Chapter 3

Recognition of Cattle using Face Images

3.1 Introduction

Cattle recognition has been a major problem for breeding of association in the livestock management based frameworks and standard animal recognition systems [148]. The identification of cattle is essential for registration and traceability of cattle. The registration of animals would prevent efforts for manipulation, swapping of cattle, and provide the procedures for verification of false insurance claims of cattle. According to Wagyu Registry Association (WRA) [8], the registration of individual cattle is done to a cattle's age of 4 months and over 14 months for proper breeding and marketing purpose of cattle throughout the world [130].

The recognition and traceability of cattle play a significant roles in controlling safety policies of livestock animals and better management of food production [140]. The 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 frameworks or systems for recognition and traceability of animals [189]. The organizations further actively promoted for these systems for the better monitoring and health management of individual cattle [15].

The proper administration of animals is the first step towards reaching the objective of accurate livestock farming that helps animal welfare, registration, health management, outbreak and control of critical disease [189]. Explicit recognition of individual livestock animals (for cattle) is necessary for precise management.

The classical cattle identification methodologies are categorized into several groups: (1) permanent animal identification approach, (2) semi-permanent animal identification approach, and (3) temporary animal identification approach [10]. The permanent animal identification approach includes ear-tattoos based marking techniques, embedding of microchips, ear-tipping or ear-notching, hot-iron, and hoof-marking scheme for the unique identification of individual cattle in the traditional identification methodologies and livestock frameworks [125]. In the traditional cattle identification methodologies, the semi-permanent animal identification method is also applied to provide a required level of security to livestock animal by using the collar-ID, and ear-tagging based marking techniques [193].

Moreover, the electrical signal based techniques, such as radio-frequency-based identification (RFID) and sketching pattern on the body of individual animal (*e.g.*, paint/dye) based identification methods are known as temporary animal identification methodology [109].

In different countries like USA, Australia, Canada and Great Britain have applied the radio-frequency based animal identification (RFID) based system for identification, tracking and monitoring of livestock which is embedded in the ear-tags for the registration and traceability of animals (cattle) [10]. For example, in Indonesia, the ear-tagging based identification systems have become the most feasible methods for the registration by performing the identification of the beef cattle because of the ear tagging based methods are informal to use and also flexible in all the types of weather conditions [9] [166].

The ear-tags are low-priced and usually easy to read the labels on ear tags for the recognizing individual cattle by scanning and processing of embedded labels in the ear of cattle. The ear-tagging techniques have been progressed for tracking and identification of animals in some ways. However, there are also the limitations with ear-tagging based identification systems for tracking, and recognition of beef animals. Ear-tags disintegrate the ear of animals (cattle) in the long term usages. The ear tagged labels since lost if it is not applied correctly to cattle's ear [2].

The classical animal identification and livestock framework systems based on ear-tagging and electronic identification of individual cattle, generally referred to as Radio Frequency Identification (RFID) has many advantages for management of farms [152]. In practice, however, implementation of RFID based identification systems can cause several problems. Reading speed and distance must be optimized for specific applications [53].

In practice, RFID implementations can cause several problems. Reading speed and distance between reader devices in RFID must be optimized for properly reading of RFID number for specific applications. In 1995, International Committee for Animal Recording (ICAR) developed a set of requirements regarding (among others) reading distance and reading speed [9]. The reading of RFID tag number should be error free possible at a distance of 0.4 meter while the animal is moving with a speed of 3 meter/second. With modern RFID transponders, reading ranges up to 0.8 meter and reading speed up to 4 meter/second proved to be possible [104], therefore, easily fulfilling these requirements.

Although RFID systems overcome some limitations of the traditional identification approaches, they present several security drawbacks that are distributed over the entire RFID system (RFID tags, communication channel, tag reader, RFID network, and the RFID back end). The identified security drawbacks include tag content changes, a high possibility of system spoofing, and Denial-of-Service (DoS) attacks [9].

The disadvantage of using RFID-based systems or animal identification systems for identification of animal is that RFID component (module) require efforts and labor work in order to be configured as an identification and tracking systems [152]. The cost of purchasing, replacing and management of RFID-based embedded ear-tags, in addition to the cost of operating and management the identification system, should be taken into consideration.

