, and management of food production for animals.

The classical animal identification method can be divided into several groups, namely (1) mechanical-based identification, (2) electrical signal-based identification and traceability technique, and (3) biometric feature-based identification of cattle. The mechanical-based identification approach includes ear tags, embedding of microchips, and freeze branding-based approaches. The mechanical identification technique suffers from many limitations [9–11].

The ear-notching method is not suitable for large-scale identification systems. The ear tagging method includes metal clips and plastic tags for identification of cattle. These systems are not much expensive concerning other techniques.However, they may cause critical infections in animals. The freeze branding and ear tattoo-based identification approaches are not achieving a relatively proper identification or verification accuracy as in one herd. Freeze branding has the ability to leave permanent, highly visible brands that can be read at much greater distances than ear tags or many hot iron brands. The process of freeze branding is much more time consuming than ear-tatoos and hot iron branding for animal identification. Freeze branding methods are not immediately legible for ownership identification. Therefore, classical approaches for cattle identification and traceability are not useful to uniquely differentiate between various heads of cattle in the same herd [12].

The unique visual numbers such as ear-tags, id-color can be easily duplicated. The embedded label of ear tags can be forged for creating the duplicate tag number for the unregistered animals under the government animal insurance scheme by users. The users (e.g., parentage, owners of livestock, and others) can false insurance claim based on duplicated registered number for the unregistered animals. False insurance claims are insurance claims filed with the intent to defraud an insurance provider. Users can get the insurance claims by replacing and repeating the previous registered unique ear-tag number. These identification methods consume more time as compared to modern techniques [13].

In the current scenario, these techniques also fail to control the widespread of the animal critical diseases by identifying and detecting infected animals, due to high cost for management of embedded microchips in the body of animal, overall system cost is more, and it does not reduce the losses of livestock producers by controlling the diseases [14].

In the current state-of-the-art-based approaches, there is no such animal biometric-based identification systems present for identification and traceability of animals. The animal biometrics system provides well-defined procedures for identification of animal. These systems can perform the identification and detection of infected animal based on their biometric features such as muzzle point image (nose pattern). This process can be utilized for decreasing the government cost by the control, intervention, and eradication of the outbreak diseases.

In this chapter, we address the problem: *How to recognize individual cattle based on biometric feature of cattle such as muzzle point image (nose pattern) features using deep learning approaches*? To address this problem, we use a 20-megapixel digital camera for capturing the muzzle point image pattern of cattle.

The proposed cattle recognition system uses deep learning-based frameworks for the identification of individual cattle based on its muzzle point image characteristics. The proposed cattle recognition system captures the image of muzzle point pattern (nose pattern) of cattle. After that, the captured image of muzzle point pattern is preprocessed using the low-pass filtering technique to remove the noises from the captured muzzle point images. The pre-processed muzzle point images are taken into the consideration for the extraction and representation of texture features of muzzle image for recognition of individual cattle. After the feature extraction, extracted features are classify recognize the individual cattle.

6.1.2 Major Research Contributions

The following are important contributions of this research:

1. Considering the non-intrusive nature of muzzle point biometrics pattern, this research explores the new possibility of determining the unique identity of individual cattle using deep learning approaches.
2. Motivated from animal biometrics research across multiple domains and interdisciplinary researches, we discuss the major challenges and opportunities of the cattle recognition system.

3. In this chapter, a novel deep learning-based stacked denoising auto-encoder framework is used to encode and decode the extracted set of salient texture feature of muzzle point image of cattle for recognition of individual cattle.
4. The deep learning framework-based approaches are suitable to address the significant variations of muzzle point images of cattle in the unconstrained conditions due to low illumination, body dynamics and blurred images due to the head movement and body dynamics of cattle, and the poor image quality of muzzle point images. Novel deep learning frameworks such as convolution neural network (CNN) and deep belief network (DBN) approaches are used to learn the muzzle point texture feature of cattle for better representation of different deep neural network layers with deep learning framework.
5. A deep belief network (DBN) deep learning model is used to learn the extracted features of muzzle images for hierarchical representation of the training datasets by stacking restricted Boltzmann machine (RBM)-based classification technique for classification and identification of cattle.
6. Restricted Boltzmann machine (RBM)-based classification model is trained in a greedy manner for learning feature extraction and representation from the given large unlabeled image database and updating the loss function of DBM by including low-rank regularization.
7. Finally, a multilayer deep learning neural network has been used as classifier to achieve the identification decision for cattle.

The remaining parts of the chapter are as follows: Sect. 6.2 illustrates the database preparation and description of muzzle point images of cattle. Section 6.3 detailed the proposed deep learning-based recognition system of cattle followed by the feature extraction and representation of muzzle point image features using deep learning approaches. Stacked denoising auto-encoder is presented in Sect. 6.4. Section 6.5 provides the pretraining and generalizability of proposed model in brief. The experimental results and brief analysis of the work are reported in Sect. 6.6. Further, it includes the performance evaluations and comparative analysis of proposed approach. Finally, the conclusions and future directions are provided in Sect. 6.7.

6.2 Biometric Characteristics of Muzzle Point Image Pattern of Cattle

The detailed description of biometric characteristics of muzzle point image is provided in Chap. 4 (Sect. 4.4.1).

6.3 Proposed System

A deep learning-based framework is used in the proposed cattle recognition system for identification of cattle. The proposed cattle recognition system takes the captured muzzle point image pattern of cattle. The captured images of muzzle point pattern consist of rich dense texture feature of muzzle point image. Therefore, the texture feature of muzzle point image is extracted and encoded using the deep learning frameworks and the existing handcrafted texture feature extraction and appearance-based feature representation techniques.

The appearance-based feature extraction and representation algorithms are unable to perform the recognition of cattle based on low illumination, poor image quality, and blurred image of muzzle point of cattle which are captured in the unconstrained environment. Therefore, texture feature descriptor techniques are utilized for unique identification of individual cattle in this work.

The proposed deep learning framework is applied to identify the cattle. The primary objective of the proposed deep learning-based cattle recognition system is used for identification of individual cattle.

The proposed system provides automatic and cost-effective solutions for cattle registration and verification of false insurance for individual cattle using the low-cost camera. It also provides the better solution for identification of cattle in the classical animal identification methodologies and classical livestock frameworks. The proposed recognition system consists of various steps for identification of cattle which are depicted in the next subsection.

6.3.1 Preprocessing and Enhancement

In this subsection, we have applied various image preprocessing techniques to mitigate the noises from captured muzzle point images. The fundamental problems involved in the acquisition of images of cattle are (a) little illumination and (b) poor image quality. The capture muzzle point images from the unconstrained environments are transformed into gray scale images to mitigate the artifacts and noises from muzzle point images [15].

After the preprocessing, the transformed images are enhanced by contrast limited adaptive histogram equalization (CLAHE)-based image processing technique. It improves the contrast between patterns of muzzle point images. Moreover, CLAHE enhancement technique overamplifies the distinct noises in approximately similar regions of interest in muzzle point image pattern [15] (shown in Figs. 6.1 and 6.2, respectively).

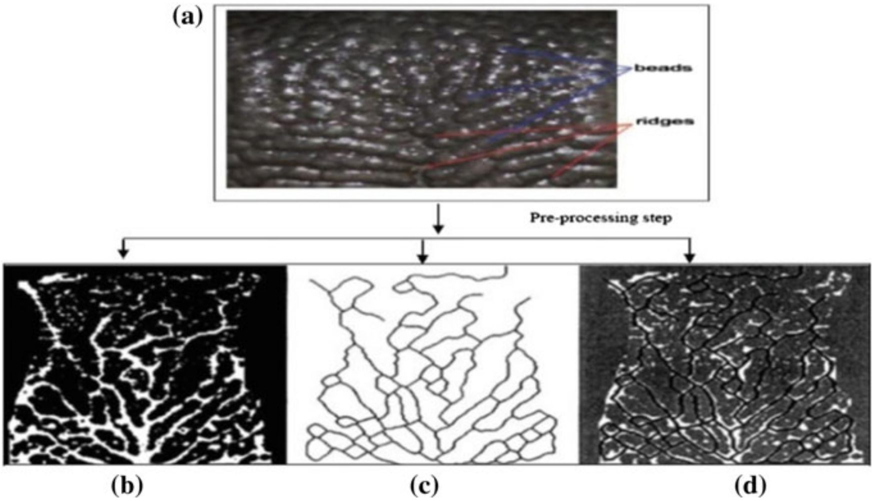

Fig. 6.1 Preprocessing process: **a** muzzle point image, **b** filtration of discriminatory features (beads and ridges), **c** the removal of background, **d** find out the ridges and bead features from the overlapped features

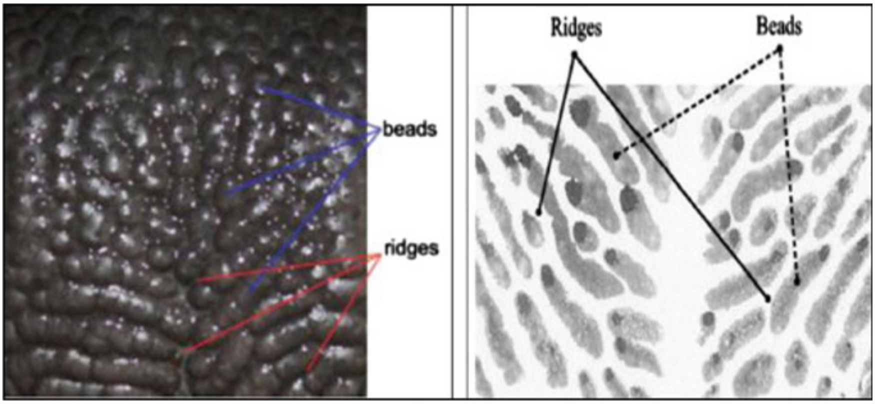

Fig. 6.2 Extraction of discriminatory feature (bead and ridge pattern features) from muzzle point image

6.3.2 Feature Extraction and Representation

The proposed system consists of a deep learning framework for the learning and representations of the extracted sets of discriminatory texture and holistic features of the muzzle point image pattern (as shown in Fig. 6.3). It is explained using different deep learning architectures: convolutional neural network (CNN) [16, 17], deep belief network (DBN) [18–20], and stacked denoising auto-encoder (SDAE)

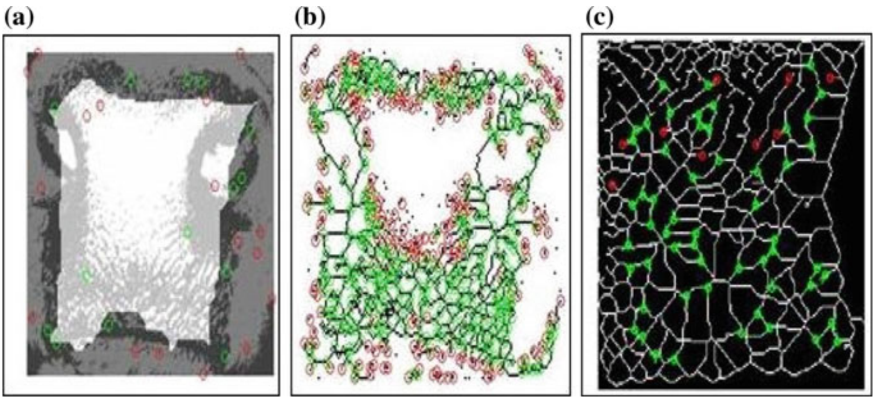

Fig. 6.3 Segmentation of muzzle point images: **a** the region of interest (ROI) of muzzle point images, **b** ridge bifurcation (green color) and ridge termination (red color) are extracted from ROI, and **c** suppression of irrelative feature information

[21, 22]. The following subsection first explains the basics of CNN, DBN, and SDAE auto-encoder techniques followed by the proposed cattle recognition system with multiple neural networks [12].

The underlying motivation behind applying deep learning-based feature extraction and representation architectures is that to learn the discriminatory texture features of muzzle point for better representation in feature space. The brief descriptions of applied deep learning methods are given in the next subsection. The proposed deep learning framework for cattle recognition is shown in Fig. 6.4.

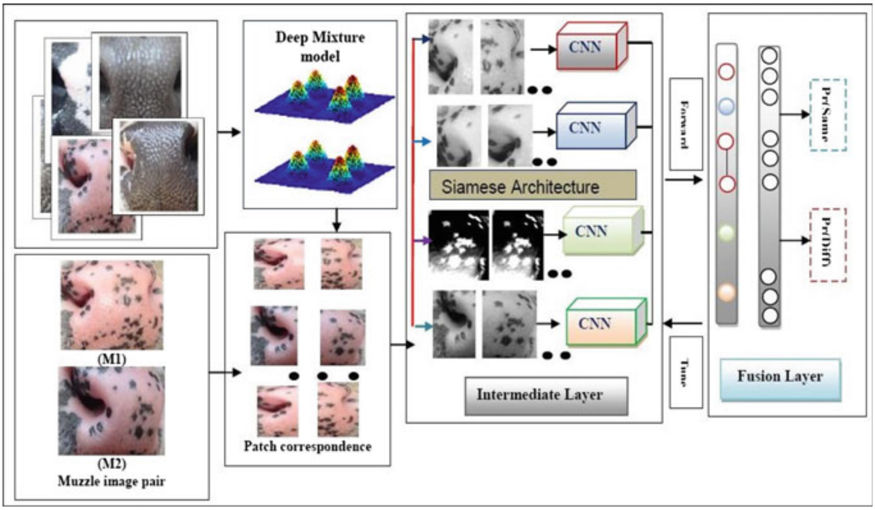

Fig. 6.4 Block diagram of proposed deep learning-based framework for cattle recognition

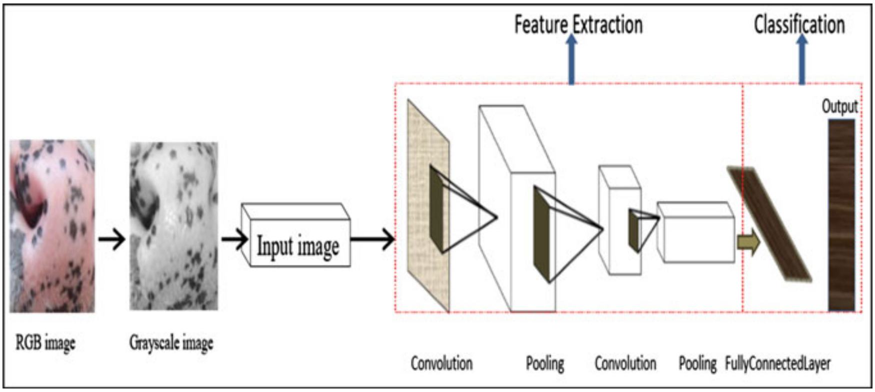

Fig. 6.5 Steps of proposed deep learning-based framework for cattle recognition using convolution neural network (CNN) technique

6.3.2.1 Convolution Neural Network-Based Recognition Framework

Convolution neural network (CNN) is a deep learning approach for the feature extraction and representation through relations between the two muzzle point image patterns of cattle which are modeled hierarchically. The CNN framework is built by stacking the multiple convolution layers and pooling layers.

The main motivation of the deep CNN framework-based recognition system for cattle recognition is that CNN network extracts muzzle point features directly from muzzle image pixel and provided the output a highly-compact representation after training of a number of muzzle point image patterns of cattle database. The CNN deep learning technique is used to accelerate the training of deep neural networks and take advantage of the multiscale structure of the muzzle point image pattern of cattle for cattle recognition. The CNN-based deep learning framework is illustrated in Fig. 6.5, respectively.

The mathematical formulation is illustrated for feature extraction and mapping of input muzzle point images using the convolution layer in the proposed deep learning-based cattle recognition system as follows:

A. **Convolution Layer**: The operation in each convolution layer is formulated as follows:

$$Y^{j(r)} = f\left(C^{j(R)} + \sum_i K^{ij(R)} * \left(X^{i(R)}\right)\right) \tag{6.1}$$

In Eq. (6.1), $(*)$ denotes the convolution operation. (X^i) and (Y^j) represent the $(i$th$)$ input and the $(j$th$)$ output in the CNN, respectively. The softmax( ) is a nonlinear activation function which is chosen in the proposed approach.

The softmax( ) activation function provides a feature gradient at the final layer of a network used as for classification, where (R) depicts a local region in the defined layers where assigned weights are shared between the layers.

The prepared database is captured from unconstrained environments, such as low illumination, the poor image due to blurriness, head movement, and body dynamics of cattle. To handle this problem, we have applied the convolution neural networks (CNNs) [7, 8] for automatically learning extracted discriminatory muzzle features.

In the fully connected layers, the input muzzle images are depicted as a vertical line of neurons. The proposed recognition system gives the input pixels of muzzle point images to a layer of hidden neurons. For each local receptive field, different hidden neurons are chosen in the first hidden layer. After that, we start the local receptive field over by one pixel to the right (i.e., one neuron) to connect to a second hidden neuron and so on, to building up the first hidden layer.

As mentioned in the above section, each hidden neuron has a bias weight (C^j) and (5×5) weights connected to its local receptive fields. For training, we have chosen the same (5×5) weight matrix and bias weight (C^j) for each of the (24×24) hidden neurons that are shown as follows:

$$\sigma\left(b + \sum_{l=0}^{l=4}\sum_{m=0}^{m=4} w_{l,m} \times \left(a_{j+l,\mathrm{k}+m}\right)\right)$$

In other words, for the $(j\text{th})$ layers, output of $(k\text{th})$ hidden neuron is given in Eq. (6.5), where (σ) is the neural activation sigmoid function. (C^j) is the shared weight value for the bias $w(l, m)$. It is a (5×5) matrix of shared weights.

Finally, we use (x) and (y) to denote the input activation at position $(x,\, y)$. The first two convolution layers are followed by max-pooling layer for feature reduction and increasing their robustness to distortions of muzzle point image pattern.

B. **Max-pooling layer**: The max-pooling layer is applied in the proposed approach for selection of the maximum values of every (2×2) grid in the muzzle point feature map. This procedure unit directly outputs the maximum activation in the input region [as shown in Eq. (6.2)].

$$P(s) = Y^i_{j,k} = \underbrace{\max}_{1 \le p,q \le s}\left(x^i_{(j-1)\cdot s+m,(k-1)\cdot s+n}\right) \tag{6.2}$$

where each neuron in the $(i\text{th})$ output map (Y^i) pools over a $(s \times s)$ non-overlapping local region in the $(i\text{th})$ input map (x^i), and max-pooling layer is represented by $P(s)$. The final convolution layer is followed by two successive fully connected layers. The final layer of connections in the network is a fully connected layer. That is, this layer connects every neuron from the max-pooled layer to every one of the output neurons.

6.3.2.2 Classification of Features Using Deep Belief Network and Restricted Boltzmann Machines

A deep belief network (DBN) is the graphical deep learning model which is applied to learn the extracted sets of extracted features of muzzle point image pattern for hierarchical representation using the Restricted Boltzmann Machine (RBMs) classification model. It can be stacked and trained in a greedy manner to form a deep learning model known as Deep Belief Networks (DBN) learning framework. It is used in the training phase of the proposed system [18, 19].

DBN learning framework is proposed by stacking restricted Boltzmann machines (RBMs) learning techniques. It is trained in a greedy manner for classification of extracted features.

The main motivation to apply the RBM a deep learning classification technique is that it is extremely useful for unsupervised learning of the feature extraction and representation of muzzle point image which is taken from the given large unlabeled muzzle point image database. The pseudocode of deep belief neural network for feature extraction and representation is shown in Algorithm 6.1.

Algorithm 6.1: Deep Belief Network Algorithm

Begin Fusion procedure ( )
1. **Procedure Fusion** (S_1, S_2, S_3), (W_1, W_2, W_3), where $S_{i \in (1,2,3)}$ is score values and corresponding tuning weights (W_1, W_2, W).
2. **Initialization**: Muzzle point image dataset $[X] = [X_1, X_2, \ldots, X_n]$ of extracted pixel intensity value of images (N) (where m and $n = 400$).
3. **Training phase**: Train the DBN deep learning model (M).
4. Train the first layer as an RBM that models the raw input as its visible layer.
5. Use the output of first layer as input for second layer.
6. Representation of features in second layer gives two solutions.
7. This representation can be chosen as being the mean activation $p(h(1) = h(0))$.
8. Train the second layer as an RBM as shown in Fig. 6.7), taking the transformed data (samples or mean activation) as training examples (for the visible layer of that RBM).
9. Iterate (steps 3 and 5) for the desired number of layers, each time propagating upward either samples or mean values.
10. Fine-tune the parameters using supervised gradient descent learning technique.
11. **Computation of Fused score**: The fused score (S_{fused}) is computed as follows:
$S_{\text{fused}} = W_1 \times S_1 + W_2 \times S_2 \times W_3 \times S_3$
12. Return S_{fused}.

End Procedure

For the classification, the logistic regression classifier is used based on $h(l)$ (the last hidden layer of DBN deep learning model). This step is similar by using the weights (w) and hidden layer biases which is generated with the unsupervised training for initialization of the weights of a multilayer perceptron layer (MLP) neural network.

The training of the proposed deep DBN deep learning model is shown in Fig. 6.6. In this approach, the DBN deep learning model is applied by constructing

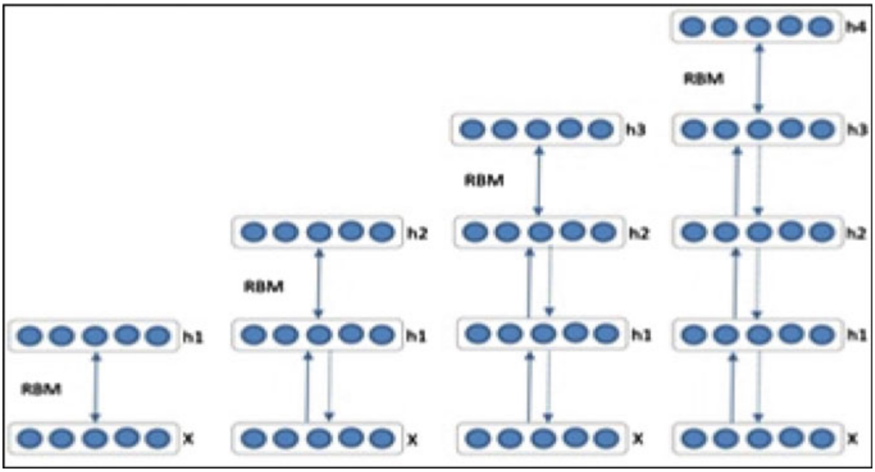

Fig. 6.6 Deep learning architecture of DBN deep learning model composed of four stacked RBM classification approaches

the multiple RBM models. The RBM classification is stacked on top of layers. Each layer consists of multiple nodes which feed into the next layer [20] (Fig. 6.7).

The basic working model of restricted Boltzmann machine (RBM) framework for cattle recognition is that a deep belief network (DBN) deep learning framework is used for extracting and learning the extracted set of texture features of muzzle point images.

The DBN learning technique is the graphical deep learning-based model. It is used to learn the extracted features of muzzle images for hierarchical representation of the training datasets by stacking restricted Boltzmann machines (RBM) classification technique for classification and identification of individual cattle based on extracted muzzle point features.

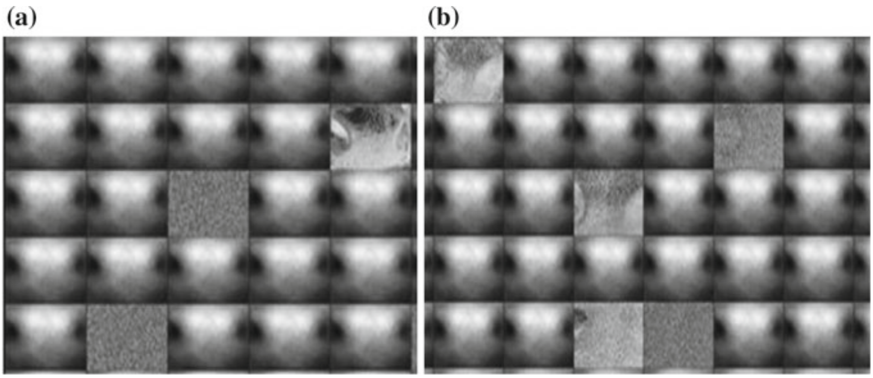

Fig. 6.7 **a** 20% corrupted images of muzzle point pattern and **b** 30% corrupted muzzle point images using stacked denoising auto-encoder

6.4 Stacked Denoising Auto-encoder Technique

Stacked denoising auto-encoder (SDAE) is encoding technique to encode and decode the extracted features [21]. In this chapter, stacked denosing auto-encoder (SDAE) deep learning technique is applied to encode and decode the extracted texture feature extraction of muzzle point image pattern of cattle and encode the extracted set of features for better feature representation in feature space. The algorithm for stack denoising auto-encoder is given in Algorithm 6.2.

Stacked denoising auto-encoders are applied to initialize the deep network. It works in much the same way as stacking the RBM models in deep belief networks. The stacked denoising auto-encoder is chosen such that the output layer of the first auto-encoder operates as the input layer of the second auto-encoder. The two fundamental components of an auto-encoder are mainly—(1) the encoder and (2) decoder. An encoder maps the input (X) to the hidden layer nodes using deterministic mapping function $(f{:}h = f(X))$ [shown in Eqs. (6.3) and (6.4)].

$$f = G\theta X = s(w \cdot X + \Delta) \tag{6.3}$$

where $\theta = \{w, \Delta\}$ the parameter set, s represents the sigmoid, (w) is $\alpha \times \alpha$ weight matrix, and $[\Delta]$ is the offset vector of size α'. Feature f is applied to map feature vector x' of dimensionality α using a decoder function $G'\theta$ such that

$$Y'' = G'\theta' f = s(w \cdot X' + \Delta') \tag{6.4}$$

where $\theta' = \{w', \Delta'\}$ the decoder parameter is set such that $\operatorname{argmin}\left(f_{\text{ae}} = \|X - Y''\|_F^2\right)$.

A decoder maps the hidden nodes back to the original input space through another deterministic mapping function $\left(\mathrm{G}_{W',\mathrm{b}'}\right)$. For real-valued input (X) computation, it is done by minimizing the reconstruction error. The calculation formulation of reconstructed error is given by as follows [shown in Eq. 6.3)]

$$\left(f_{\text{ae}} = \|X - Y''\|_F^2\right) \tag{6.5}$$

The parameters of auto-encoder and auto-decoder can be learnt for recognition of cattle. The parameters are optimized by utilizing the unsupervised training data. Then, the output of the hidden layer is used as the feature for image representation. The auto-encoders are arranged to form an underground network by nursing the latent representation (output code) of the denoising auto-encoder found on the layer below as input to the current layers [22].

Algorithm 6.2: Stacked Denoising Auto-encoder (SDAE)

Begin Encoding Procedure ( )
1. **Encoding Procedure** $(X_1, X_2, \ldots, X_n)$, $(Y_1 Y_2, Y_3, \ldots, X_m)$,
2. **Initialize**: Muzzle point image dataset $[X] = [X_1, X_2, \ldots, X_n]$, $[Y] = [Y_1 Y_2, Y_3, \ldots, X_m]$,
3. Muzzle point images $M_{(X,Y)} \in N$, where N is total number of images in the muzzle (M) database,
4. **Initialize learning model**: SDAE model (m_1), logistic learning model (m_2), and multilayer perceptron learning model (m_3),
5. **Training phase**: To train the SDAE model (m_1),
6. Train the first layer of proposed deep learning framework using the unsupervised techniques,
7. Apply the models: SDAE model (m_1), logistic learning model (m_2), and multilayer perceptron learning model (m_3) to train first layer $X = h(0)$,
8. Use the output of first layer as input for second layering, the proposed system,
9. Second layer represents the features using mean activation $p(h^{(1)} = h^{(0)})$,
10. Train the second layer using the same techniques,
11. Output of the second layer is used as input to the third layer,
12. Repeat steps (9 and 10) to train the (K) number layer of proposed network,
13. Apply the output of layers (step 10) to learn upward layers using mean values,
14. Compute the output from kith layer of proposed system,
15. Multilayer perceptron learning model (m_3) is used to tune the proposed network,
16. **Fine-tune** the parameters k^ith layers using supervised gradient descent,
17. Output of step (13) is fed as input data to logistic regression layer of model,
18. **Fine-tuning**: tune the whole trained network with the logistic model on top of the layers,
19. Apply the unsupervised training model to train and learn the trained model,
20. **Output**: Encoded feature of muzzle point images from each auto-encoders,

End Encoding Procedure

The primary motivations to apply the stacked denoising auto-encoder technique are to reduce the noises and other artifacts from the muzzle point image pattern.

The image of muzzle point pattern is captured from the unconstrained environment which is accompanied by variances in illumination, occlusion (covering and non-covering during vegetation or body movement), body dynamics (due to head movement), and image blurriness. Compared to the denoising auto-encoder, these test muzzle point images are seen as clean data and these test images can be seen as corrupted data. For robust recognition of cattle, we have applied the SDAE technique to learn the muzzle point features which are robust to these variances. The success of denoising auto-encoder convinces us of the possibility to learn such features.

The unsupervised pre-training of stacked denoising auto-encoder architecture is performed one layer at a time. Each layer is trained as a denoising auto-encoder by mitigating the reconstruction error its input (which is the output code of the previous layers). Once the first (K) layers are trained, we can train the $(K+1)$. Specifically, the parameters of these mapping functions are computed via back-propagation by greedily minimizing the loss function (J) (shown in Eq. (6.7)). The nonlinear mapping function $\left(f_{W,b}\right)$ is applied for vectored input image (X), and the hidden representation (Y) is calculated as follows [shown in Eqs. (6.6)–(6.8)]:

$$Y = f_{W,b}(X) = S(W \cdot X + b) \tag{6.6}$$

where $S(\cdot)$ denotes the sigmoid activation function, (W) and b are the weight matrix and bias of the mapping function, and (w_{ij}) represents the weight of the connection from the (ith) input node to the (jth) hidden node. The decoder maps the learnt features to the data space, using the following Eq. (6.4). A reconstruction step (GW', b') is implemented on the lower dimensional mapping (y) as follows:

$$(GW', b') = (Y'') = S(W'.Y + b') \quad \textit{and} \quad J(W, b) = ||Y - Y''||_F^2 \tag{6.7}$$

In Eq. (6.4), (W') represents the weight matrix. W_{ij} shows the weight function of the connection from the (ith) hidden node to the (jth) decoder output node, and b' presents the bias constraint of mapping function. Next, we have evaluated loss function of an auto-encoder as follows (show in Fig. 6.8)

$$f_{\text{ae}} = ||X - Y''||_F^2 = ||X - S(W'S(WX + b) + b')||_F^2 \tag{6.8}$$

The stacked denoising auto-encoder is a nonlinear auto-encoder for representation of extracted feature which is different from PCA [23] and linear discrimination analysis (LDA) [24] techniques. It has been decided that training an auto-encoder is to reduce reconstruction error by maximizing a lower bound on the mutual feature between input layer representation and the learned representation [18, 19]. We added the sparsity constraints to further boost the ability of auto-encoder for representation of extracted muzzle point images in proposed deep networks. The proposed deep learning approach enhances the generalization of auto-encoder by training with locally corrupted inputs of muzzle point image pattern. In denoising auto-encoder, input (X) is first corrupted by some predefined denoise, for example, additive Gaussian noise $\left(\overbrace{\widetilde{X}|}\; X \sim N(x,\, \sigma^2 I) \right)$, masking

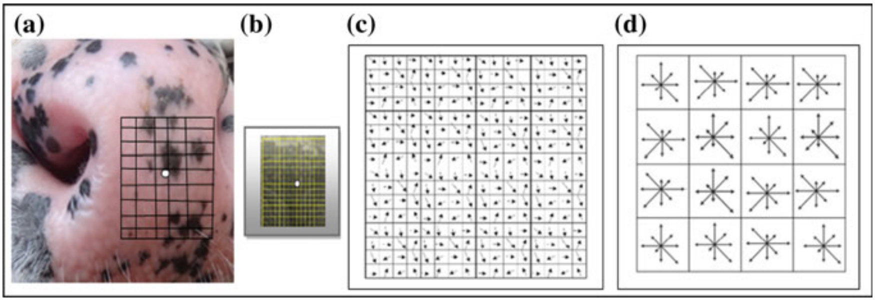

Fig. 6.8 SIFT keypoints descriptor: **(a)** input muzzle point image, **(b)** a SIFT descriptor of the size ($m \times n$) is chosen from muzzle point image, **(c)** selection of 16×16 pixel orientations, **(d)** 4×4 cell descriptor with 8 pixel orientations is chosen. The size of single SIFT keypoints feature descriptor is $4 \times 4 \times 8 = 128$ element

noise (a fraction of X is forced to 0), or salt-and-pepper noise (a fraction of X is forced to be 0 or 1) (show in Eqs. (6.3), (6.4), and (6.5), respectively). Figure 6.7a, b represents the 20 and 30% corrupted muzzle point images for better representation of extracted muzzle point images.

The Rectified Linear Unit (ReLU) activation function is used in all the encoder layers of proposed cattle recognition system. A ReLU layer class contains the name of the neural layer. It performs a threshold operation. In thresholding operation, any input value is less than zero value; it is set to zero [shown in Eq. (6.9)].

$$f(x) = \begin{Bmatrix} X, & X \geq 0 \\ 0, & X < 0 \end{Bmatrix} \tag{6.9}$$

For supervised fine-tuning, a softmax(0), activation-based layer with 35 nodes, has been incorporated on top of each stacked denoising auto-encoders. The four dropout [6] modules are applied in between layers to prevent overfitting. We have chosen the dropout probability as 0.35.

6.5 Pretraining and Generalizability of Proposed Recognition Model

In this subsection, pretraining of a proposed deep learning recognition model is illustrated in detail. Deep learning architecture needs the massive amount of datasets for training the proposed models because the optimization functions are formulated to diminish the training error of the proposed model. The proposed design tends to learn maximum information from the given muzzle point image dataset.

The second major challenge is generalizability [18–20]. It provides a method to train the model which can improve the generalizability without reducing the power of the proposed deep learning model. It is accomplished by including a penalty variable to loss function, known as the regularizer function.

The primary objective to apply the regularization is to provide the better representation of the information in the feature space to avoid overfitting of a given problem and yield to a solution faster by offering ancillary features. The pretraining of each auto-encoder is implemented in greedy fashion one layer at a time. Each layer of an auto-encoder is trained by lessening the rebuilding of its input.

The performances of the above three deep learning such as CNN, DBN and SDAE frameworks are measured over a set of test images of muzzle point images. The extracted features are obtained using these deep learning models. These frameworks give relatively better performancefor the recognition purpose. The various identification settings and standard protocols are used for evaluating the experimental results of proposed system and existing handcrafted texture feature descriptor techniques. The experimental results and discussion of proposed system is illustrated in the next section.

6.6 Experimental Results and Discussions

In this section, we have performed the experiments to compute the effectiveness of the proposed deep learning approach for the recognition of cattle using muzzle point image pattern. The comparison with existing benchmark algorithms (texture feature descriptor technique, appearance-based feature extraction and representation, and learnt feature techniques) is accomplished to evaluate the identification accuracy in multiple identification settings.

For performance evaluation of experimental results, the database of muzzle point image pattern is segmented into following phases: (1) training phase and (2) testing phase. In the training phase, 100 muzzle point images (10 cattle (subject) $\times$ 10 image of each subject) are utilized to train the proposed deep learning approach. In the testing phase, 400 testing pairs [40 cattle (subject $\times$ 10 image of each subject)] of muzzle point image pattern in each fold are used to test the probe images.

The deep learning-based framework demands the massive amount of database to train the proposed network. The proposed deep learning-based cattle recognition system uses the muzzle point images of cattle database. The size of muzzle point image database is 5000 images which are a relatively smaller image database. It is not satisfactory to adequately train a deep belief network or a stacked denoising auto-encoder. Therefore, a transfer learning approach is applied for the fine-tuning the weight between the input and hidden layer is applied to trained the proposed deep learning model.

6.6.1 Performance Evaluations

The proposed deep learning-based approach for cattle recognition is motivated by the observation that the muzzle point image pattern of cattle consists of rich and dense texture features in the form of bead and ridge pattern. The bead and ridge pattern of muzzle point image is salient biometric features for cattle recognition.

Moreover, it is challenging to restrict the body movement due to head movement and unconstrained environments during the data acquisition of cattle. During data acquisition, the unconstrained environments such as low illumination, poor image quality, and blurriness due to head movement are also the biggest problems for recognition of individual cattle, implying that appearance-based feature extraction and representation algorithms may not yield good results.

On the other hand, local feature-based feature extraction and representation algorithm can provide good results. The hypothesis is that feature (information) content present in the muzzle point image pattern varies with unconstrained environments for cattle.

To efficiently extract and encode texture features of muzzle point image pattern of cattle, local feature descriptor techniques must be used. The bead and ridge

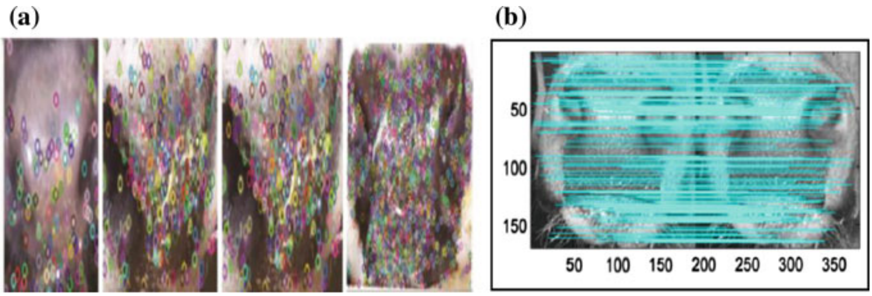

Fig. 6.9 **a** The process of SIFT keypoints localization and detection and **b** matching of test muzzle point image with stored muzzle point image using SIFT keypoints descriptor

texture features are extracted from the muzzle point image pattern of cattle database using the handcrafted texture feature descriptor techniques.

The handcrafted texture descriptor features and learnt feature techniques are used for feature extraction and representation. These approaches are mainly local binary pattern (LBP) [25], Circular-LBP [26], scale-invariant feature transform (SIFT) [27], Dense-SIFT [27], speeded up robust feature (SURF) [28], and vector of locally aggregated descriptor (VLAD) techniques [29].

The computation of features and encoding of the local binary pattern-based feature, SIFT and SURF feature of muzzle point image is shown in Figs. 6.8, 6.9, 6.10, 6.11 and 6.12, respectively.

Moreover, the appearance-based feature extraction, representation methods, and learned feature-based techniques are used for the evaluation and comparison of the experimental results of proposed approach.