Comparing RFID-based identification systems and other classical identification methodologies has highlighted a number of advantages of the former. RFID ear-tag- based identification systems can hold relatively massive amounts of data that assign a unique code to every ear-tag [2]. Thus, a single tag can track an animal from birth to slaughter. Given the possibility of data storage, an RFID tag can host further information about the tracked animal, such as age, sex, breed, and color [125]. Furthermore, it can host information about the owner, the farm, diseases, and the animal's vaccination status. RFID- identification systems generally interact with other animal data recording systems for improved credibility and usability. It can also be integrated with smart devices such as smart phones, digital camera, and computing systems for enhanced accessibility, scalability, and performance [152].

According to the survey report of Johnston, et al. [95] and Wardrope [193], the label of ear tags can also be eventually damaged and corrupted due to the long-term usages. The low reliability and recognition rate (accuracy) have been major problems for identification and tracking of individual cattle. Therefore ear tagging based techniques unable to provide a competent level of security to cattle or livestock in classical cattle identification approaches. The sketch patterning and paint or dye based body marking techniques have also used to recognize the individual animals based on the broken color of different breeds (*e.g.*, Ayrshires, Guernseys, and Holsteins) [140] [5]. However, it required a skillful drawing ability of individual for coloring and sketched pattern process of cattle's body.

The sketching and coloring process has always bestowed the poor image quality of (*e.g.*, high resolution) of described pattern on the cattle body, therefore, sketch patterning based techniques affects the representation and recognition of cattle using drawing pattern based images on their body. Moreover, it cannot be applied for the identification of solid colored based pattern of different cattle breeds (*e.g.*, Redpoll, Milking Shorthorn and Brown Swiss breed). Therefore, traditional cattle identification methodologies provide the security to animals using invasive based techniques (*e.g.*, ear-tagging, freeze branding, ear-tipping or notching based techniques). The ear-tipping or notching technique also takes more cost for the development of artificial markings for the animal identification in the livestock management based framework [57]. Therefore, the classical artificial marking techniques are not able to cater a required level of security to missed, swapped, false insurance claimed and reallocation at slaughter houses of cattle [126] [166].

3.1.1 Motivation

According to a survey of Cattle Today Online (http://www.cattletoday.com/) of 1.3 billion cattle populations, about 30 % of total populations of cattle are in Asia, 20 % in South America, 15 % in Africa, 14 % in North and Central America and 10 % in Europe [166]. The non-availability of biometric-based identification approaches, efficient, affordable and scalable livestock management framework and recognition system for cattle have 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 [9].

Moreover, the electric and mechanical (non-biometrics based techniques), cattle identification techniques, such as ear notching, freeze branding and radio frequency identification (RFID) [152] based cattle identification techniques provide a low reliability, longevity and minimum recognition rate to identify cattle [10].The traditional non-biometric based identification techniques have their own boundaries[140]. Therefore, these techniques do not provide a competent level of security to livestock cattle and making it open for missed, swapped, theft of cattle [152] [159].

On the other hand, verification process has been a severe problem for cattle due to failure of classical animal identification systems and livestock framework based systems. These systems do not have any efficient methodology to perform verification of registered and insurance cattle easily, without cutting the ear of cattle for the verification false insurance claims of livestock animals by verification officers [166]. Therefore, it is still difficult to prevent the activities such as forgery, duplication, fraudulent and manipulation of ear tags numbers of cattle [193]. These problems of cattle cannot be ignored by biometric techniques, scientist, experts and different research communities of multidisciplinary to contribute valuable efforts for the design and development of robust, non-invasive and automatic recognition system for cattle [140]. All the artificial marking techniques for cattle identification can be duplicated easily.

Identification, monitoring, and tracking of cattle's physiological and behavior characteristics can supplement the better utilization of cattle recognition systems. Therefore, the need for a robust cattle identification scheme has become desirable [9] [57] [95].