For comparative analysis, we have also applied the appearance-based face recognition and representation approaches, such principal component analysis (PCA) (eigenvalues) [23], linear discriminant analysis (LDA) [30], Kernel-LDA

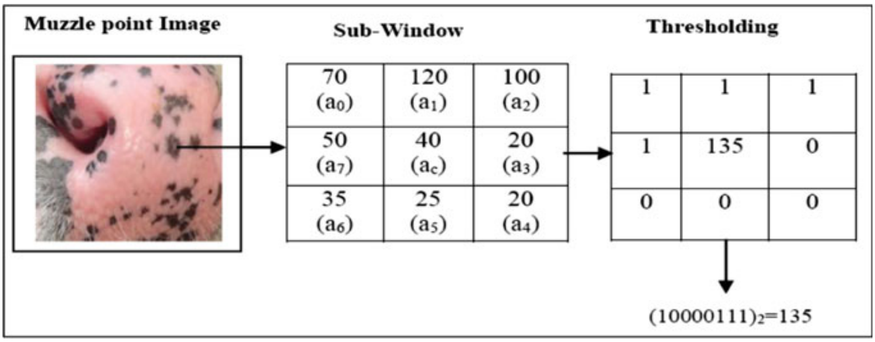

Fig. 6.10 Extraction and encoding of local binary pattern-based descriptor features from the muzzle point image pattern

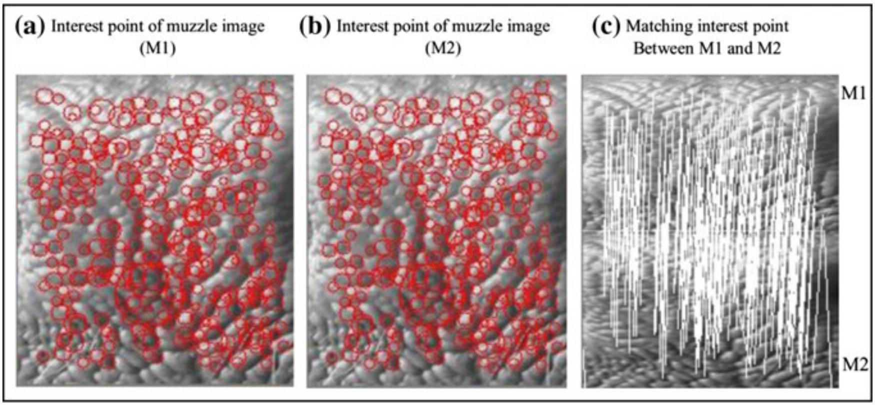

Fig. 6.11 Process of building of SURF descriptor: **a**, **b** the detection of keypoints in the muzzle point images, **c** matching of muzzle point images based on keypoints SURF descriptor with size (for a neighborhood of size 6 X s where s is scaling parameter of wavelet responses in horizontal and vertical directions)

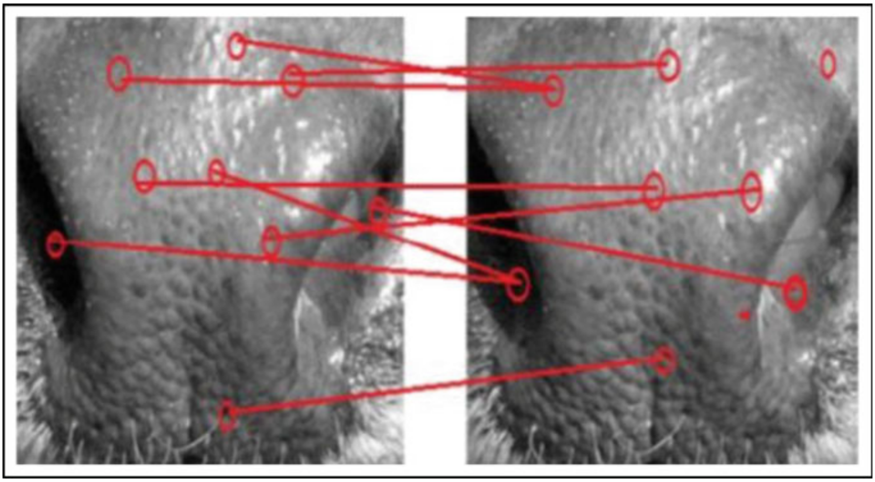

Fig. 6.12 Matching of keypoints of muzzle point images using SURF descriptor technique

[31], and Direct-LDA [32], for the evaluation of experimental results. Dense-SIFT (D-SIFT) feature descriptor technique is applied to extract the set of keypoints of muzzle point images. These keypoints are distributed at regular intervals on a uniform grid. In each grid (cell), the discriminatory keypoints are selected from a descriptor of length $n \times 16$, where n is the number of orientations.

For the evaluation of performance, we have performed the three experiments to evaluate the effectiveness of the proposed approach and compare existing benchmark texture descriptor technique and appearance-based feature extraction and representation algorithms in multiple identification settings. In this section, we have illustrated the detailed evaluation of the experimental results of cattle recognition as follows:

A. **Experiment 1: Accuracy analysis of different state-of-the-art deep learning approaches**

Muzzle point images of 100 cattle (subject) are randomly chosen for training the system, and the remaining muzzle point images corresponding to 400 (cattle) are used for testing with 1, 2, 3, and 4 muzzle point images per subject in the gallery. The least one-shot similarity-based matching scores are obtained per subject. It is used as the similarity match score. Further, all the experimental results are reported with five-time random subsampling-based cross-validation technique. The identification experiments are performed, and the results are reported in terms of rank-1 identification accuracy along with Cumulative Match Characteristics (CMC) curves as follows:

1. The experimental results are also analyzed with varying gallery sizes and summarized in Tables 6.1 and 6.2, respectively. The experimental results are also depicted in Figs. 6.13 and 6.14, respectively. With the proposed deep learning approaches, CNN, SDA, and DBN yield 75.98, 88.46, and 95.99% identification accuracy for identification of individual cattle, respectively.
2. The proposed approach has two components: (1) learning the robust texture feature of muzzle point image feature for representation and learning the distance learning-based metric with one-shot similarity (OSS)-based similarity matching techniques.
3. For evaluation of effectiveness of both the components of proposed approach, we tactically replaced one component at a time with existing descriptors or matchers (chi-square (χ^2)-based dissimilarity matching technique) and compared the experimental results with four gallery muzzle point images per subject (cattle).

As shown in Table 6.1, it can be observed that with increasing the number of muzzle point texture feature of cattle database per subject from one to four, the identification performance of deep learning framework using the DBN learning technique provides the highest identification accuracy for identification of individual cattle.

Table 6.1 illustrates the average identification accuracy based on individual patches of the muzzle point image pattern of cattle for recognizing individual cattle. Identification accuracies using the proposed deep learning framework are calculated

Table 6.1 Identification accuracy (%) of CNN, SDAE, and DBN deep learning approaches

S. No.	Proposed approach	Identification accuracy (%)
1	CNN	75.98
2	SDAE	88.76
3	DBN	95.99

Table 6.2 Identification accuracy (%) of CNN, SDAE, and DBN deep learning approaches

Number of feature sets	Identification accuracy (%)		
	CNN	SDAE	DBN
50	63.75	67.75	65.95
100	67.98	68.65	69.85
150	73.85	71.96	75.85
200	76.75	76.92	77.94
250	79.98	78.67	82.99
300	82.99	85.98	86.92
350	86.75	89.79	94.75
400	95.98	96.92	98.99

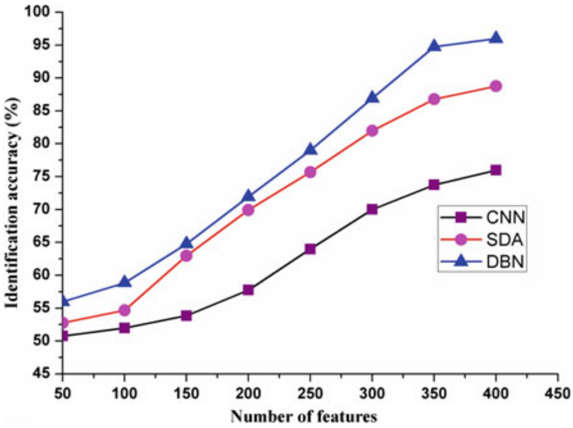

Fig. 6.13 CMC curve illustrates the identification accuracy versus number of features

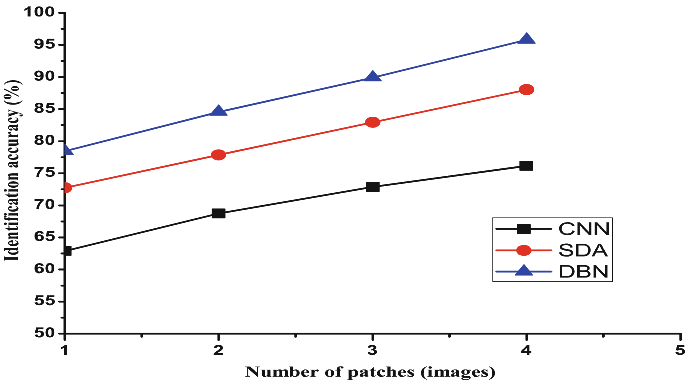

Fig. 6.14 CMC curve illustrates the identification accuracy versus number of patches (images)

by considering different number of muzzle point image features among the calculated ones. It can be observed that with the increase in usage of number of texture features of muzzle point image pattern of cattle, the identification accuracies are gradually increasing in all the three deep learning algorithms (as shown in Table 6.2). This explains the importance of all the muzzle point image features.

As explained earlier, as the number of features is increasing, the identification accuracies are gradually increasing but at every instant DBN technique provided the good experimental results among the three deep learning approaches.The identification accuracy of DBN is higher as compared to convolution neural network and stacked denoising auto-encoder-based deep learning approaches for recognition of individual cattle.

The deep learning-based DBN approach yields 98.99% of identification accuracy for identification of cattle. It is observed that the identification accuracies of the three deep learning frameworks are gradually increasing with the increase in the number features of selected patches from the muzzle point texture features.

After the selection of 400 numbers of features from each patch (size: 200×200 pixels), deep learning algorithms provide the robust representation of muzzle point features in the different layer of the proposed framework.

When the size of each patch of muzzle point images is reduced, the selected discriminatory set of the muzzle texture feature has also reduced; therefore, we have selected 400 numbers of features as better muzzle point feature sets from the extracted patches. This shows us that all the patches of muzzle point image pattern of cattle have been calculated collectively to describe and represent the discriminatory set of muzzle point features to the best extent than a set of few patches (as shown in Tables 6.1 and 6.2, respectively).

B. **Experiment 2: Average accuracy analysis with standard deviation of existing handcrafted texture feature and representations**

In this section, we have evaluated the performance of the existing handcrafted texture feature and representation algorithms. The existing handcrafted texture feature-based representation algorithms are used for evaluations of experimental results for identification of cattle. The experimental results are summarized in Table 6.3, respectively.

1. In Table 6.3, the existing handcrafted texture feature-based descriptor algorithms such as local binary pattern (LBP) and Circular-LBP (Circular-LBP) feature descriptors provide the rank-1 identification accuracy of $72.84 \pm 0.80\%$ to 74.97 ± 1.2 and 73.87 ± 1.5 to 79.87 ± 2.2, respectively, with four muzzle point images of cattle as gallery image per subject (cattle).
2. The SIFT feature descriptor techniques such as SIFT and Dense-SIFT (D-SIFT) yield identification accuracy of 69.75 ± 2.6 to 72.85 ± 1.3 and 69.75 ± 2.6 to 75.89 ± 1.65, respectively.
3. Muzzle point images of 150 cattle (subjects) are randomly choosen for training the proposed system and the remaining images corresponding to 350 cattle are applied for testing with 1, 2, 3, and 4 muzzle point images per cattle subject in the gallery. The evaluation of the experimental results is performed based on the test muzzle point images of cattle in the gallery. The least distance-based similarity score achieved per subject is used as the match score. Moreover, all

Table 6.3 Experimental results are reported in terms of average accuracy with standard deviation over tenfold cross-validation for existing handcrafted texture feature-based methods

Existing handcrafted texture features based method	Methods	Number of muzzle point images per subject (cattle) in gallery			
		1	2	3	4
	LBP + (χ^2)	72.84 (0.8)	73.52 (0.83)	73.76 (1.23)	74.97 (1.2)
	Circular-LBP	73.87 (1.5)	76.5 (1.83)	78.96 (1.56)	79.87 (2.2)
	SIFT + (χ^2)	67.98 (1.2)	69.97 (1.2)	70.97 (2.2)	72.85 (1.3)
	Dense-SIFT + (χ^2)	69.75 (2.6)	71.84 (2.6)	73.98 (1.4)	75.89 (1.65)
	SURF	75.48 (0.9)	78.99 (1.5)	85.49 (1.3)	89.76 (1.43)

the experimental results are measured with five times random based cross-validation. During the experimental results on every test muzzle point images, we have calculated the least distance matching scores for every subject.

4. The matching score values are used for the evaluation of the experimental results. The experimental results illustrate that even with multiple gallery muzzle point images, the identification accuracies are reported in the increasing order; however, the performance learning remains the same.
5. The better performances of texture feature-based descriptor algorithms are attributed to spatial collation in regional blocks that are able to good deal with the covariates, such as pose due to head movement, body dynamics, poor image quality, and low illumination.
6. Vector of locally aggregated descriptors (VLAD) [29] is a feature extractor learning-based descriptor algorithm. It extracts visual information (features), the training datasets [29].
7. As illustrated in given Table 6.4, the better recognition accuracy is achieved with OSS [33] (SVM [34] classification model) for this representation when the gallery consists of four images per cattle subject, with rank-1 accuracy of 45.98 ± 0.8 to $59.64 \pm 1.12\%$ and VLAD + LDA + SVM technique yields 50.76 ± 1.6 to $67.98 \pm 1.17\%$, respectively.
8. Based on overall performance of the existing handcrafted feature descriptor techniques, the SURF descriptor method provides better identification accuracy of 75.48 ± 0.9 to 89.76 ± 1.43, respectively. The main reason behind that the detected SURF keypoints features of the SURF descriptor method are computed with Laplacian of Gaussian (LoG) with Box Filter-based approximation method. The main advantage of this approximation is the convolution with box filter can be easily calculated with the help of integral images of muzzle point pattern. Further, SURF descriptor method finds the orientation of feature using wavelet responses in horizontal and vertical direction for a neighbourhood of size 6 X s. as compared to SIFT and Dense-SIFT approaches.

Table 6.4 Experimental results are reported in terms of average accuracy with standard deviation over tenfold cross-validation for texture holistic feature-based recognition algorithms

Existing learnt feature-based method	Methods	Number of muzzle point images per subject (cattle) in gallery			
		1	2	3	4
	VLAD + LDA + (OSS)	45.98 (1.5)	49.89 (1.47)	53.94 (1.22)	59.64 (1.12)
	VLAD + LDA + SVM	50.76 (1.6)	54.92 (1.27)	58.74 (1.02)	98 (1.17)

C. Experiment 3: Average accuracy analysis with standard deviation of appearance-based face recognition algorithms

Features of muzzle point images were extracted using the appearance-based feature extraction and representation approaches, such as PCA, 2-D PCA, LDA, and its modified LDA version (e.g., Kernel-LDA, Direct-LDA) algorithms, respectively. As shown in Fig. 6.14, following operations are applied to perform matching of extracted set of features and representation of muzzle point texture feature for identification of individual cattle:

1. Principal components analysis (PCA) technique is used to perform the dimensionality reduction of extracted feature of muzzle point image database. PCA technique computes the feature space. Principal components corresponding to 99% eigenvalues in the PCA subspace are retained.
2. The extracted texture features are classified by using supervised learning-based linear discriminant analysis (LDA) technique.
3. The cosine similarity matching-based method, one-shot similarity (OSS), distance learning-based metric technique are used for the similarity matching score after matching a pair of samples (muzzle point image patterns of cattle).
4. After that, the similarity matching scores are measured. The identification accuracies of cattle are shown in Table 6.5. Based on the observation of Table 6.5, it is shown that the Kernel-LDA and Direct-LDA techniques provide 60.89 ± 1.87 to $68.97 \pm 1.28\%$ and 63.77 ± 1.79 to 69.97 ± 1.33, identification accuracies for cattle recognition.

On the other hand, texture feature descriptor techniques, such as SURF, LBP, Circular-LBP, SIFT, Dense-SIFT and VLAD, are handcrafted existing feature-based descriptors for the better representation of muzzle point features for identification of individual cattle.

The LBP and Dense-SIFT descriptor algorithms illustrate the low recognition accuracy as compared to VLAD + LDA with one-shot similarity (OSS) and VLAD + LDA with support vector machine (SVM) techniques for identification of individual cattle using their primary muzzle point image pattern. The learnt feature descriptor techniques, such as VLAD + LDA + OSS and VLAD + LDA + SVM

Table 6.5 Experimental results are reported in terms of average accuracy with standard deviation over tenfold cross-validation on holistic feature-based recognition algorithms

Holistic feature-based methods	Number of muzzle point images per subject (cattle) in gallery			
	1	2	3	4
PCA	65.89 (1.67)	68.95 (1.83)	69.86 (1.23)	70.97 (1.2)
2D-PCA	67.89 (1.84)	69.65 (1.63)	73.86 (1.51)	75.67 (1.45)
LDA	69.96 (1.98)	72.91 (1.64)	73.48 (1.43)	74.99 (1.37)
Kernel-LDA	60.89 (1.87)	65.65 (1.73)	67.86 (1.57)	68.97 (1.28)
Direct-LDA	63.77 (1.79)	65.96 (1.63)	68.96 (1.53)	69.97 (1.33)

technique, yield 60.89 ± 1.5 to 59.64 ± 1.12% and 50.76 ± 1.6 to 67.98 ± 1.17 identification accuracy, respectively.

The capture muzzle point image database has several significant challenges due to the unconstrained environment, such as poor illumination, image quality, low contrast, and blurred. Therefore, existing feature extraction and representation algorithms are unable to perform identification of cattle using muzzle point images. The learning-based feature extraction and matching approaches cater an explicit encoding mechanism of extracted feature to improve the recognition accuracy of individual cattle.

One-shot similarity (OSS) using Fisher linear discriminant analysis (FLDA) and incremental support vector machine (SVM) classification models are applied in this chapter. The 1-class online incremental SVM (1-online ISVM) model is used to classify the extracted texture features of muzzle point images.

The OSS matching is a semi-supervised based matching similarity technique. It selects the unlabeled training data as a set of negative constraints against which two input sample images of muzzle point pattern are matched. Based on the overall experimentations and achieved recognition accuracy, our belief is that handcrafted existing benchmark-based texture feature extraction and representation have are bound and limited representation of extracted features. These local feature descriptors are not applicable for better recognition of cattle in the specific problem domain because the local feature descriptor methods are is highly distinctive yet invariant to variation like illumination, pose and affine change. Therefore, these are major challenging problems for recognition of individual cattle.

The proposed deep learning-based framework performs the encoding and learning of the discriminant feature representation of muzzle point image pattern, and the machine learning-based distance metric techniques capture the semantic representation of features and understanding of the SDAE encoding and decoding scheme.

6.6.2 Comparative Analysis

In this subsection, we have performed the detailed analysis of experimental analysis of proposed deep learning approach for recognition of cattle based on muzzle point images. The performance of proposed deep learning framework-based system has been compared against current state-of-the-art approaches for recognition of livestock based on their muzzle print images from the literature.

To perform the identification of cattle, the muzzle point image database is prepared from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (IAS), Banaras Hindu University (BHU), Varanasi, India-221005, using 30-megapixel digital camera.

For capturing the muzzle image pattern of cattle, the manual acquisition methodologies are not applied. The classical acquisition methodologies of muzzle point images include various equipment and materials (such as A5-size white papers, black ink and stamp (impacted), soft cottons, hard ropes, tissue paper, and assistant team of the dairy staff members) to capture the images of muzzle print of cattle.

The captured images of cattle on A-5 paper with blue ink have provided few motives to perform the research for identification and monitoring of cattle by researchers, scientists, and veterinary professionals. Therefore, captured muzzle point database of cattle using 30-megapixel camera is original images of muzzle point pattern of cattle. The prepared database also includes various covariates of muzzle point images due to poor image quality, low illumination, pose, variation-based images due to head movement and blurred.

In the available literature, there is no availability of muzzle point image database in the public domain. Very few researches have been done for the identification of cattle based on the muzzle print images. Based on printed muzzle images, we have compared the experimental results of proposed approach with previously published results on muzzle print images including results that use different computer vision and pattern recognition techniques. The comparative analyses of experimental results are shown in Table 6.6.

Noviyanto et al. [35] proposed a method using SURF and eigenface-based approaches for recognition of individual cattle. The major shortcoming of this method is that the authors performed the experimental results on the small dataset of muzzle print images. The proposed approach cannot handle various configuration of rotation and scale of muzzle print images. In [36], authors proposed a cattle recognition-based framework for identification of cattle using eigenvalue-based approaches. The authors have applied principal component analysis techniques to mitigate the dimensionality of extracted features.

The proposed approach by Minagawa et al. [36] has not reported exactly experimental results, the same due to the unexplained filtering techniques. In [37], the author Barry et al. proposed cattle identification using principal component analysis and Euclidean distance classifier techniques based on muzzle print images.

The proposed approach is selected for training separately on a different number of normalized muzzle image sets of 2, 4, 6, 8, and 10 training images from 29 cattle. The drawback of the approach is that an experimental result was taken on a separate set of three muzzle point images only per animal. The authors have not performed any cross-validation of the experimental results. The implementation of the approach proposed by Barry et al. [37] is also not exactly the same due to the watershed segmentation technique which is not implemented properly. The approach proposed by Barry et al. [37] has been very strict due to the false match that has been zero. Four hundred and sixty-eight false non-matches have been reported over 560 genuine matching.

In the similar direction, the author Awad et al. [38] proposed a method to improve the performance of proposed cattle identification system. They have applied the SIFT keypoints matching-based descriptors. The SIFT descriptor technique is utilized to find out the keypoints for matching of muzzle print images.

For better identification, RANdom Sample Consensus (RANSAC) technique is utilized with the SIFT to mitigate the noises such as outlier points. However, the

Table 6.6 Comparison of our proposed approach with the literature

Authors	No. of images (face and muzzle print images) of cattle	Technique used	Identification accuracy (%)
Noviyanto et al. [35]	80 images	SURF + kappa statistic + eigenface algorithm	89.30%
Minagawa et al. [36]	43 muzzle print images using blue ink	PCA + Eigenvalue-based approaches	30%
Barry et al. [37]	29 cattle breeds	Eigenvalue + segmentation-based technique	98.50%
Awad et al. [38, 39]	15 cattle breeds	SIFT + RANSAC	93.30%
Noviyanto et al. [40]	48 muzzle print images	SIFT + PCA	0.0167 (EER)
Kumar et al. [41]	300 face image of cattle	PCA + LDA + ICA	85.95%
Gaber et al. [42]	31 cattle	WLD + ABD	99%
Cai and Li [43]	30 cattle	RASL + WLBP	95.30%
Tharwat et al. [44]	31 cattle	Gabor + SVM	99.50%
Kumar et al. [45, 46]	Pet animals (dog), 50 dog breeds	PCA + LBP +modified algorithms (Batch-ILDA, CCIPCA, Incremental-SVM)	94.86%
This research study	5000 muzzle point image (500 subject and each subject has 10 images)	Deep learning approaches [convolution neural network (CNN) + deep belief network (DBN) and stacked denoising auto-encoder (SDAE)] + SVM + one-shot similarity (OSS)	95.98% (CNN), 95.99% (DBN) + 96.92% (SDAE), 98.99% (DBN)

WLD Weber's local descriptor, *ADB* AdaBoost classifier, *WLBP* Weber's local binary pattern descriptor, *RANSAC* random sample consensus algorithm

proposed approach has the following major limitations: (1) no cross-validation of experimental results and (2) identification accuracy is suffered from the noises such outliers, blurriness, and poor image quality. Noviyanto et al. [40] implemented the proposed matching refinement technique based on SIFT keypoints matching technique.

In [42], authors proposed a method for identification of cattle using Weber's Local Descriptor (WLD) technique. The proposed approach extracts the features from cattle muzzle print images (images from 31 head of livestock).

The extracted features are classified by AdaBoost classification model to identify the head of individual cattle from their WLD descriptor features. There is no cross-validation done to validate the experimental results.

The author Cai and Li [43] proposed a method for automatic recognition of cattle using local binary pattern-based feature descriptor and extended LBP descriptor techniques. The robust alignment by sparse and low-rank decomposition approaches is applied to align the face images of cattle due to poor illumination, image misalignment, and occlusion problem in the test face image of cattle.

The dissimilarity between test and trained images is performed on a separate set of face images using the weighted chi-square distance technique. The major shortcomings of this method are: (1) authors have not performed the experimental results on slight datasets, (2) no preprocessing technique is applied for processing of facial images of cattle using image processing technique, and (3) any cross-validation is not applied to verify the identification accuracy. In [44], the authors proposed a cattle identification using Gabor filter-based feature extraction technique. The proposed extract Gabor features from muzzle print images. The extracted features are classified by using support vector machine-based classification technique at different kernels.

The author Kumar et al. [47–50] proposed a real cattle recognition system using Fisher locality preserving projection-based recognition algorithm for the recognition of individual cattle in real time. The proposed systems capture the images of cattle using surveillance camera, and captured image of muzzle point of cattle transferred them to the server side by using wireless network communication technology.

The proposed recognition algorithm based on muzzle point feature approach yields 96.87% accuracy for identification of cattle. The author Mishra et al. [51, 52] proposed a system for analysis of muzzle print image based on their the dermatoglyphics of cattle [52, 53]. The muzzle print patterns are captured by using blue ink for identification of bovine races. In his study, they have performed the identification of cattle using classification techniques [49].

Recently, the authors Kumar et al. [54, 55] proposed a real time monitoring and tracking systems for the pet animals in smart cities using animal biometrics and computer vision techniques. The proposed system extracts the facial image-based pixel intensity feature for identification of pet animal (dogs). The systems uniquely identify the pet animal based on their primary animal biometric identifiers. The proposed recognition system applies the one-shot similarity matching techniques to calculate the similarity matching score after the matching of query face image of cattle with stored image datasets of animal. Moreover, the distance metric-based learning method is used for matching and classifying the extracted features of face images for recognition of pet animals (dog). The efficacy of proposed recognition system yields 96.87% recognition rate.

Based on overall observations, we conclude that the proposed method uses the deep learning-based framework for recognition of cattle and achieves better identification accuracy over all of the existing handcrafted feature descriptor, and baselines algorithms for cattle [56–60].

6.7 Summary

In this chapter, a novel deep learning-based cattle recognition system is proposed to identify the individual cattle using muzzle point image pattern. The deep learning-based feature extraction and representation approaches are applied to learn the discriminatory texture feature representation of muzzle point images with limited training dataset. The proposed deep learning approaches, such as convolution neural network, stacked denoising auto-encoder technique, and deep belief network, yield 75.98, 88.46, and 95.99% identification accuracy for cattle, respectively.

The handcrafted texture feature-based representation algorithms are utilized for evaluations of experimental results. The local binary pattern (LBP) and Circular-LBP (Circular-LBP) feature descriptor-based technique provide the rank-1 identification accuracy of 16.80 ± 0.80 to $26.97 \pm 1.2\%$, respectively, with four muzzle point images as gallery image per subject (cattle). The case of appearance-based feature extraction and representation approaches, such as principal components analysis, is used to perform dimensionality reduction on the feature space.

The identification of cattle based on their muzzle point images is performed using linear discriminant analysis (LDA) with one-shot similarity (OSS) technique. It is used to match a pair of samples and generate the match scores. The identification accuracies are shown in Table 6.5, respectively. It can be observed that Direct-Kernel-LDA provides 15.89 ± 1.7 to $29.97 \pm 1.13\%$ identification accuracy.

The learnt feature descriptor techniques, such as VLAD + LDA + OSS and VLAD + LDA + SVM techniques, yield 45.98 ± 1.5 to $59.64 \pm 1.12\%$ and 50.76 ± 1.6 to 67.98 ± 1.17 identification accuracy, respectively. Based on observation, we conclude that deep belief network deep learning approach provides better identification accuracy for recognition of individual cattle. Hence, it can be concluded that the DBN-based framework is the right choice for recognition purpose.

For further improvisation of deep learning-based recognition framework, the proposed framework can be implemented on the android platform that can easily available for smart or android devices for verification and identification and verification of false insurance claims in real-time scenario.

We postulate the traditional animal recognition methodologies and automatic animal recognition algorithms that are tailored specifically for identification of cattle, via unambiguous training. It can be able to perform the recognition of cattle more efficiently. The proposed deep learning-based recognition of cattle caters a friendly, noninvasive, robust, as well as cost-effective solution using smart devices or low-cost camera for the identification of species or individual animals.

In future, we plan to extend the proposed cattle recognition system for the identification of different animals in the real time. We would like to include the following points as part of our future work:

- We would like to design multimodal cattle recognition system using muzzle point image and face image of cattle for accurate identification and verification in real time.
- We would like to increase the performance of the proposed cattle recognition system using multimodal system and feature fusion techniques. The fusion technique can fuse the discriminatory set of texture features of the muzzle point images with facial images of individual cattle.
- In future, we can design a hybrid deep learning model or framework for training deep convolutional neural networks to identify, count, and analysis the behaviors wild species and other species. It can be more helpful for depth level analysis of experimental results of proposed multimodel-based system for species or animals.
- Finally, we would like to increase the size of cattle database for validation of experimental results with benchmark existing handcrafted texture descriptor techniques and deep learning-based feature learning and representation techniques in the computer vision [50].

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Chapter 7
Real-Time Recognition of Cattle Using Fisher Locality Preserving Projection Method

Abstract With the arrival of adequate computer vision techniques, animal biometrics-based recognition systems have accomplished attention for the identification and monitoring of jeopardized species and individual animal. In this chapter, a novel fisher locality preserving projection-based cattle recognition framework is proposed for extraction and representation of cattle identification in real time. The biometric muzzle point image of cattle is captured using the surveillance camera and transferred them to the server of cattle recognition framework by using wireless network technology. The motivation of proposed method is to maximize the inter-class (between-class) scatter feature matrix of the muzzle point image and efficiently minimize the intra-class (within-class) scatter matrix of muzzle point images. This strategy of proposed method improves the accuracy of cattle identification. The efficacy of proposed recognition approach for cattle is estimated under different identification settings. The proposed method yields 96.87% recognition rate for identifying individual cattle. Further, the method assessed the 10.25 recognition time (seconds) for enrollment and recognition of biometrics muzzle point feature for cattle on the different image database.

Keywords Computer vision · Muzzle point · Animal biometrics
Cattle recognition · FLPP · Identification · Classification

7.1 Introduction

Currently, the International Union for Conservation of Nature (IUCN) has reported that more than 50% of the total species are endangered and extinct [1] worldwide. The recent biodiversity crisis is perceived all across the world. The major crisis hits primates and belongs to a species that is seriously threatened in the habitats.

According to the International Union for Conservation of Nature (IUCN), it has been reported that more than 50% of the total species are threatened and extinct throughout the worldwide. The recent biodiversity crisis is distinguished all across

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the world. The major disaster hits primates and belongs to a species that is seriously threatened in the habitats.

In [2], the author, Walsh et al. [2], studied that the total population of endangered and extinct species in the western Equatorial Africa. He reported a decrease in overall population of the endangered species. In this country, the entire species community is confronted by more than a 50% of the whole apes and chimpanzee population between 1983 and 2002.

In the similar direction, a survey of the species population was done by author Campbell et al. [3]. In their report study, they depicted that the chimpanzee and ape animals are in the threatened zone throughout the world. Based on their research, more than 90% chimpanzee is lost in Ivory Coast (West Africa) between 1990 and 2007 [3].

According to available literature, the total population of pets (dogs) in the throughout world is more than 700 million [4], and 7 million dogs enter the animal shelters in the USA every year. Only 10% of the total population of pets are adopted or make it back to their owners or parentage in the smart cities [5]. According to reference [6], in the USA, there is one pet animal for every three humans, and the increasing rate of domestic animals (i.e., canine breeds) and other pets ownership keeps rising continuously. Based on the current report of pet animals in 2015–17, the total number of pets is about 153,000 (especially dogs) in the city of Seattle which is greater than the number of children of each family (e.g., 107,000 children).

Similarly, New York City also recorded a rapid increase in the number of production of dog breeds, and in owners of pet animals (e.g., 600,000 dogs) which is greater than the previous year [7, 8]. It is a huge problem in the monitoring and recognition of huge population of pet animals using existing approaches and traditional identification systems in the smart cities of the USA.

In a similar direction, author Maroto [7] reported that more than 50,000 starving stray pet animals (dogs) swarmed Detroit when the pet's owners left the bankrupt city leaving their pet animals behind. Based on the current survey of pet animals, the average number of pets per household varies in different countries, generally depending on the total population [9].

In India, the total population of livestock cattle is 512.05 million [10]. The population is reported in 2016. Due to lack of proper health monitoring of livestock cattle, total livestock population has decreased by about 10.33% over the previous census.

The classical animal identification systems are unable to cater the protection and health monitoring of cattle. The livestock animals are identified by using the invasive marking–based techniques. The invasive techniques include generally embedding of different microchips in the RFID device to track the individual cattle [11]. The classical livestock framework-based monitoring system is also unable to identify the infected animals in herd.

Recently, cattle recognition has gained much attention and proliferation because of the availability of better identification solutions for these major problems using computer vision and animal biometrics techniques.

Due to these significant problems and continuing biodiversity collapse, individual animal and species including chimpanzees, giant panda (*Ailuropoda melanoleuca*), cattle, Tasmanian devil (*Sarcophilus harrisii*), tiger (*Panthera tigris*), and Asian elephant (*Elephas maximus*), and snow leopard (*Panthera uncia*) are on the verge of stifling [12, 13]. Thus, there is a fundamental need to protect the outstanding populations of endangered and extinct species or individual animal throughout the world.

Recently, to overcome the difficulty of time-consuming-based manual routine work, the real-time recognition and monitoring systems are required for monitoring of species or individual animal. Various emerging intelligent sensor-based technologies have been applied for monitoring and tracking of animals.

Emerging technology has been investigated to give the better solution by overcoming the complexity of interfaces between hardware and software components of animal biometrics-based recognition systems in real-time scenario. These techniques use the global positioning systems (GPSs), bluetooth-enabled sensing devices for transferring the captured images and video database using the Wi-Fi architecture-based communication networks, and RFID sensing devices [14, 15]. However, maintenance of these hardware devices and better component integrations with interfaces during the practical implementation is very tedious work for inclusion and embedding the electronic-based intelligent sensing devices for identification and monitoring of species or livestock animals [16].

Based on the above extensive discussion, it is the requirement to design and develop a real-time cattle recognition-based system for identification and monitoring of individual cattle.

7.1.1 Contribution Are Illustrated in Brief

The contributions of this work are as follows:

1. The proposed real-time automatic cattle recognition framework recognizes individual cattle-based muzzle point features using camera.
2. The proposed cattle recognition system uses the fisher locality preserving projections method. It is a new linear subspace-based feature extraction and representation method for unique identification of individual cattle.
3. The novelty of proposed system using fisher locality preserving projection method is to maximize the inter-class (between-class) muzzle point of cattle. It effectively improves the identification accuracy by minimizing the intra-class (within-class) scatter matrix of muzzle point images.

The rest of the chapter is organized as follows: Section 7.2 illustrates the real-time cattle recognition system followed by its major components. Section 7.3 depicts the proposed Fisher locality preserving projections (FLPPs) approach for feature extractions and representation of muzzle point image of cattle. The feature fisher encoding of muzzle point image of cattle is done by linear discriminant analysis (FLDA) technique which is illustrated in Sect. 7.4. Section 7.5 presents matching of muzzle point images of cattle using learning distance-based similarity matching of muzzle images. Section 7.6 presents brief description of feature extraction and representation algorithms using existing handcrafted texture feature and appearance-based feature extraction techniques for the evaluation of experimental results. Section 7.7 presents the experimental result and analysis with proposed feature extraction and representation approach. Finally, Sect. 7.8 is dedicated to the summary of the chapter.

7.2 Real-Time Cattle Recognition System

A real-time cattle recognition system is a system that intended to provide the better solutions of real-time applications [17, 18]. In this chapter, a real-time cattle recognition system is proposed for identification of individual cattle based on muzzle point image. The muzzle point of livestock is captured using the smart devices such as the camera. The captured image of livestock (especially cattle) is transferred to the server of the real-time cattle recognition system-based server database (shown in Fig. 7.1).

Figure 7.1 depicts the transferring of cattle images to the server. The database of cattle is updated continuously by storing the images of muzzle point of livestock.

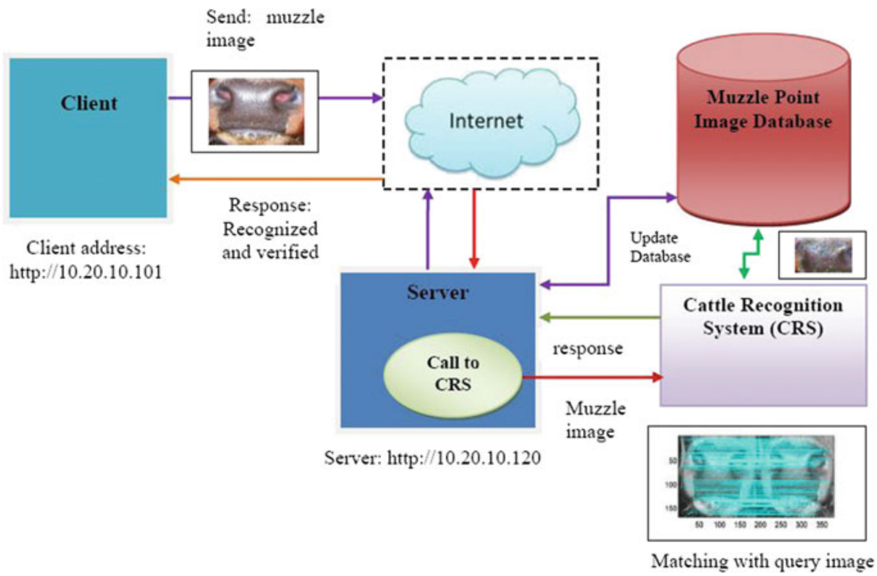

Fig. 7.1 Block diagram for transferring the cattle images to server

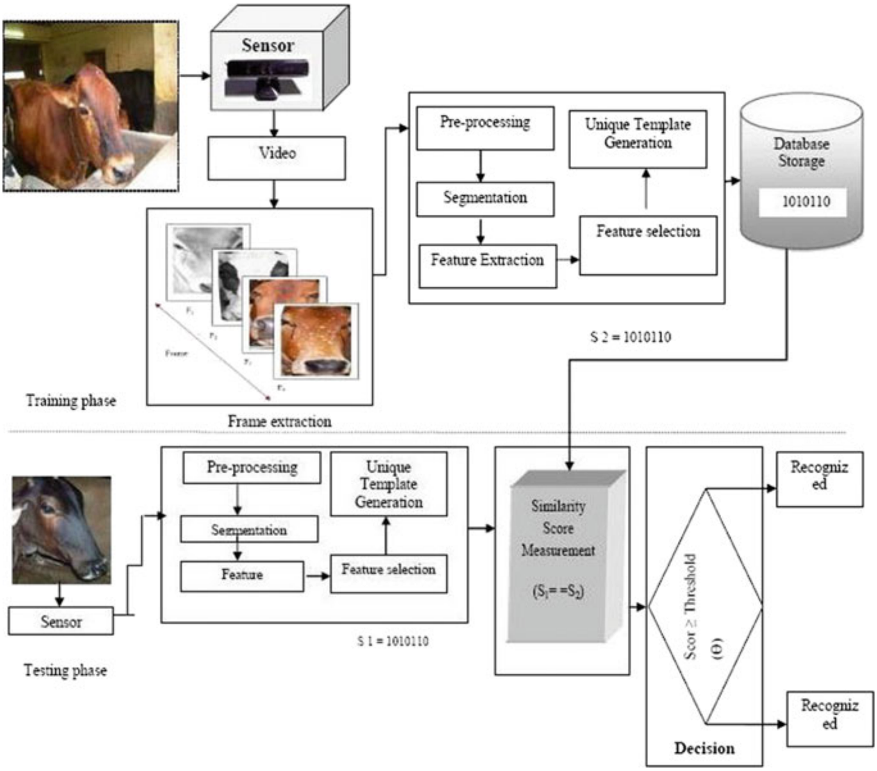

Fig. 7.2 Block diagram model of proposed cattle recognition system

For verification of livestock (especially cattle), users (e.g., parentages, owners, and others) want to verify the false insurance of the registered cattle. The verification of cattle is done based on the biometric feature of captured images of animals against the illegal and imposter users of cattle.