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, tracking cattle, from 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, a cattle recognition system is proposed for identification of cattle based on the face image of cattle (shown in FIGURE (3.4)). A cattle recognition system is a pattern recognition based system. The recognition system captures the face images of cattle using the camera. The face image of cattle has been considered as a primary animal biometric characteristics for identification of individual cattle because the face images of cows have rich skin texture information and distinct facial features. The primary property of facial feature includes universality, distinctness and permanence [166]. The salient sets of facial features (*e.g.*, pixel value intensity) can identify the cattle faces. Therefore, the proposed approach provides an affordable, non-invasive, efficient, cost efficient and robust system for the cattle based on the face image of cattle.

The cattle recognition system can also play the important role for the registration and traceability of livestock. It is also necessary for breeding, production, and distribution of the beef cattle [140]. The proposed approach based on face recognition of cattle can also provide the improvement in the traditional identification methodologies and livestock framework based systems. Thus, addressing the current challenges facing animal biometrics-based cattle recognition system would eliminate several major problems inherent in the standard animal identification methods and electronic sensor-based RFID identification technology.

For recognition of individual cattle, the face image database of cattle has been prepared for training and testing of the proposed cattle recognition system. The preparation and description of cattle face image database are given in the next subsection.

FIGURE 3.1: Some face images of cattle from database.

3.2 Database Preparation and Description

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 Dairy, Institute of Agricultural Sciences (I.A.S), Banaras Hindu University (B.H.U), Varanasi, India. The preparation of cattle database has taken more than seven months with preparation of an adequate number of face image database of cattle for validating the proposed cattle recognition system using training and testing phases.

The preparation of face image database is considered in two different sessions. The size of the cattle face image database is 5000 (*e.g.*, 500 subjects $\times$ 10 face images per subject). The sample face images of cattle are shown in FIGURE (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).

TABLE 3.1: Details of face image of cattle database

Breeds(Races)	no. of subjects (cattle)	no.of images
Balinese cow	150	1500
Hybrid Ongole cow	150	1500
Holstein Friesian cow	100	1000
Cross breed cow	100	1000

Face recognition is a well studied problem in the field of computer vision, and many challenges have been well-known by the researchers incorporated pose, expression, illumination, aging, and disguise [23] [202]. The challenges of low illumination, 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 [9]. The covariates of cattle face images are captured during face database acquisition from the uncontrolled light of indoor and outdoor environment.

In the data acquisition, many problems were due to the non-cooperative behavior of cattle and the unconstrained environment. Moreover, quality of captured face images 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 face image of cattle have captured due to low illumination and increases the 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 [23]. FIGURE (3.2) illustrates the intra-class and inter-class variability between face images of cattle from different subjects. The covariates of face images are produced by pose variations due to head movement and body dynamics of cattle, low illumination, poor quality and image blurriness in the unconstrained environment [166]. It significantly affects the appearances of face images of cattle and their representations in the feature space.