The user captures the muzzle point image of cattle using the smart devices such as digital camera, smartphone, and other capturing devices. The captured image is transferred to cattle recognition system using communication protocols and architectures. The transferred images are matched with stored muzzle point database e of cattle using similarity matching techniques (shown in Fig. 7.2).

After the matching of images with the stored dataset, the system sends the message to the registered mobile number of the users. The authentication message ensures the parentage or ownership of cattle. The cattle are registered with government insurance schemes under different plans. The primary objective of recognition system is to provide the cost-effective solution for verification of cattle-based biometric features of muzzle point images.

The cattle recognition system extracts the video frames (e.g., set of image sequences) from the captured video. The video frames are used as input images for recognition of cattle. The detail description of the proposed recognition algorithm and steps are described below:

A. **Preprocessing and Enhancement of Image**

The preprocessing is an important step for feature extraction and matching of features. The preprocessing technique is used to mitigate the noises from the extracted set of muzzle image sequences (video). For image enhancement, image processing and enhancement techniques are implemented to enhance the image quality of set muzzle point image dataset using contrast image enhancement techniques.

The filtering technique such as low-pass filter technique is applied to pre-process the video frames of muzzle point images. The low-pass filtering technique mitigates a specific degradation and noises by performing the Gaussian pyramid-based smoothing technique from the images. The segmentation of muzzle point image is presented as below.

B. **Segmentation of Muzzle Point Image**

After the image pre-processing and enhancemnet, image segmentation algorithms are implemented to find the distinct region of interest from the segmented muzzle point images of cattle [19].

The color *K*-means clustering and texture-based image segmentation algorithms are used to detect the area of beads and ridge region of muzzle point features (shown in Fig. 7.3). The muzzle point region of interest-based segmentation algorithm is illustrated in brief. It performs the localization and segmentation of only the most discriminatory and biometric informative region of bead and the ridge image pattern of muzzle points. The texture feature-based segmented muzzle point pattern texture is shown in Fig. 7.4.

After preprocessing and enhancement of video frames of cattle, feature extraction and representation steps play a vital role to extract the muzzle point feature from preprocessed set of images. The muzzle point image consists of texture features known as bead and ridge features.

The muzzle point features are extracted by using the texture feature-based descriptor techniques and holistic-based feature extraction algorithms [20].

However, the region of interest of muzzle point images must be chosen carefully to cater all the discriminatory features are matched using learning distance-based similarity matching technique.

The existing benchmark-based linear projection-based feature extraction and representation techniques cannot handle the nonlinearity variations of the extracted set of texture feature of the captured muzzle point image database for cattle recognition.

A class of nonlinear discriminant analysis using kernel discriminant techniques has been utilized for object recognition. The kernel-based discriminant methods include principal kernel component analysis (KPCA) [21], Kernel Fisher Discriminant Analysis (KFDA) [22] and generalized discriminant analysis (GDA) [23].

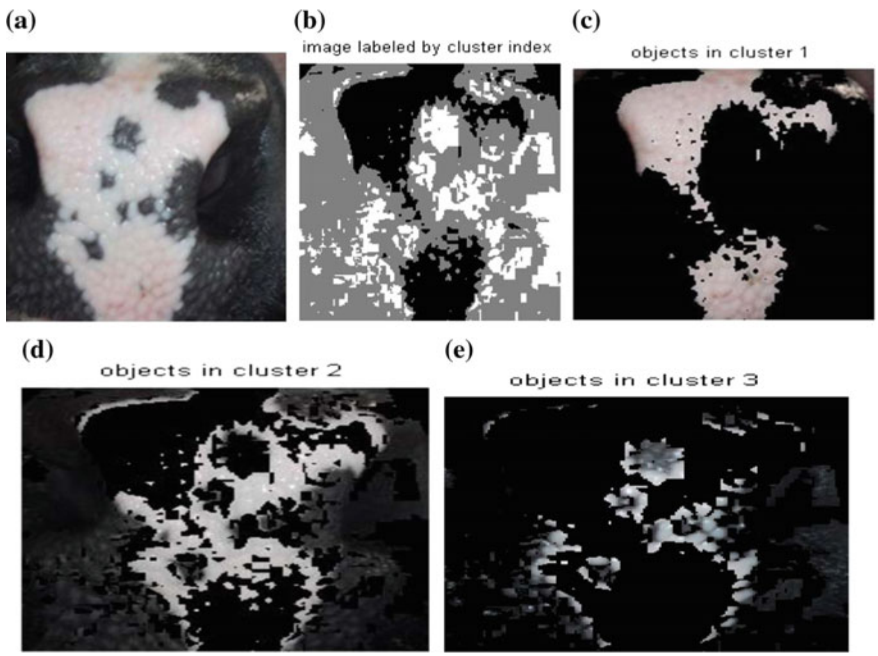

Fig. 7.3 Segmentation process of muzzle point image

In computer vision fields, the manifold graph-based machine learning methods are used. These methods include the linear preserving projections (LPPs) [24], Laplacian feature eigenmaps (LFEs) [25], linear discriminant projections embedding (LDPE) [26], and unsupervised feature discriminant projections (UDPs) [27] have also explicated great potential in recognition of objects recently.

In the fusion-based recognition approaches, various biometric features such as the muzzle point texture feature of cattle have been combined with the face image feature of cattle. The fusion process increases the identification accuracy of the single modality of biometric system for cattle identification. However, it is also desirable that the false rejection rates are diminished while still keeping a high identification accuracy of the proposed system for cattle.

In this chapter, the main motivations are aimed to address these major issues and provide the better solution for cattle identification. For proposed system, more than one biometric features of cattle are used at the same time so that false rejection rates can be reduced. Therefore, this chapter proposes recognition system that can concurrently perform the extraction and selection of the discriminatory set of features from muzzle point image and fuse the muzzle point features from the different class of image database.

To improve the accuracy of proposed system, Fisher locality preserving projections (FLPPs) method is proposed. It maximizes the feature scatter matrix of

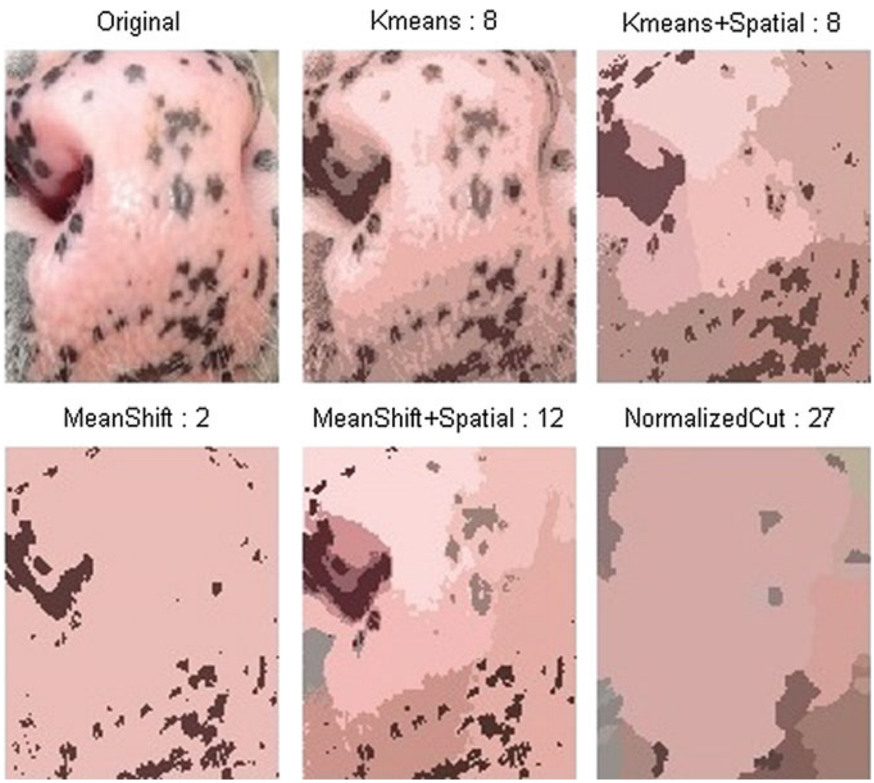

Fig. 7.4 **a** Input muzzle point images **b** texture feature-based segmentation algorithm

between-class and effectively minimizes the feature scatter matrix of within-class [28, 29]. The proposed FLPP approach is illustrated in detail in the next subsection.

7.3 Proposed FLPP Feature Extraction and Representation Approach

The Fisher Linear Preserving Projection (FLPP) [30] determines the directions in the feature space using linear projection. It maximizes the between-class scatter matrix and maintains the local geometrical data in the feature space. The mathematical formulation of the proposed method is shown in Eqs. (7.1)–(7.6).

$$S_{\mathrm{B}} = \sum_{K=1}^{N} \left(N_K(\mu_K - \mu) \times (\mu_K - \mu)\right)^{\mathrm{T}} \tag{7.1}$$

$$S_{\mathrm{W}} = \sum_{K=1}^{N} \sum_{x_k} \left(N_K(\mu_K - \mu) \times (\mu_K - \mu)\right)^{\mathrm{T}} \tag{7.2}$$

$$\mu = \frac{1}{N} \sum_{K=1}^{N} N_K \tag{7.3}$$

$$W_{\mathrm{OPT}} = \arg\max_u \frac{u^{\mathrm{T}} S_{\mathrm{B}} u}{u^{\mathrm{T}} S_{\mathrm{W}} u} \tag{7.4}$$

$$\begin{aligned} W_{\mathrm{OPT}} &= \arg\max_u \frac{u^{\mathrm{T}} S_{\mathrm{B}} u}{u^{\mathrm{T}} (S_{\mathrm{W}} + S_{\mathrm{B}}) u} \\ W_{\mathrm{OPT}} &= \arg\max_u \frac{u^{\mathrm{T}} S_{\mathrm{B}} u}{u^{\mathrm{T}} (S_{\mathrm{R}}) u} \end{aligned} \tag{7.5}$$

$$S_{\mathrm{R}} = \sum_{j=1}^{N} \sum_{x_j \in X_i} (x_j - \mu_i) \times (x_j - \mu_i)^{\mathrm{T}} \tag{7.6}$$

In the above equation, (S_{B}), (S_{W}), and (μ) are the between-class, within-class, and mean of classes of muzzle image database, respectively. (S_{R}) is defined as total scatter matrix shown in Eq. (7.6).

In Eqs. (7.1)–(7.6), the total scatters feature matrix depends on the total mean value of the extracted set of features not on the class mean values. The total scatter feature matrix is illustrated into a generalized eigenvalue computation as follows (shown in Eq. 7.7):

$$S_{\mathrm{B}} V = \lambda S_{\mathrm{R}} V \tag{7.7}$$

The pseudocode of the proposed method is presented in Algorithm 7.1. The proposed FLPP algorithm uses OSS-based learning, distance matching, and model of incremental-SVM (online) for the classification and recognition of muzzle point features of cattle.

Algorithm 7.1: FLPP Feature Extraction and Representation approach
1. **Begin Procedure**: Training the learning of FLPP model
2. **Initialization of muzzle point feature matrix**: Initialize feature matrix of muzzle point image of cattle $[X] = [X_1, X_2, \ldots, X_n]$, between-class (S_{B}) and within-class (S_{W})-based two simple graphs $G_{\mathrm{B}}(V_1, E_1)$ and $G_{\mathrm{W}}(V_2, E_2)$. The graphs are applied for finding the feature representation of muzzle point image of cattle. The simple graphs are defined as follows:
A. **Definition of simple graph**: Define two graphs $G_{\mathrm{B}}(V_1, E_1)$ and $G_{\mathrm{W}}(V_2, E_2)$ neighbors sharing $N_{\mathrm{W}}X(I)$ and $N_{\mathrm{B}}X(I)$. These are the two subsets of neighbor sharing the similar class label with (x_i) and $G_{\mathrm{W}}(X, S_{\mathrm{W}})$, and $G_{\mathrm{B}}(X, S_{\mathrm{B}})$ is two simple graph structure to compact representation and modeling of the within-class

(continued)

(continued)

B. The within-class (S_W) compactness is build by joining an edge between two graph nodes (x_i, x_j) if feature points belong to the same class. The computation of $G_W(X, S_W)$ is given as follows (shown in Eq. 7.8):

$$S''_W = \sum_{(i,j)x_i \in N_W} \sum_{(x_j \in N_W(i,j))} (u^T x_i - u^T x_j) \times 2u^T \times u(D_W - S_W) \quad (7.8)$$

The within-class (S_W) is illustrated in Eq. (7.9):

$$S_W = \begin{bmatrix} \exp^{-\frac{(x_i - x_j)^2}{t}, \text{if}(x_i) \in N_W(x_j) \text{ and } (x_j) \in N_W(x_i)} \\ 0 \end{bmatrix} \quad (7.9)$$

where (t) is a constant variable which can be calculated empirically. The similarly, the graph for the scatter matrix is also measured based on the similarity matrix (S_B). The calculation of between-class (S_B) scatter of muzzle point image calculated as follows (shown in Eq. 7.10):

$$S_B = \begin{bmatrix} \exp^{-\frac{(x_i - x_j)^2}{t}, \text{if}(x_i) \in N_W(x_j) \text{ and } (x_j) \in N_W(x_i)} \\ 0 \end{bmatrix} \quad (7.10)$$

where D_B is calculated as follows (Eq. 7.11):

$$D_B = \sum_{j=1}^{N} S_W \quad (7.11)$$

The separability between classes is evaluated by a defined class graph $G_W(X, S_W)$ and $G_B(X, S_B)$ by connecting and inserting the two node values (x_i), and (x_j), if the two nodes belong to different classes. The between-class of muzzle point image data is illustrated as follows (shown in Eq. 7.12):

$$\begin{aligned} S''_B &= \sum_{(i,j)x_i \in N_W} \sum_{(x_j \in N_W(i,j))} (||u^T x_i - u^T x_j||) \times S_B \\ &= 2u^T \times (D_B - S_B) \times (X^T u) \\ &= 2u^T \times (T) \times (X^T u) \end{aligned} \quad (7.12)$$

where $T = (D_B - S''_B)$ is defined as a Laplacian matrix. The objective function of Fisher discriminant analysis is applied to represent muzzle point feature of cattle. The fisher discriminant is applied to select the prominent muzzle point feature using proposed FLPP feature extraction and representation learning model as follows (Eq. 7.13):

$$\begin{aligned} W_{OPT} &= \arg\max_u \frac{u^T S''_B u}{u^T S''_W u} \\ W_{OPT} &= \arg\max_u \frac{u^T X P X^T u}{u^T X T X^T u} \\ W_{OPT} &= \arg\max_u \frac{u^T X P X^T u}{C} \end{aligned} \quad (7.13)$$

where $u^T X T X^T u = C$, C is a constant. The maximization problem of proposed FLPP approach can be illustrated into Eigenvalues problem shown in Eq. (7.14):

$$XPX^T W = \lambda XTX^T W \quad (7.14)$$

The proposed methods do better than the conventional FLDA and linear preserving projection (LPP)-based methods. For instant, performance comparisons of LPP method, proposed method caters a superior compaction feature representation of the within-class of muzzle point images by minimizing the distances between feature points and its neighbors of the same class. Figures 7.5 and 7.6 represent the various feature points from muzzle point image classes.

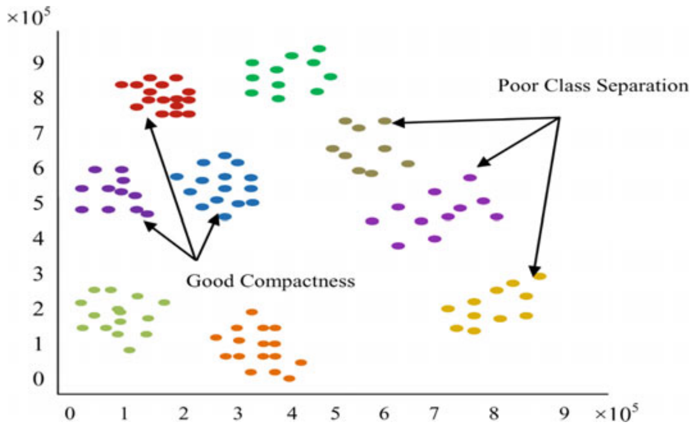

Fig. 7.5 Feature points of 10 different pixel values of muzzle classes

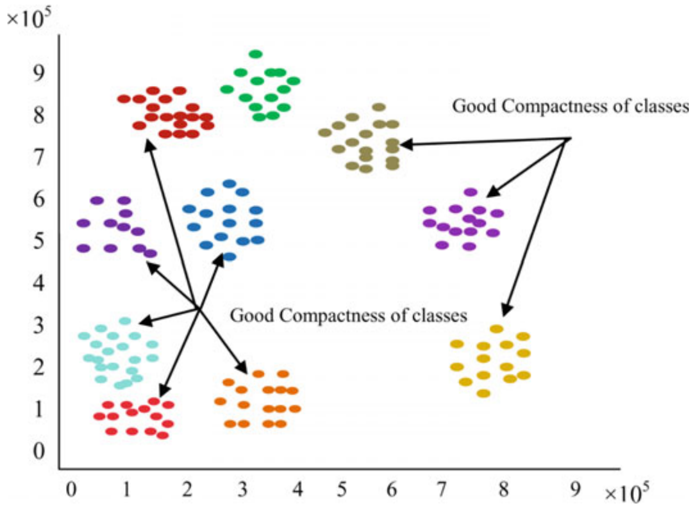

Fig. 7.6 Feature extraction and representation using FLLP approach

7.4 Feature Encoding

Feature encoding is a mechanism to perform the encode process for the extracted set of discriminatory features. To perform the identification of individual cattle, feature encoding and decoding algorithms are essential. These algorithms provide an explicit encoding mechanism of the muzzle point feature in the feature space to improve the identification accuracy of cattle. Therefore, the proposed approach is motivated by representation and learning-based feature encoding [30, 31].

7.4.1 Classification Model Using One-Shot Similarity and One-Class-Based SVM

In this subsection, we have applied the distance metric-based learning technique for encoding the extracted set of muzzle point feature. It is used to mitigate the semantic gap effect for the feature representations of individual cattle. Further, the suitable distance-based learning technique is used for the classification of extracted set of features.

Definitely, for identification of individual cattle, a distance metric-based learning technique has been applied to learn the extracted set of features with mapping space. In the feature space, two muzzle images of cattle are matched exactly. Therefore, this process improves the performance of recognition system.

In this chapter, we have used the soft-margin support vector machine-based model [30]. The model has been used to learn from training samples (x_i, y_i), $(x_i) \in R^m$ and $y_i \in [+1, -1]\ \forall i \in [1, 2, 3, \ldots, N]$ that is of objective form function $[f(x) = w\varphi_k(x_i) + b]$. The objective function can be illustrated in Eqs. (7.15)–(7.19):

$$f(x_i) = \mathrm{Min}_{w,b,\xi} \frac{1}{2} \|W\|^2 + C'' \sum_{i=1}^{N} \xi_i \tag{7.15}$$

Equation (7.15) is subjected to the following constraints for the accurate classification of extracted set of muzzle features as given by

$$Y_i(W, \phi_k(x_i) + b) \geq 1 - \xi_i \tag{7.16}$$

where $(\xi_i) \geq 0,\ \forall i \in [1, 2, 3, \ldots, N]$.

Equation (7.16) presents the learning formulation of SVM. It is solved by applying the quadratic programming paradigm. It can be represented in the different form which is known as dual form.

$$f(x_i) = \min_{0 \leq \alpha_i \leq C} (W) = \frac{1}{2} \sum_{i=j=1}^{N} \alpha_i \times Q(i,j) \times \alpha_j - \sum_{i=1}^{N} \alpha_i + b \times \sum_{i=1}^{N} (Y_i \alpha_i) \tag{7.17}$$

$$Q(i,j) = Y_i Y_j \times (\phi_i(x) \cdot \phi_j(x)) \tag{7.18}$$

$$f(x_i) = \sum_{i=1}^{N} (Y_i \alpha_i) \times \phi_i(x) \cdot \phi(x) \tag{7.19}$$

where b is defined as offset and Lagrange multiplier $Q(i,j)$ is illustrated that results in the dual form solution. The Karush–Kuhn–Tucker (KKT) technique is used. It uniquely finds the solution of the parameters (α, b) by minimizing the dual form and determining support vectors from the training set [32]. The one-class online-incremental-SVM classification model is employed to classify the muzzle images [32, 33].

7.4.2 Fishers Linear Discriminant Analysis (FLDA) and OSS Classification Techniques

A metric function is represented as a positive certain distance determination function for the estimation of distances between two elements of a given set. For a given set (S) metric function $|(D) : S \times S \rightarrow [0, 1]|$. The metric function impersonates a distance function. It is utilized to estimate the dissimilarity within two elements in the given set (S) [30, 31].

In the available literature, the classical Euclidean distance function and chi-square distance measure (X^2) techniques are unable to compute the discrete values for finding the similarity. It expostulate only a set of discrete binary (0 or 1) labeled pairs of elements or instances from a set (S). One-shot similarity (OSS) method is adopted for finding the similarity between the extracted set of muzzle point features. It is a semi-supervised matching-based similarity technique. It chooses the unlabeled training database. It is known as a set of negative sample image/data for matching the two input sample images of muzzle point pattern [30].

The matching of distance between the levels is computed by using the classifier shown in Fig. 7.7 [34]. The output is accomplished utilizing each muzzle example and negative background set (L).

The similarity-based distance measure technique estimates the similarity between the set of scores ($S1$) and ($S2$) using the summation rule [30, 35]. The computation using FLDA classification technique is given in brief as follows:

According to [36], the between-class (S_B) and within-class (S_W) of the muzzle point image database are defined as follows (shown in Eqs. 7.20–7.22):

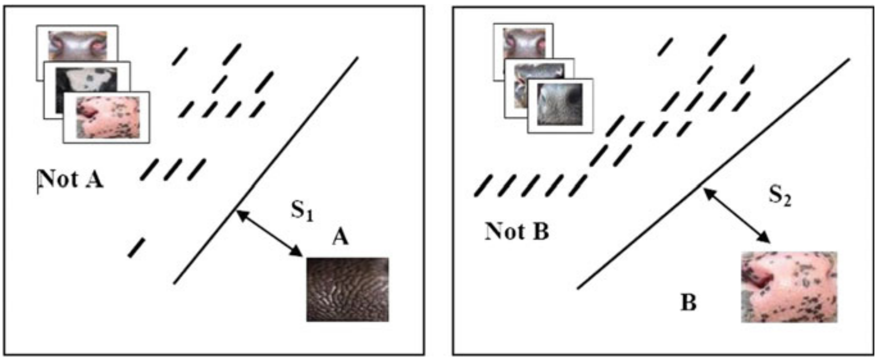

Fig. 7.7 Matching of muzzle point images using one-shot similarity matching technique

$$S_{\mathrm{B}} = (\mu_r - \mu_s) \times (\mu_r - \mu_s)^{\mathrm{T}} \tag{7.20}$$

$$S_{\mathrm{W}} = \frac{1}{(N+K)} \sum_{i=1}^{N} (P_i - \mu_s) \times (P_i - \mu_s)^{\mathrm{T}} + Q \tag{7.21}$$

$$Q = \frac{1}{(N+K)} \sum_{j} (K(\mu_i - \mu_s) \times (\mu_i - \mu_s))^{\mathrm{T}} \tag{7.22}$$

The mean values (μ_i), (μ_s) and (μ) are used. Fisher linear discriminant analysis technique initial estimates a linear projection (u). It maximizes the scatter matrix separation of between-classes of muzzle images by reducing the within-levels. The estimation is shown in Eqs. (7.23) and (7.24):

$$W_{\mathrm{OPT}} = \arg\max_u \frac{u^{\mathrm{T}} S_{\mathrm{B}} u}{u^{\mathrm{T}} S_{\mathrm{W}} u} \tag{7.23}$$

$$\left[u_0 = u^{\mathrm{T}} \times \frac{(x + \mu_r)}{2} \right] \tag{7.24}$$

Therefore, the similarity between scores is estimated and calculated from these set of sample image (background (L) sample) using OSS learning distance metric system.

7.5 Matching of Muzzle Point Images

In this section, matching of minutiae feature points based on learning, distance-based matrices, OSS using SVM technique, and distance matrices via OSS with online incremental SVM of classification techniques are employed in the matching of muzzle point images of individual cattle.

The prevalence of implementing support vector machine-based classification models is to perform updates automatically to modify the variations of the pixel intensity values of the extracted set of muzzle point features of individual cattle.

Besides, we have done the code customization in the batch-based learning formulation of 1-class SVM model [31] for enhancing the accuracy of the system. The incremental-SVM (I-SVM) classification model is utilized with the batch formulation method [32]. The incremental-SVM models achieve the incremental or decremented (online) of sample muzzle point images by the online learning procedure.

The matching of two muzzle images using fingerprint techniques is shown in Algorithm 7.2. Figure 7.8 illustrates the detection of minutiae points and inverted

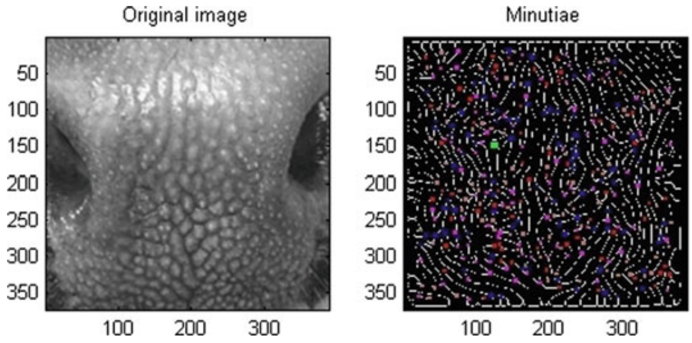

Fig. 7.8 Minutiae feature points of muzzle images of cattle

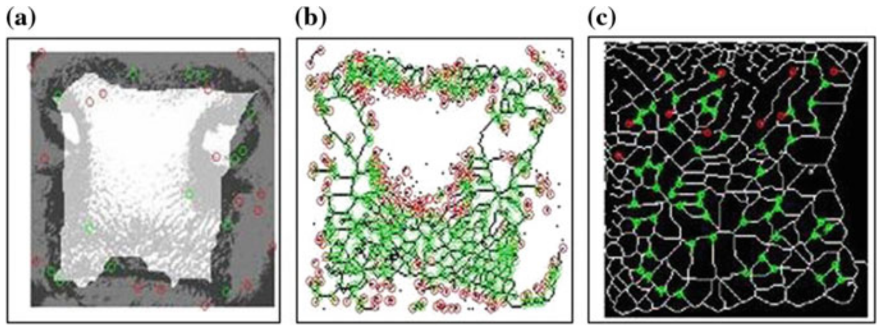

Fig. 7.9 Finding of the region of interest of muzzle points

skeleton image with core point (green color), lower core points (gold color) [0°–180°], bifurcations (blue color and purple) for [180°–360°], and ridge endings (orange color) for [0°–180°], and (red color) for [180°–360°]. The finding of the ROI, suppress of extreme points of extracted of muzzle point from the ROI of muzzle point images is shown in Figs. 7.8 and 7.9, respectively.

Algorithm 7.2: Matching algorithm for Muzzle Points

---

1. **Begin Procedure: Muzzle point** Matching Algorithm (*M*1, *M*2).
2. **Initialization step**: Initialize input muzzle point images of cattle: *M*1, and *M*2 are two muzzle point images, models of incremental-SVM, and 1-class SVM classification, match scores (*S*), *S*1, *S*2, Mi-1 (remaining muzzle point images), counter (*i*), total muzzle point images (*N*), and decision threshold (ϑ), (For $i = 2, 3, 4, \ldots, N$).
3. **Learning Model 1 for Muzzle point image (*M*1)**: *Incremental-SVM* (*M*1) = Update incremental-SVM model with *M*1 as positive sample image of muzzle point as training image with remaining muzzle images Mi-1.
4. **Calculation of matched score (*S*1)**: *S*1 = calculation of Euclidean distance from decision boundary of *M*2 from Incremental-SVM online (*M*1).

(continued)

(continued)

5. **Learning Model 1 for Muzzle point image ($M2$)**: 1-class SVM learning model (online) ($M2$) = Update SVM model online with $M2$ as positive sample image of muzzle point with remaining images Mi-1.
6. **Calculation of matched score ($S2$)**: $S2$ = calculation of Euclidean distance from decision boundary of $M1$ from 1-class SVM online $M1$.
7. **Matching step**: If $\{(S1 == S2)\}$ return matched similarity score ($S = S1$) **Else**.
8. **Update the matching scores**: update the scores of muzzle point images in the similarity matching matrix and perform matching again with remaining query muzzle point image (Mi-1).
9. **Output (Identification of Cattle)**: if ($S \leq$ Threshold (θ)).
10. Report genuine cattle.
11. Else report imposter cattle.

End procedure

7.6 Algorithm for Evaluation for Experimental Results

In this section, we have given the detail description of algorithms for the experimentation. It also provides the encoding mechanism to encode the extracted set of features. For feature extracted and encoding purpose, the database of muzzle images is classified into two major classes. This classes are known between-class and within the category of database. For the accurate recognition of cattle and improve the identification rate, there is a requirement to implement a better separability of extracting features of muzzle point images among these classes.

The comparative analysis of experimental results using handcrafted texture feature [37–39] and appearance-based recognition algorithms [40] is used. A brief explanation of the texture feature extraction methods and appearance-based feature extraction and representations is given below:

7.6.1 Appearance-Based and Texture-Based Feature Extraction Algorithm

The combination of well-known appearance-based feature extraction and representation methods are principal component analysis (PCA), PCA-LiBSVM [40], linear discriminant analysis (LDA) [41, 42], independent component analysis (ICA), ICA-LiBSVM [43], batch-incremental-LDA [44], and its modified version algorithms. The modified algorithms also play a vital role for feature extraction and representation of muzzle point images. We have done customization for Batch-CCIPCA [45] LDA-LiBSVM [46], ILDA-LiBSVM [46], local projection preserving (LPP) [47], and SIFT [48].

7.7 Experimental Result and Analysis

The proposed system uses the Intel core-2 duo-2.00 GHz computer with 400 GB of random access memory for computation of experimental results. After, preprocessing and enhancement of muzzle point images, muzzle point features are extracted from the muzzle point database using texture feature-based descriptor techniques and appearance-based feature extraction techniques. The brief description about the evaluation of experimental results of system is illustrated in the next subsection.

7.7.1 Performance Evaluation

For performance evaluation, beginning, we have divided the muzzle point image database into following parts: (1) training and (2) testing. For the experimental results, we have considered six muzzle point images of each cattle (e.g., 500 cattle $\times$ 6 muzzle images = 3000). The muzzle images are utilized for the training the proposed system.

For the testing, four muzzle point images are employed as query muzzle point image for the matching with stored image template for the recognition purpose. The segmentation of the muzzle image database is completed for the training and testing purpose. The evaluation of rank-1 recognition accuracies is computed, and validation of accuracy is made on five-times cross-validation. The experimental results are shown in the form of Cumulative Match Characteristics (CMCs) curves for the identification accuracy of systems. The identification rates of cattle are shown in Figs. 7.10, 7.11, and 7.12. Further, the identification accuracy is depicted in Tables 7.1, 7.2, and 7.3.

The LDA method shows excellent identification accuracy than PCA technique. The best identification accuracy of LDA method is 79.95%. The eigenvalue-based PCA method caters the minimum identification accuracy 75.57% on 50 feature vectors. Nevertheless, PCA techniques generate the 75.86% identification accuracy by applying the eigenfaces with 200 feature sets because the eigenvalue-based PCA method leaves the low variance features of muzzle point images of cattle.

As presented in Table 7.1, ICA method produces the best identification accuracy of 87.95% at the high level of extracting feature sets. The ICA method obtains set of muzzle point feature vectors by mitigating the dimensionality of used input muzzle images. The ICA technique produces the valid identification accuracy as compared to PCA (eigenfaces) and LDA face recognition techniques in the unconstrained environment [49].

Table 7.2 demonstrates the identification accuracy of the modified version of appearance-based face recognition algorithms.

The customized formulation for the batch training of sample image of cattle is used. In this procedure, the incremental-SVM (ISVM) classification model is also

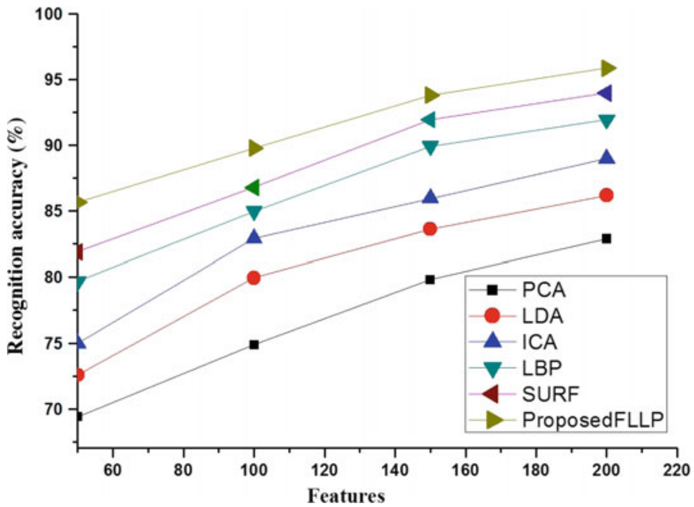

Fig. 7.10 Identification accuracy of cattle based on number of muzzle point features

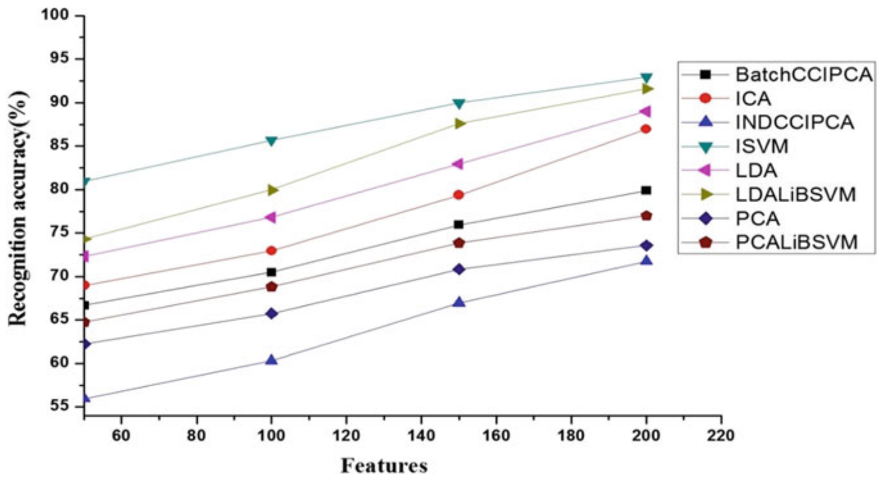

Fig. 7.11 Identification rates (%) based on muzzle point features

applied with Batch-CCIPCA, PCA, and LDA method for updating the sample muzzle point images of cattle database. Hence, the identification efficiency obtained by the ISVM technique is higher than other object recognition algorithms. The accuracy is high because it deletes the previous history of sample images and regularly updates the stored database by adding the sample images. Table 7.3 shows the identification accuracy as obtained by different classification techniques.

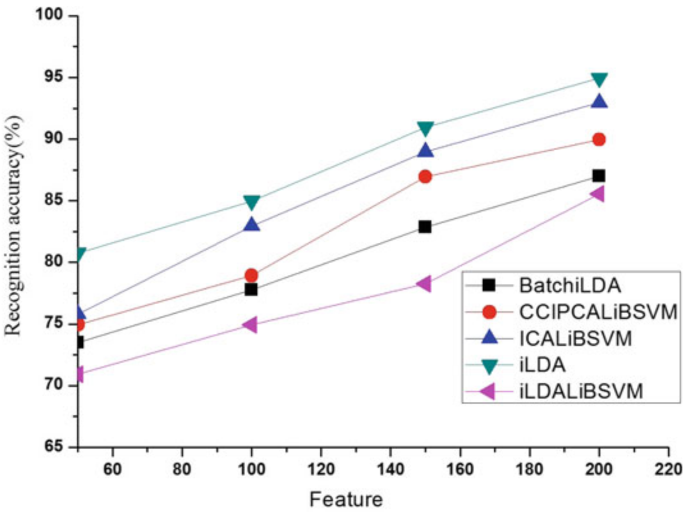

Fig. 7.12 Identification accuracy (%) of cattle using Batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, incremental-LDA, and ILDA-LiBSVM

Table 7.1 Identification accuracy (%) of PCA, LDA, ICA, SURF, LBP, and proposed method

Feature sets	PCA	LDA	ICA	LBP	SURF	Proposed approach
50	74.39	75.57	86.97	78.68	83.40	86.67
100	79.81	80.64	79.92	82.20	62.10	89.78
150	81.89	84.19	78.97	85.92	85.92	93.83
200	75.86	79.95	87.95	92.95	94.57	96.87

Further, Fig. 7.12 shows the identification accuracy of five different classification techniques. It determines that the ISVM algorithm gives 86.98% identification accuracy concerning other algorithms.

The incremental-LDA LiBSVM method gives 85.57% identification rate. However, the incremental-LDA (iLDA) classification method generates 94.95% identification accuracy which is higher than other used methods. The identification time of muzzle images is shown in Table 7.4.

Figure 7.13 demonstrates the impact of recognition time for different muzzle image of cattle. In this result, surveillance camera performed first detects of cattle and captured the image of cattle [50–53]. Referring Fig. 7.13, it is noticed that the size of cattle image increases, the cattle recognition system requires more time to processing and matching of muzzle features for recognize and verify the cattle. Further, the success rate (identification accuracy(%)) of the proposed cattle recognition system is estimated on the cattle image-3 which is higher than other cattle images [34, 35, 54–60].

Table 7.2 Identification accuracy of modified version of algorithms

F-sets	Batch-CCIPCA	ICA	IND-CCIPCA	ISVM	LDA	LDA-LiBSVM	PCA	PCA-LiBSVM
50	66.67	82.75	50.95	82.40	73.33	74.29	60.25	64.78
100	70.49	84.29	79.92	54.32	87.68	76.79	79.95	63.75
150	74.95	86.34	58.95	90.98	80.95	87.59	66.85	71.86
200	75.86	88.95	62.75	94.95	84.57	84.57	91.57	74.98

Table 7.3 Identification accuracy of Batch-iLDA, CCIPCA-LiBSVM, ICA-LiBSVM, iLDA, incremental-LDA-LiBSVM techniques

F-sets	Batch-iLDA	CCIPCA-LIBSVM	ICA-LiBSVM	iLDA	iLDA-LiBSVM
50	73.49	74.95	75.79	80.75	70.93
100	77.78	78.93	82.95	84.97	74.92
150	82.85	86.95	86.95	90.95	78.25
200	86.98	89.95	92.95	94.95	85.57

Table 7.4 Recognition time (s)

Cattle image	Image size (kB)	Recognition time (s)
Cattle image-1	10	11.50
Cattle image-2	20	13.25
Cattle image-3	40	14.85
Cattle image-4	50	20.98
Cattle image-5	60	21.78
Cattle image-6	70	22.98
Cattle image-7	75	25.68
Cattle image-8	80	26.98
Cattle image-9	95	27.99
Cattle image-10	100	30.74

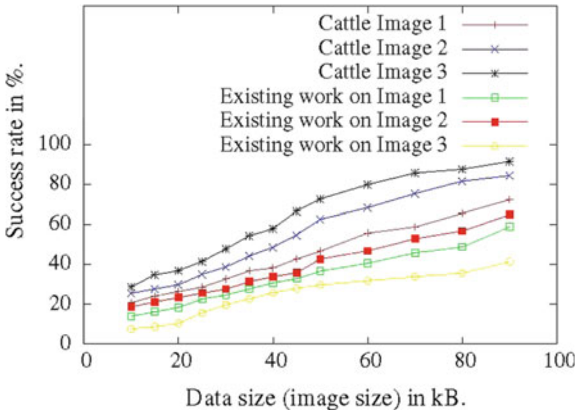

Fig. 7.13 Illustrates the impact of recognition time (t) of cattle recognition system on the different sizes (kB) of muzzle point images

7.8 Summary

In this chapter, a cattle recognition system is proposed for identification of cattle in real time. This research exhibits a current state-of-the-art based approach for the recognition, verification, and monitoring of cattle in the real time using surveillance camera. A comprehensive description of proposed muzzle point recognition algorithm is also illustrated. The system performs the various steps for identification of cattle. It includes the extraction of video frames, preprocessing, extraction of muzzle point features from these frames, and matching of muzzle point images based on similarity scores of feature vectors using one-shot similarity and incremental-SVM-based learning.