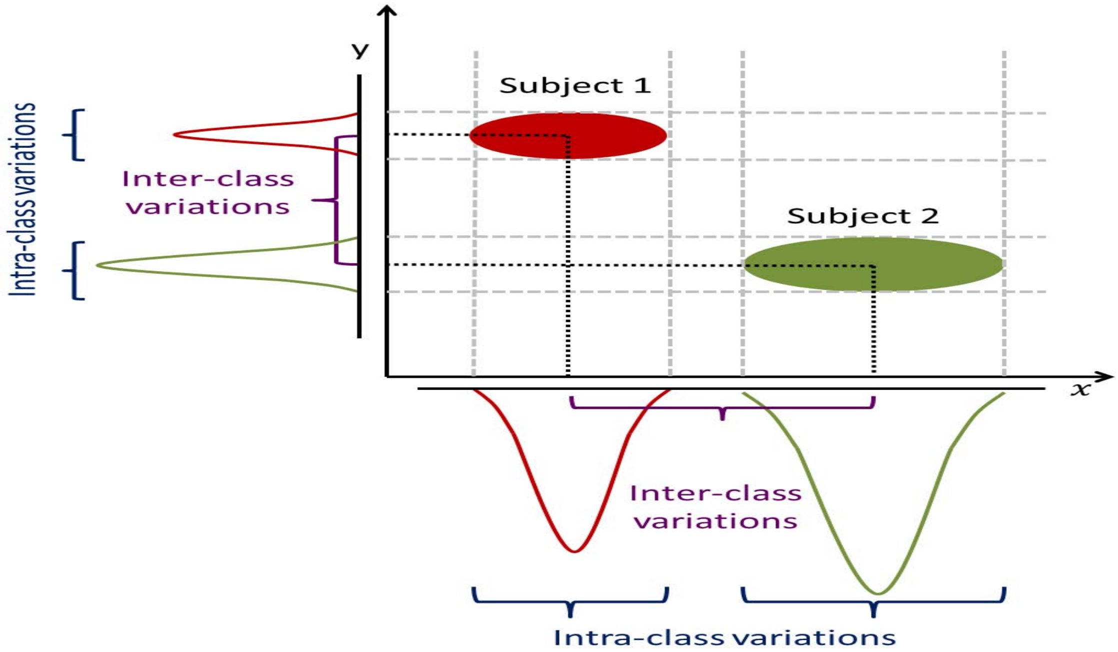


FIGURE 3.2: Illustrating the inter-class and intra-class variations.

FIGURE 3.3: Some challenging face images of cattle from the database.

Currently, the extensive researches have been devoted to developed algorithms that can efficiently address these covariates for the accurate recognition of individual. 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 [167].

The covariates of illumination, blurriness and pose of face image due to body dynamics of cattle are shown in FIGURE (3.3). Moreover, there are challenges in the acquisition and preparation of a cattle's face database, 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 variation. It took about 25 to 30 minutes 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 does 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 non-cooperative with identification. It is a big challenge to capture the images of frontal face for cattle with pose and illumination problems [166].

3.3 Proposed Cattle Recognition System (CRS)

This chapter explores the effectiveness of a novel computer vision and pattern recognition framework based cattle recognition system for identification of individual cattle. The proposed recognition system is a pattern recognition based system. The cattle recognition system consists of several steps. The steps involved in the proposed cattle recognition system are illustrated with several modules. The modules of recognition system are namely- (1) sensor module (data acquisition phase), (2) pre-processing and enhancement of face images, (3) feature extraction module, (4) similarity matching module, (4) decision module based on matching scores of 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 FIGURE (3.4). The pseudo code for recognition of cattle based on face image of cattle is illustrated in Algorithm 1.

The main objective of proposed approach is used to validate the prepared face image database of cattle by applying the computer vision techniques such as, handcrafted texture feature-based descriptor techniques and appearance based feature extraction and representation techniques for recognition of individual cattle.

Algorithm 1 illustrates the number of steps for recognition of individual cattle based on their face images. It depicts the representation of face image for cattle in the feature space after extraction of the facial features of cattle database. It also measures the mean and variance of cattle face image database for the computation of the discriminatory set of facial features based on Eigen face of individual cattle images using the co-variance matrix.

Keeping components and generating a feature vector: Once Eigenvectors of face image are estimated from the measured covariance matrix. After that, it is to order them by selecting the eigenvalue, highest to lowest. This procedure gives the discriminant components in order of significance. The eigenvector with the largest eigenvalue is known as the principle component of the face image database. The feature vectors are generated from the highest eigenvalue of cattle face image.