We would like to further determine the performance of the method, which will be reported in future communication.

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Chapter 8
Biometric Methods for Animal: Recent Trends and Future Challenges

Abstract This chapter provides an extensive view about the state-of-the-art animal biometric recognition systems for different applications and environments. The chapter also introduced animal biometrics databases of different species or individual animal in tabular format. In addition, visual animal biometrics followed by the issues and challenges is presented in brief. Finally, some opinions as to the future directions are presented in the summary of the chapter.

Keywords Animal biometrics · Computer vision · Phenotypic appearance

8.1 Introduction

Over few years, animal biometrics has become an emerging area of research in computer vision and animal cognitive science [1]. The great progress has advanced to point that animal biometrics-based recognition systems and modeling systems are being demonstrated in the real-time applications and applicability for representing and detecting the phenotypic appearance of species, visual features, individuals, behaviors, and morphological characteristics of species [2]. Moreover, Long-term research of known individuals is critical for understanding the demographic and evolutionary processes that influence natural populations.

The coherent set of fundamental ideas and algorithms of computer vision also achieved more attention for designing and development of animal biometric recognition systems. Therefore, availability of massive amount of tools, animal biometric techniques, these systems have more applicability in the wide range of applications and uses [1, 2]. Still more, innovative deep learning approaches have started to combine animal biometrics with intelligent sensor networks and crowdsourcing to encourage the feasibility and impact of systems to monitor endangered animals and species.

The emerging field of animal biometrics is on the verge of providing powerful methods recognition systems and real-time recognition frameworks or systems, tools, and quantified methodologies for detecting and representing the visual

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https://doi.org/10.1007/978-981-10-7956-6_8

appearances, morphological image pattern, and biometric characteristics of species or individual species [2].

Animal biometric approaches use a large spectrum of well-defined methods for capturing the data, detection, and representation of species, matching, storage of database, and communication among interdisciplinary researchers. This diversity of methods frequently proscribes their transferability across studies, which, ironically, it is one of the objectives of animal biometrics [2, 3].

Identifying widespread of identification methodologies and introducing more modular system designs, customizable to individual studies, is a significant goal to make solutions more generic and cheaper to produce and maintain. Any move toward this goal will help to standardize the field and promote its wider application. This diversity of computing systems, paradigms and algorithmic approaches caters new opportunities for new interdisciplinary researchers, practitioners, ecologists, biologists, scientists, veterinary professionals, and different research communities.

The methods can provide better efforts for designing of emerging algorithms, frameworks, and systems for identification and representation of appearances of species in the emerging field of animal biometrics [2, 3].

Building on this foundation, the current advancements in automatic human recognition, monitoring and tracking of objects using surveillance techniques, and animal biometrics have produced a plethora of complex technologies. These techniques can be used to locate targets [4], identification and proper assessment of movement patterns [5] and pose of animal [6], identification and classification of species or an individual animal in the herds [7]. It also determines the behavior of animals [5, 6] and evaluates facial expressions (e.g., for identification of chimpanzee and apes based on their face biometric features) [7, 8]. The computer vision-based identification and tracking systems are highly applicable to study the animal populations. Moreover, they automatically provide formalized and repeatable measures, independent of a subjective human observer.

In current state-of the-art-based approaches, biologists and scientists have begun to adopt these computer vision-based frameworks and well-defined identification methods. They have transformed essentially the way in which ecological and evolutionary researchers can acquire and interpret field data. The requirement for individual animal identification has been long recognized, as has the tedious and error-prone nature of the task when performed identification manually [9]. There are three broad categories of methods: (1) those designed for humans to follow manually, (2) semi-automatic identification techniques developed with a specific species in mind, (3) and semi-automatic methods that can be implemented to a class of species or animal that share similar phenotypic appearances and morphological biometric characteristics [5, 10].

In fact, semiautomatic photo-identification has also become well established in the areas such as marine animal observation and to study the population and behavior analysis of different species [11, 12]. It also and enables researchers to study the changes in the morphological characteristics of species and tracking thousands of individuals over time and space. It is far beyond what can be achieved manually [13]. Even more innovative computer vision and pattern recognition algorithms and its methodologies have started to combine animal biometrics with intelligent sensor networks [13]. The emerging field animal biometrics illustrates the design and use of animal biometrics-based recognition system, the first image retrieval system for individual animal identification incorporating crowd-sourced relevance feedback. The emerging and cutting-edge technologies also boost the feasibility and impact of animal biometrics-based recognition systems and monitoring frameworks to tracking and monitoring of the endangered species or animals throughout the world. The iterative retrieval strategy of the animal biometric system advances deformation and correspondence-based approaches, template matching for individual identification across several species. It uses the hierarchical and aggregated matching and relevance feedback consistently to improve the matching accuracy. The crowdsourcing strategy is successful in utilizing relevance feedback on a large scale.

Identification of species or individual animals based on captured images of their morphological features, biometrics image characteristics of species accumulated over time is known as a non-invasive animal identification method for ecological monitoring and conservation.

In this chapter, we have provided a comprehensive design develop and use of animal biometrics-based recognition systems and frameworks for identification and classification of individual animal and species.

The remainder of the chapter is organized as follows: Section 8.2 depicts the current state-of-the-art animal biometrics-based recognition systems, models or frameworks for identification of animals or species. Section 8.3 illustrates the animal biometrics-based classification systems for identification and monitoring of pets based on their biometric face image features. In Sect. 8.4, identification of horses based on their face biometric features using computer vision techniques is demonstrated. Section 8.5 presents the proposed animal biometrics-based recognition framework for chimpanzee using deep learning approaches. Section 8.6 illustrates the shared tools, models, and publically available databases of animals or species for identification and classification of animals in the real time. Section 8.7 explores the major issues and challenges of visual animal biometrics. Finally, the chapter concludes with future directions in Sect. 8.8.

8.2 Animal Biometrics-Based Recognition Systems

In this section, the comprehensive current state-of-the-art-based animal biometrics-based recognition system and framework are demonstrated. The working of animal biometrics-based recognition systems and frameworks is given for identification and classification of individual animal or species. The brief descriptions of the working prototype of animal recognition system or frameworks are presented in the next subsections.

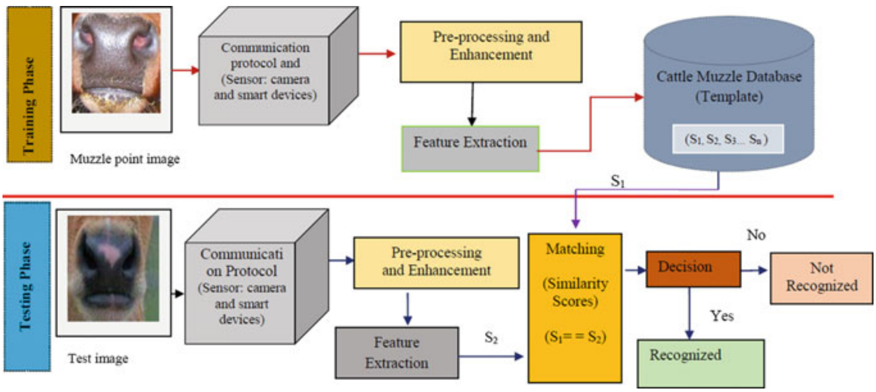

Fig. 8.1 Low-cost cattle recognition system using multimedia wireless network

8.2.1 Low-Cost Cattle Recognition System Using Multimedia Wireless Network

In this section, a real-time cattle recognition system is proposed for verification of individual cattle based on its muzzle point image pattern using wireless multimedia networks. The muzzle point images of cattle are captured using a 20-megapixel camera (system configuration: 14.48 centimeters (5.7-inch) IPS capacitive touchscreen with 1440 x 720 pixels resolution and 283 ppi pixel density, 4GB RAM) and transferred them to the server of cattle recognition using Wi-Fi communication technology. The cattle recognition system performs the image pre-processing on the captured muzzle point image of individual cattle. It mitigates and filter the noise from the captured images and increases the quality, and enhance the contrast [14]. The muzzle point features are extracted using computer vision techniques and supervised machine learning based multi-classifer pattern recognition techniques are used for recognizing the individual cattle. The server has a database of cattle images which are provided by the owners.

The support vector machine-based classification model is used to classify the extracted set of texture muzzle point feature of cattle. The similarity score measurement is applied for matching the test (query) muzzle point image with the stored muzzle point image database. We also developed a working prototype for evaluating the accuracy of the cattle recognition system (shown in Fig. 8.1).

8.2.2 Cattle Verification System Using Smart Devices

An animal biometrics-based recognition system plays a significant role in livestock biometrics. The recognition systems provide assistant in registration, tracking, recognition, and verification of livestock in case of missed or swapped animals, false insurance claims, and reallocation of animals at slaughterhouses.

In this subsection, a fast and cost-effective animal biometrics-based cattle verification system is proposed using smart devices. The proposed system quickly recognizes and verifies the false insurance claims of cattle using their primary muzzle point image pattern characteristics [15].

To solve this major problem, users (e.g., owner, parentage, or other) have captured the images of cattle using their smart devices (e.g., smartphones, intelligent computing-based devices, tablets, and other). The captured images are transferred to the server of cattle verification system using a wireless network or Internet communication technology. The verification system performs preprocessing on the captured muzzle point image of cattle. In the preprocessing steps, the removal and filtering of noise increase the image quality and enhance the contrast of captured image is done by system. The texture feature of muzzle point images is extracted using computer vision techniques (e.g., appearance-based and texture feature-based feature extraction and represenattion approaches) and supervised machine learning multiclassifier pattern recognition techniques are applied for recognizing the cattle.

8.3 Identification and Monitoring of Pet Animal Using Animal Biometrics

Health monitoring and tracking of pet animals in smart city is a big challenge for authorities concerned. The traditional animal identification and monitoring methods fail to cater the required level of security and monitoring of individual pet animals. Animal biometrics-based pet recognition systems are considered a good alternative for the identification and security of pet animals throughout the world [9].

In this chapter, we emphasize how to recognize the pet animal (dog) based on their biometric feature characteristics to provide the efficient level of security of pet animal.

Based on available literature, recently current state-of-the-art method is proposed by Kumar et al. [9] for identification and monitoring of individual pet animal (dogs) based on their face image biometric feature characteristics using animal biometrics.

The complete description of each component of proposed animal biometrics-based pet animal recognition system is shown in Fig. 8.2. The animal biometrics-based recognition system recognizes the pet (dog) animal based on their face biometric features. The proposed system consists of two phases: (1) Training phase and Testing phase. In the training phase, the proposed recognition system uses the surveillance camera for capturing the video of the pet animal for identification purpose. The video frames (set of images) are extracted from the captured video and stored in the pet animal database. The video frames are pre-processed using image processing techniques to removes the noises and enhance the image quality of images. The segmentation technique is used to find the region of interest (ROI) by partitioning the images. After that, extracted set of the feature is used to generate the biometric face template and stored in the database. In the testing phase, query face image of the pet animal is classified by similarity matching of the query face template with stored face

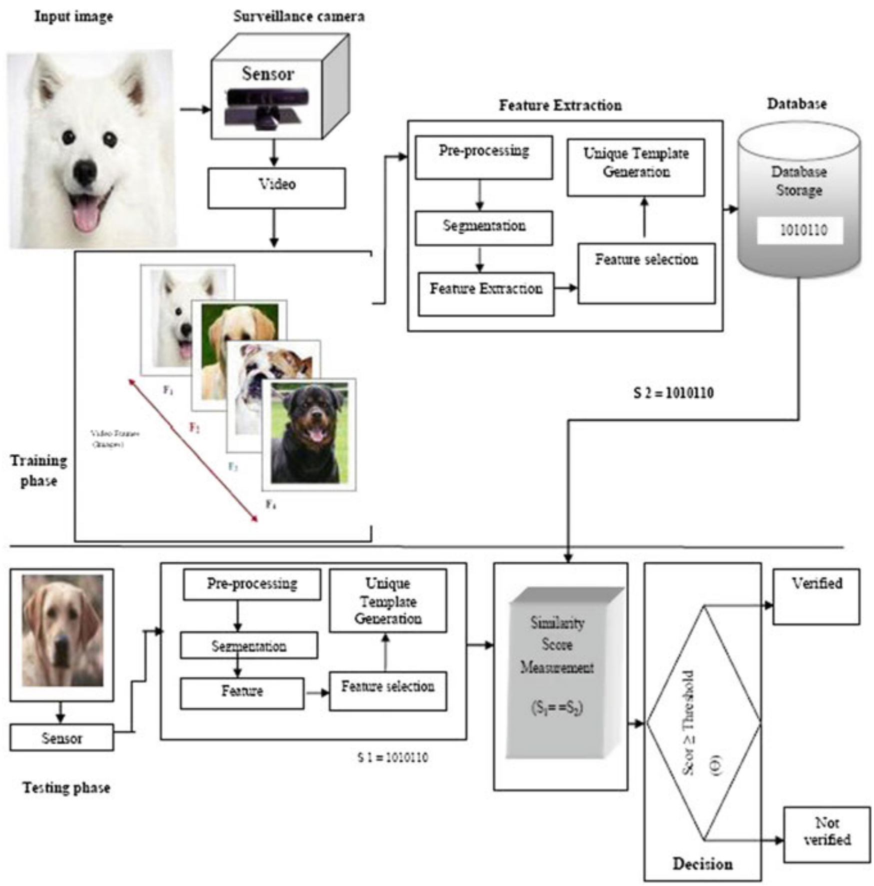

Fig. 8.2 Proposed animal biometrics-based recognition system for pet animals [9]

biometric templates of trained model. The wellness screening on a regular annual or biannual basis for companion pet animals and species is important and does lead to early diagnosis and the possibility of successful intervention using the animal biometrics-based system. The proposed working prototype of pet animal system can provide health monitoring of pet in the following ways: (1) The proposed system can be integrated with the internet of things (IoT) technology, wearable devices and the intelligent sensor devices for analysis of any changes in dog or cats behavior. (2) It also used to identify issues and critically as your dog ages and (3) to know how to take care of pet animals based on actual medical information using smart devices. Online monitoring of pet animals which display video images on system monitors, video wall, or large system monitors which are located in central as well as local control rooms of owner or parentages of pet animals.

In this proposed animal biometrics-based recognition systems, the author designed a low-cost animal biometrics-based recognition-based framework using surveillance systems. The surveillance system consists of surveillance camera. Surveillance system is required to ensure effective surveillance of an area of pet animal as well as to create a tamperproof record for post analysis of events.

The specifications of surveillance camera includes CCD sensor (Artificial Intelligence Cameras with better focal length 3.5–91 mm, 18 × indoor zoom, 20 × outdoor zoom, number of pixels: 720 × 576, scanning systems: Phase Alternating Line (PAL) color encoding system, resolution 480 TVL or better).

The proposed animal biometrics-based recognition system is depicted in Fig. 8.2. Figure 8.2 presents the working framework for transferring of captured face images of pet animal to the server of pet animal recognition system using Internet communication protocols. The pet animal recognition system consists of two phases (1) training phase and (2) testing phase. In the training phase, the proposed system is trained with face biometric feature of pet animal. The training of proposed recogition system is done with stored database of face images which is stored in the sever system. For training, the working prototype recognition system receives the transferred face image (video frames) for the preprocessing and enhancement using the image processing techniques. The set of video frames (face image) are extracted from the captured surveillance video and transferred via Internet communication protocols and settings. After the enhancement process, facial biometric features are extracted from preprocessed face image of pet (Fig. 8.3).

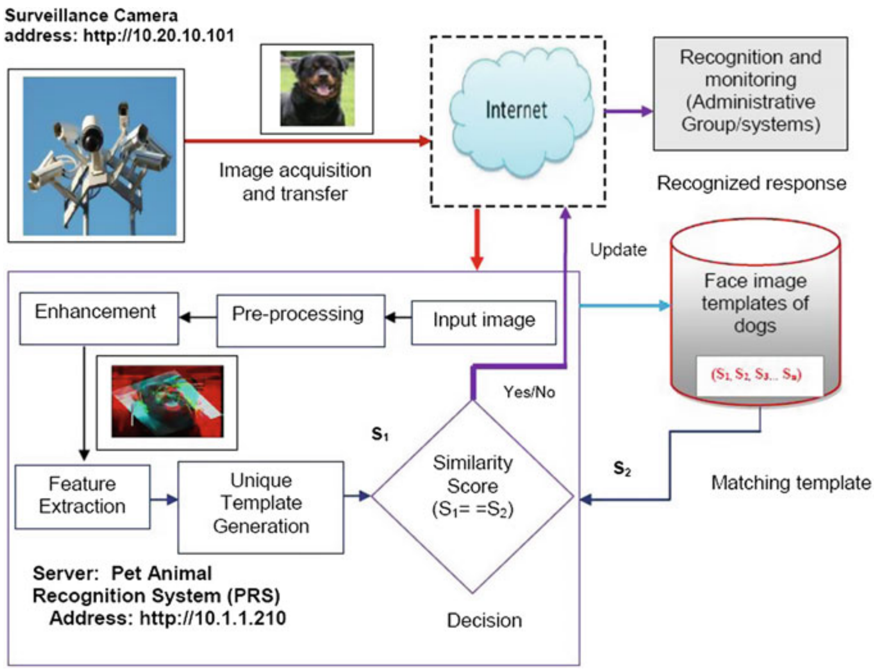

Fig. 8.3 Major steps of proposed framework for pet animals

The extracted feature sets are normalized and stored in the feature matrix [m × n]. The unique biometric face templates are generated and stored in the face image template database. In the testing phase, query face image of pet animal is used for matching with stored face image templates of pet. If face biometric template (S_1) of query image is matched with stored face image template (S_2), the animal biometrics-based recognition system identifies the pet animal and sends the message to acknowledge the recognition and monitoring control room or administrative group (owner of pet animal) and system.

The face biometric features of pet animals are extracted by holistic and texture feature-based descriptor techniques for recognition of pet animals. The proposed animal biometrics-based recognition systems use the one-shot similarity and distance metric-based learning methods for matching and classifying the extracted facial features of pet animals (dog). The efficacy of pet animal recognition system is evaluated under identification settings and yields 96.87% recognition rate.

8.4 Horse Identification System Using Animal Biometrics

Horse recognition is a significant task for trainers of horse racing game. It is necessary work to identify and verify individual horse before taking any participation in horse riding games with authority. It is necessary in this case to identify each horse to be distinguished. All classification methods used for identification are invasive. These classical identification approaches can threaten the well-being of horses like ear tattoo making and freeze branding-based marking schemes. In this section, the current state-of-the-art methods and systems are given in detail for identification of horse based on their biometric features.

Suzaki et al. [16] proposed a horse identification-based animal biometrics system using their iris biometric pattern feature. In this research work, Suzaki et al. [16] address the several problems for horse identification. These problems are to be solved in horse iris recognition: (1) horse are noncorporative for animal biometrics-based recognition systems because it is very difficult to remain motionless for horses, which leads to mislocation and loss of focus during iris image pattern acquisition, therefore the iris images often have poor image quality, (2) iris image patterns of horse are not clear.

To solve these major problems of horse identification, they used the reflection of the illumination sources employed for image acquisition and chose adequate images suitable for recognition. They proposed region extraction method appropriate to the equine eye structure, a stable coordinate model for pupil variation, and recognition using orthogonal wrinkles in the iris pattern. The experimental results of proposed method for horse identification are performed on 100 sets of horse iris image datasets.