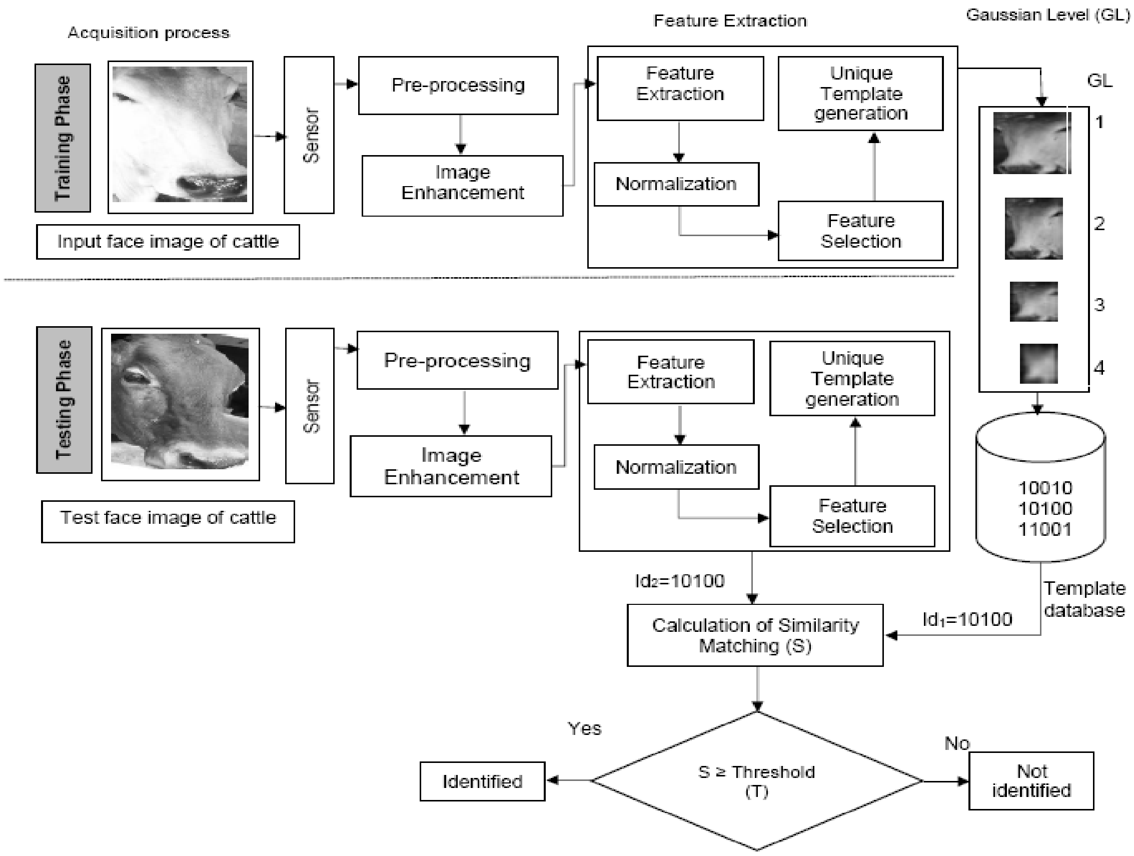


FIGURE 3.4: Illustrates the proposed block diagram of cattle recognition.

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 Eigen vectors indicates that there are a face image and display the face image of cattle.

Algorithm 1 Recognition algorithm for cattle face

procedure FACE RECOGNITION((F_1), (F_2))

Initialization: input face images [X] = $(X_1, X_2, \ldots X_N)$ with m$\times$ n (where m and n = 200 pixel).

Pre-processing and Enhancement: input face images are pre-processed and quality of images are improved by (CLAHE) image processing based enhancement technique.

Feature extraction: Feature are extracted from the pre-processed face image of cattle database.

Compute the mean: The mean (μ) of extracted feature of cattle face image database is computed as follows (shown in Equations (3.1),(3.2)):

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

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

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

Compute the Eigenvalues λ_i and the Eigen-vectors of S:

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

Where, Equation (3.3) provides the solution V that contains the most discriminant projection directions.

Principal components are the Eigen-vectors corresponding to the largest Eigen-values.

The K–principal components of the observed vector are then given by (shown in Equation (3.4)):

$$Y = W^T(X-\mu) \;\; where \;\; W = (W_1, W_2, \ldots, W_N) \tag{3.4}$$

The reconstruction from the PCA basis feature is given by (shown in Equation (3.5))::

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

Eigenvalue decomposition: decomposition of Eigen value is given as follows(shown in Equation (3.6))::

$$S = XX^T \;\; and \;\; X^T XV_i = \lambda_i V_i \tag{3.6}$$

Obtained original Eigen-vectors: The original Eigen-face is computed (shown in Equation (3.7))

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

Return original face image of cattle

3.3.1 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 store 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 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.

3.3.2 Preprocessing and Enhancement

The face images of cattle are captured on unconstrained environment. The face images can be defective, poor quality, contrast, and blurred. The proposed cattle recognition system performs the pre-processing to mitigate and filter the noise and specific artifacts from the captured face images of cattle using Gaussian pyramid based low pass filtering technique [1] and increases the image quality of cattle's faces [28]. The Contrast Limited Adaptive Histogram Equalization (CLAHE) image processing based enhancement technique is applied to enhance the contrast of the face images of cattle [206].

The primary objective of the pre-processing 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 (FIGURE (3.3)). 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 [206] is applied for enhancement of face images of cattle database.

3.3.3 Feature Extraction and Matching

Feature extraction is an essential step in the pre-processing phase. 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) feature extraction and representation techniques are namely: Principal Component Analysis (PCA) [21] [179], Linear Discriminant Analysis (LDA) [60] [172], Independent Component Analysis (ICA) [18] [110] [117], and modified version of appearance based face recognition algorithms (*e.g.*, Batch-Candid Co-variance-free Incremental PCA (CCIPCA) [194], Independent-Candid Co-variance-free Incremental PCA (IND-CCIPCA) [179] [194], Incremental-Linear Discriminant Analysis (ILDA) [102] for the recognition of cattle's face. In this chapter, Support Vector Machine library package (LiBSVM) [35] [72], and Incremental-Support Vector Machine (I-SVM) [50] [143] are adopted to classifying the sets of facial features of cattle database with techniques (*e.g.*, PCA-LiBSVM [21] [179] [35], LDA-LiBSVM [60] [35], ICA-LiBSVM [18] [35], Incremental-SVM [50] and Incremental-Local Discriminant Analysis-SVM (ILDA-SVM) [60] [172]).

The primary motivation to apply the classifier models using Incremental Support Vector Machine (I-SVM) [143] is that 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 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 [35].

The appearance-based (holistic) face recognition approaches have been applied to cater better identification accuracy due to rich, dense skin texture (information) and facial features [179]. Moreover, face images of classes in the cattle database are affected from the two major covariates, such as poor illumination and pose due to body dynamics and head movement during data acquisition (shown in FIGURE (3.3)).

The covariates of face images provide some problems in the feature extraction and representation by applying the local feature extraction techniques. Therefore, texture feature based descriptor techniques can be 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 algorithms utilize images for feature extraction and matching process [23]. To achieve higher resilience towards covariates, such as illumination, image quality and blurriness. To mitigate the covariates problems and smoothing of extraction of discriminant features from the face image of cattle database, Gaussian pyramid smoothing technique [1] [28], and a low pass filter technique has been applied to reduce the noise from the face image database at four levels for recognition of cattle.

3.4 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 proposed framework were performed on Intel (R) Core 2 Duo and 1.7 GHz computer with 20 GB of RAM (memory). The AdaBoost based face detection technique [189] is applied to detect the face image of cattle.

“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 Dairy 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.

3.4.1 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, (ii) testing (probe) part. This database was selected for validation of proposed framework for recognition of cattle and contain 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 $\times$ 6 face images from a total of 500 subjects (cattle) $\times$ 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 approaches (appearance face recognition algorithms): Principal Component Analysis (PCA) [21] [179],Linear Discriminant Analysis (LDA) [60] [172], Independent Component Analysis (ICA) [18], and their modified version of appearance based face recognition algorithms (*e.g.*, Batch-Candid Co-variance-free Incremental PCA (CCIPCA) [194], Independent-Candid Co-variance-free Incremental PCA (IND-CCIPCA) [179] [194], Incremental-Linear Discriminant Analysis (ILDA) [102] for the recognition of cattle's face.

In this chapter, the Support Vector Machine library package (LiBSVM) [35] [72] and Incremental-Support Vector Machine (I-SVM) [50] [143] are adopted to classifying the sets of facial features of cattle database with techniques (*e.g.*, PCA-LiBSVM [21][35] [179] , LDA-LiBSVM [60] [35], ICA-LiBSVM [18] [35] Incremental-SVM [50] and Incremental-Local Discriminant Analysis-SVM (ILDA-SVM) [60] [172]) using customized version of available source code [20].