In similar direction for face recognition of horses, author, Jarraya et al. [17] proposed an animal biometrics-based recognition system to identify individual horse using the facial biometric modality. The Gabor feature technique and LBP texture

Table 8.1 Current state-of-the-art method for recognition of animal using face biometric modality

References	Features extraction and classification	Face image database/ number of subjects	Identification accuracy
[22]	Image normalization + PCA + ICA + Cosine distance	50 sheeps (subjects)	96%
[23]	RASL + WLBP + Chi square distance	30 cattle (subjects)	95.30%
[24]	Gaussian smoothing + LBP	400 face image of pet animal (dogs)	94.86%
[25]	The associate neural memory algorithm	12 black cattle	100% (with transformed)
[26]	Speeded up robust feature (SURF) and local binary patterns (LBPs) from different Gaussian pyramid levels	300 cattle face imaged database	92.5%
[27]	Deep neural network with the auto-encoder, Gabor filter, SVM	Tunisian Horses Database of ReGIMLab (THoDBRL'2015)	Not reported
[28]	Reduced normalized Gabor local binary pattern (RNGLBP), texture descriptors Gabor and local binary pattern (LBP), principal component analysis (PCA)	Japanese Female Facial Expression (JAFFE), horse face image database (THoDBRL'2015)	Not reported
[18, 29]	Computer vision and image processing techniques	462 face images of 80 red-bellied lemurs 190 face images of other lemur species	98.70%

feature-based descriptor technique are applied to extract the facial features of horse for characterization of horse faces.

The Euclidian and Math cosine distance-based similarity matching technique is used for classification of horses. The experimental results of proposed method were performed and validated on horse face image database 'THoFDRL' 2015 database. The proposed approach achieved 95.74% recognition rate.

Recently, Jain et al. [18] proposed an animal biometrics-based recognition system for face recognition of lemur species. Jain and his biometrics research group [18] have modified their human facial recognition-based system to build the LemurFaceID recognition system. This is the first animal biometrics-based facial recognition system for lemur animal. The main objectives of LemurFaceID-based animal biometric system are (1) to provide better assistance with long-term research of endangered species or individual animal, (2) proposed face recognition system recognizes individual Lemur or other animal within an animal population.

This system can provide fundamental way to conservation and management of endangered lemur species. Based on the above research, it is concluded that lemur species has unique facial biometric characteristics similar to human that can be recognized by animal biometrics-based face recognition system [18].

In the animal biometrics-based recognition systems, linear discriminant analysis (LDA) supervised classification technique is used for reducing feature vector dimensionality to avoid overfit problem due to intra-class variation of face image of lemur (Table 8.1).

8.5 Face Recognition Framework for Chimpanzee Using Deep Learning Approach

Deep learning-based neural networks are powerful tools and visual analytics [19] in computer vision and machine learning research. It has achieved more attention due to wide range of application and used for identification and monitoring of wildlife animal or species.

Deep learning-based neural network framework has superior performance in various tasks [20]. In this chapter, a novel deep learning-based recognition model is proposed for face recognition of chimpanzee. The proposed animal biometrics-based recognition framework uses deep learning-based convolutional neural network algorithm. The detail description of animal biometrics-based recognition system using deep learning framework is illustrated in the next subsection.

Recently, deep learning has achieved more attention for identification and tracking of species or individual animal. Having automatic tracking and identification systems for species based on their accurate biometric information, detailed and up-to-date information about location and behavior of species or individual animal across broad geographic areas have revolutionized our ability to study, conserve, and manage endangered species and ecosystems throughout the world [21].

For image analysis of species, currently, relevant multimedia data are mostly collected manually at great expense. There are no such techniques and tools available for identification of the endangered animal. Therefore, animal biometrics, emerging research field is on the verge to provide a coherent set of fundamental tools, computer vision-based frameworks, learning techniques and model for better representation and classification of species and animal.

Possibly, proposed face recognition of chimpanzee using CNN deep learning-based animal biometric recognition system is shown in Fig. 8.4. The brief description of each step of proposed animal biometrics-based face recognition for chimpanzee is depicted as follows:

- **Image acquisition**: The digital camera captures the picture of a chimpanzee. The captured pictures of the chimpanzee are used for preprocessing to mitigate the noises using image processing technique. After that, the eyes, nose, and mouth are detected using Voila and Jones detecting algorithm.
- **Image segmentation**: The preprocessed images are segmented to find the region of interest from the images using K-means color segmentation and texture feature-based segmentation techniques. The segmentation process is shown in Fig. 8.4.

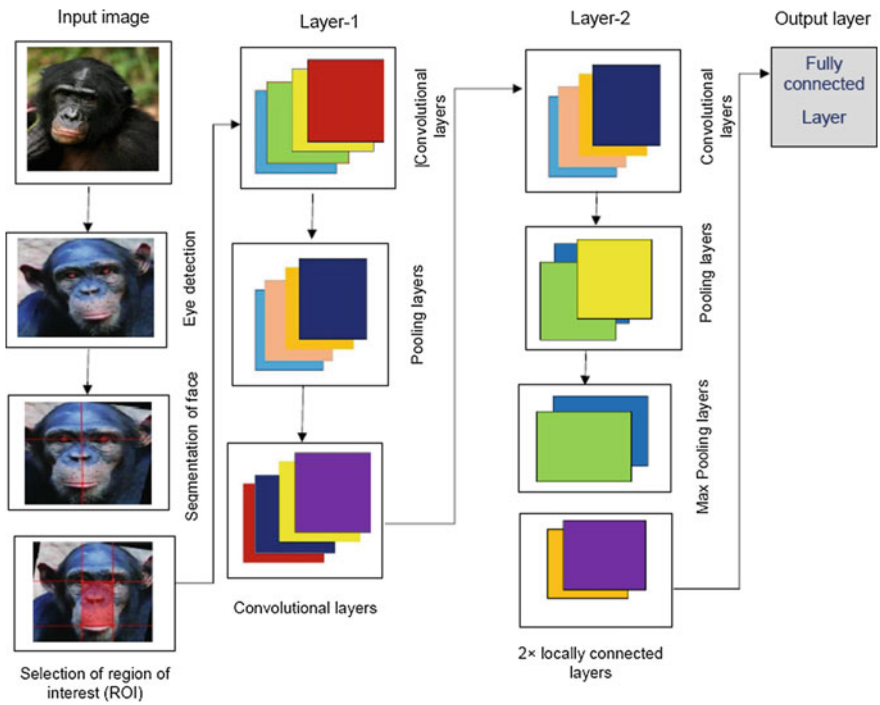

Fig. 8.4 Deep learning-based face recognition model for chimpanzee

- **Feature extraction and representation**: The facial features are extracted using convolutional neural network (CNN) from the face image of chimpanzee using the convolutional neural network-based deep learning framework. The proposed underground learning-based system is trained and uses such deep learning-based recognition architecture in the species or individual animal recognition problem [30].
- **Feature extraction and representation using CNN-based Architecture**: The CNN framework is used for feature extraction and representation of species. The main objective of the convolutional neural network (CNN) framework is to achieve high levels of identification and classification accuracy on species or animal classification tasks. To achieve better representations of extracted features of species, the proposed model contains the repeated use of convolutional layers in the given framework as shown in Fig. 8.4. The CNN-based recognition framework is followed by max-pooling layers [30] to obtain the better mapping of an extracted set of features in the feature space.

8.6 Shared Tools, Availability of Animal Database

Animal biometrics is yet in its starting stage and remains an open field. Nevertheless, animal biometrics is also a highly interdisciplinary research field. It requires input from different disciplines such as animal ecology, computer science, electronics engineering, and other to develop genuinely robust, widely applicable recognition systems and useful tools. Therefore, the rate of improvement that is made will depend principally on successful collaborations and sharing of expertise among various members of the different scientific communities [31–33]. There are no such databases available in the emerging field of animal biometrics for identification and classification of species. In reference [32], the author presents a method for analysis of a dataset of 3.6 million underwater trajectories of the fishes. A species of fish are labelled with the water temperature at the time of acquisition. There are many false detections and incorrect trajectory assignments, by a combination of data binning and robust estimation methods. The author demonstrated reliable evidence for an increase in fish speed as water temperature increases. The proposed method is applied for data cleaning for removing the outliers arising from false detections and incorrect trajectory assignments using deep learning based clustering algorithm.

Due to the lack of publicly available animal biometrics databases of species or individual animal, we have provided the detail description about the public availability of species or animal database in this chapter (shown in Table 8.2). Table 8.2 gives details about datasets of animal biometric feature that can be used for designing and development of animal biometrics-based frameworks.

8.7 Visual Animal Biometrics: Issues and Challenges

Visual animal biometrics is pattern retrieval and recognition-based system. It takes the visual biometric feature characteristics such as coat pattern, body coat pattern, and spot point pattern, and other visual features of species or individual animal. The major issue and challenges of visual animal biometrics-based recognition systems are demonstrated as follows [1, 2, 10, 45–48]:

- How do species or individual animal gets its body coat pattern? [1]
- What type of suitable algorithms and animal biometrics recognition systems or frameworks is available to compute the visual features from the body coat pattern of species? [1, 2]
- Can detection and representation of visual feature of body pattern of species be possible in their habitats? [2]
- How visual animal biometrics-based recognition and framework can monitor animal population? [2]
- How visual animal biometrics-based recognition system generates unique templates from stored visual biometric feature of species? [1]

Table 8.2 Animal biometrics database of different species or individual animal

Name of animal	Used database	Description of database	Utilization	Future scope
Horse [34]	Tunisian Horses Database of ReGIMLab (THoDBRL'2015)	– Multiview horses' faces Database 47 horses 10 images of each horse × 3 number of views (e.g., frontal, left, and right) × 47 (total horses (470 frontal face images 470 left profile images and 470 right profile images	– Face identification, verification of horses – Verification of false insurance claims of horse using smart devices	– Animal biometric system can be developed for health monitoring of species – Novel animal biometrics system can be designed and developed for smart riding club (SRC) – Registration and enrollment of horse based on their biometric features (face)
Chimpanzees, Zoo [19] Leipzig, Germany website http://www.saisbeco.com	**Chimp Zoo dataset**: 2617 face images	24 individual chimpanzees are considered 598 face image of chimpanzees	– Monitoring of chimpanzee by detecting their facial biometric feature	– Chimpanzees are threatened, and these animals are needed to be protected
	ChimpTaï dataset: 3905 face images chimpanzees	71 individual and 1432 face images head, eyes, and mouth were annotated – The annotations are stored separately for each image in a XML file		
Lion [35–37]	5000 lions (Serengeti Lion Project)	225 camera traps are used to capture the image and video database	– Animal biometrics-based systems can be used to study 30 different species distributed across the landscape – How they interact with lions and one another	– Observing animals in the wild protection and health monitoring of lion
Bat [38]	1212 photographs	230 individual bats	– Re-identification of bat species using photographs	– Conservation and management of bat species

(continued)

Table 8.2 (continued)

Name of animal	Used database	Description of database	Utilization	Future scope
				using animal biometrics-based recognition
Red-bellied lemurs (Eulemur rubriventer), medium size (∼2 kg) [18, 29]	462 images	80 red-bellied lemur individual – Each individual lemur had a name Avery, or its code is M9VAL – Capturing devices name: Canon EOS Rebel T3i with 18 55 and 75 300 mm lenses	– Face recognition of endangered lemur species	– Security and management of endangered species (lemur)
Cat [39]	**Cat database**: 700 cat nose images	70 different cats 10 nose image of each cat	– Nose recognition of cat using the locality constrained sparse representation method	– Preserve the social impact between species and human using animal biometrics
Northern leopard frog (Lithobates pipiens)	Database of northern leopard frogs	– The database consists of images of northern leopard frogs with following character tics: Number of leopard frogs: 209 separate identities The cutout along natural contours of the frog: Rectangular arrays of 256 × 128 pixels and converted to grayscale image A photographic light diffusing dome (Cloud Dome, www.clouddome.com) take an average of 3–4 images per frog for all 209 identities 966 images taken with the Shade Dome images 420 additional images taken of frog identities 109–209 that did not use the		– The database and proposed system can monitor the health by recognizing them

(continued)

Table 8.2 (continued)

Name of animal	Used database	Description of database	Utilization	Future scope
		shaded dome (hereafter, referred to as No Dome images)		
Plantas image database [40]	Database contains fifty common species and cultivars	– It is divided into three sets – Plantas50Basic – Plantas50Extra – Plantas50Internet. The Plantas50Extended set is the union of Plantas50Basic, Plantas50Extra, and Plantas50Internet **Training, validation, and testing of database**: 70% of database is used for training, 15% for validation, and 15% for test using convolutional neural networks (CNNs)	Identification and classification of plant species	– The database and proposed system can visually recognizing plant species in the wild
Cattle breeds [41, 42]	Face image database of cattle	**Characteristics of face image database e of cattle**: – Size of database: 300 cattle and each cattle have 10 face images	Identification and classification of cattle breeds	– Proper monitoring and registration of cattle using their biometric face image feature
Cattle breeds [43]	Face recognition database	**Size of database**: 30 cattle – Size of each cattle set of six, seven, eight, and nine images	local binary pattern (LBP) texture features based classification	– Cattle enrollment using facial features
Cattle breeds [44]	Muzzle point (nose pattern) image pattern database	**Size of muzzle point image database**: 500 (cattle) $\times$ 10 muzzle point image of each cattle	Muzzle point-based identification and classification of cattle	– Design and development of minutiae point-based algorithm for identification of cattle in the real time

In visual animal biometrics, various issues and challenges exist for identification and representation of appearances of species or individual animal.

Particular computer vision-based algorithmic challenges also lie in coping with unconstrained environment such as variable lighting, partial occlusion of animal body, complex organic deformation, and the requirement to annotate manually massive amount of captured datasets such as image sets, video and audiovisual datasets to train various computer vision models, framework, and methods.

Current advancements and improvement in computer vision modeling, pattern recognition, cognitive sciences, image processing, mathematical modeling, and machine learning [10, 29, 39, 45–49] promise to address these major issues and challenge in the animal biometrics. Figure 8.5 depicts complete description of the major issues and challenges of visual animal biometrics.

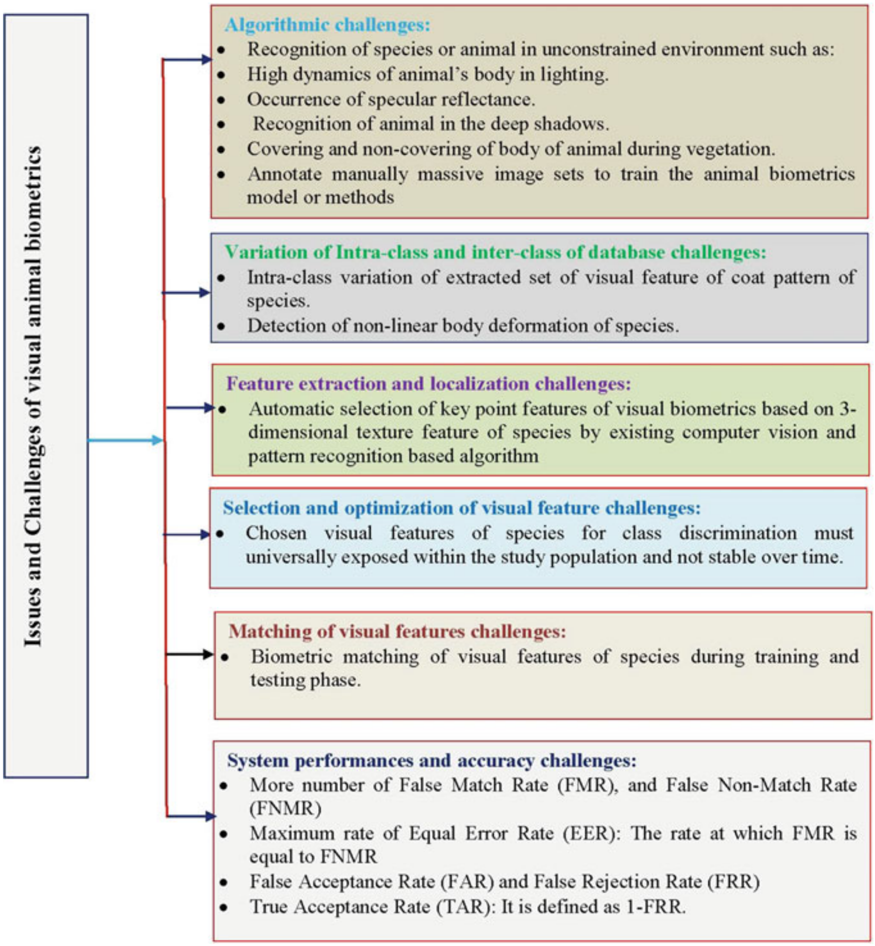

Fig. 8.5 Major issues and challenges of visual animal biometrics for identification and classification of species

8.8 Summary and Future Directions

This chapter explores the current state-of-the-art-based methodologies, efficient representing and detecting algorithms, and frameworks for detecting the visual appearance of animal or species. The animal biometrics-based recognition systems are also utilized for behavior analysis and identification of individuals based on morphological image pattern, phenotypic appearances, and biometric characteristics in the field of animal biometrics.

In addition, some novel deep learning-based animal biometrics-based recognition systems are provided for feature extraction and representation of species.

For further improvisation of deep learning-based recognition framework, the proposed framework can be implemented on the android platform that can be easily available for smart or android devices for verification and identification and verification of false insurance claims in real-time scenario.

The proposed deep learning-based recognition of animal caters a friendly, noninvasive, robust as well as a cost-effective solution using the smart devices or low-cost camera for the identification of species or individual animals.

Future Directions: The proposed animal biometrics-based recognition system and framework proved to be accurate and fulfilling the objectives with which this entire work was initiated. However, prospective future directions in animal biometrics can conveniently be widened. These are enlisted point-wise as follows:

1. **Design of Multimodal Fusion-based Animal Biometric Recognition Systems**: The multimodal fusion-based recognition systems or framework can be developed for accurate identification and classification of animal or species. The fusion of hybrid features of species or individual can improve recognition rate of the system. The low false rejection rates (FRRs), false acceptance rate (FAR) can be reduced.
2. **Real-time Animal Biometrics-based Recognition Systems**: For monitoring and tracking of species, the real-time animal biometrics-based recognition system can be developed based on their biometric image features.
3. **Incorporating New Ideas**: The complexity of recognition system design challenge can be solved by incorporating new coherent set of ideas and fundamental algorithms. For system design ahead calls for a new breed of researches, biologically knowledgeable scientists, engineers, and technically motivated biologists.
4. **Design and Development of Drone or microunmanned aerial vehicles (UAVs)**: Long term, broadscale, and massive amount of video and ecological databases are critical to animal biometric research, however, often impossible to capture on various scales. Classical data collection and preparation methods may be time consuming for analysis or dangerous and can compromise manual work that is error prone and sensitive to human impact. Drones and unmanned aerial vehicles (UAVs), aerial robotics with various sensors and devices can gather unobtrusive aerial image and video databases [50–53].

5. Innovative and novel ideas can also include automatic robotic systems that actively seek data by traversing the habitat to increase both the quality and quantity of acquired ecological and animal biometric datasets.
6. The machine learning and reinforcement deep learning systems can adapt better to highly unpredictable and constrain environments, continuously improving on animal biometric and classical animal monitoring system capabilities.
7. **Development of New Framework and Efficient Solutions**: Computer vision technology has achieved more attention. It is rapidly advancing the services for animal monitoring and tracking. The smart ear tags and unmanned aerial vehicles or drones can be deployed to remotely monitor the health of animal or species, and wireless cameras with long-range capability can transfer the messages to respective authorities and organization by smart devices (smartphone).
8. The future will determine whether animal biometrics can live up to its guarantee of revolutionizing the way we look at the biometric feature characteristics, morphological image pattern, phenotype appearances, ecological database, biological databases of species or individual animals.

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