The appearance based face recognition and representation algorithms have been applied for comparison the experimental results. The brief descriptions of holistic face recognition and representation techniques are illustrated in next subsection:

3.4.1.1 Principal Component Analysis

Face recognition is the well-studied problem in the field of computer vision. Some face recognition algorithms apply representations of face images found by unsupervised learning based statistical methods[21]. Learning methods find a set of basis images and represent the image as a linear combination of those images. Principal Component Analysis (PCA) [179] is a popular feature extraction representation approach for recognition of the individual face.

The basis images found by PCA depends only on pairwise relationships between pixels in the image database. The PCA technique computes Eigen values from the Eigenface of cattle images using unsupervised statistical-based method to find the minimum mean squared error in the linear subspace that maps from the original (N) dimensional data space into a M-dimensional feature space.

By this procedure, Eigen-faces $(M << N)$ obtains dimensionality reduction by using the (M) Eigenvectors of the covariance matrix corresponding to the largest eigenvalues. The resulting basis vectors are achieved by finding the optimal basis vectors that maximize the total variance of the projected data (*e.g.*, set of basis vectors that best describe the data) [179].

Consider a set of (N) basis face images of cattle each of which has (N) pixels. A standard basis sets consists of a single active pixel with intensity 1, where each basis face image has different active pixel values. Any given face image of cattle with (N) pixels decomposed as a linear combination of the standard basis images. In fact, the pixel values of a face image can then be seen as the coordinates of that image on the standard basis. The primary objective to apply the PCA unsupervised learning technique is to find a *better* set of basis face images of cattle so that in this new basis, the image coordinates (the PCA coefficients) are uncorrelated, (*i.e.*, they cannot be linearly predicted from each other). The mean value cattle face image is computed using PCA face recognition and representation technique for recognition of individual cattle shown in FIGURE (3.5). The brief description of recognition algorithm is shown in Algorithm 1. The computation of Eigenvectors of cattle face images and reconstruction of original face images of animals using PCA technique is shown in FIGURE (3.6).

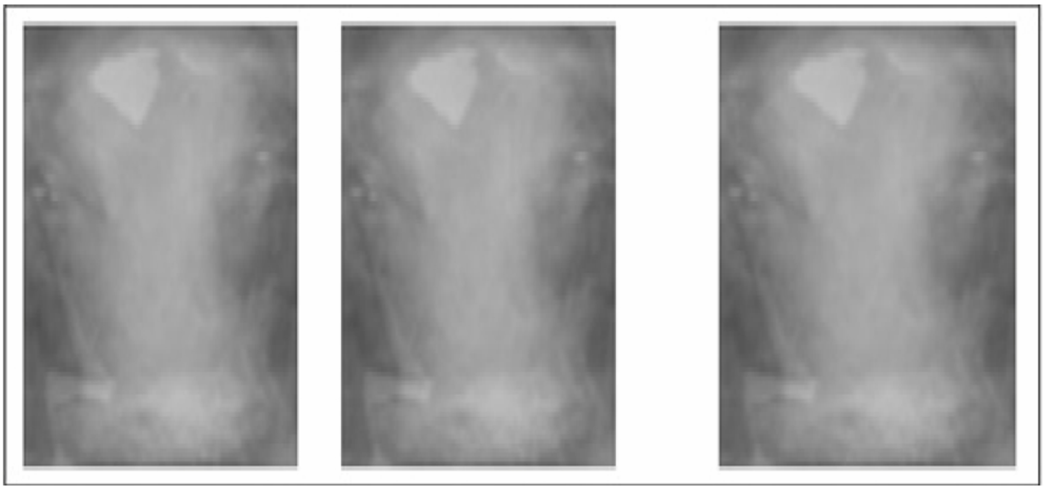
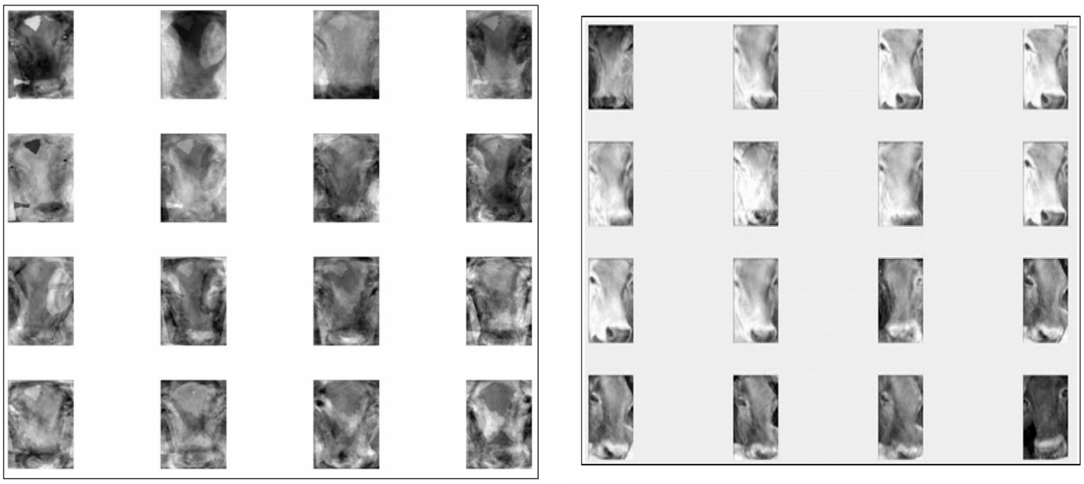


FIGURE 3.5: Illustrates the computation of mean of face images of cattle.



(a) (b)

FIGURE 3.6: Illustrates the computation Eigenfaces of face of cattle on (a) and (b) and reconstruction of original face images using Eigenvectors.

3.4.1.2 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) [60] is a supervised learning approach for face recognition. It finds the feature vectors of face images in the underlying space through linear projection techniques that the best discrimination of face images among all the classes of cattle faces.

The cattle face image database is divided into inter-class scatter matrix (S_B) and the intra-class scatter matrix (S_W). The motivation to apply the LDA classification approach is to maximize the ratio of (S_B) and (S_W) scatter matrices (*e.g.*, maximize (S_B) while minimizing (S_W)), in other words, maximize the ratio $\frac{S_B}{S_W}$. The ratio is known as Fisher discriminant ratio. Linear Discriminant Analysis maximized when the column vectors of the projection matrix are the Eigen-vectors of $(S_W{}^{-1} S_B)$.

LDA supervised learning technique is applied to learn the set of feature vectors for discriminating the different classes of cattle based on learning feature of facial image database of cattle [60]. Therefore, LDA learning algorithm is more efficient for the recognition and classification of face images compared to the PCA unsupervised learning algorithm. LDA learning algorithm applied the Fisher discrimination criterion based strategy to maximize the ratio of the determinant of between-class (S_B) and within-class (S_W). The (S_B) and (S_W) are defined as follows (shown in Equations (3.8-3.11)):

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

$$S_W = \sum_{i=1}^{c} \sum_{x_j \in X_i} (n_i(m_i - m) \times (m_i - m))^T \tag{3.9}$$

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 the (Equation (3.10)) as follows:

$$Fisher_{(W_{OPT})} = argmax_w \frac{W^T S_B W}{W^T S_W W} \tag{3.10}$$

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

In the above Equation (3.11), (μ) and (c) are defined as mean value of face image database and the number of classes of face images database of cattle. The primary aim to apply the LDA classification technique is to build the feature subspace that discriminates the various classes of face images of cattle using Fisher discriminant ratio [60]. In Equation (3.10), Fisher discrimination criterion is evaluated to maximize the ratio of the determinant of between-class (S_B), and within-class (S_W) of face image database of cattle. The computation and reconstruction of Fisher face value for each subject (cattle) and best three matches of face images of cattle are shown in FIGURE (3.8), FIGURE (3.9), and FIGURE (3.10), respectively.

In order to minimize the misclassification error, Fisher Linear Discriminant Analysis (FLAD) technique is applied to maximize the weight matrix (w) of face feature of cattle to achieve maximum class-separation in the feature space. The term $Fisher_{(W_{OPT})}$ denotes the maximum separation between-class (S_B) and within-class (S_W) of face image database of cattle. 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 FIGURE(3.13). Fisher discriminant technique has been applied to compute the projection 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 $Fisher_{(W_{OPT})}$ (shown in Equation (3.10)).

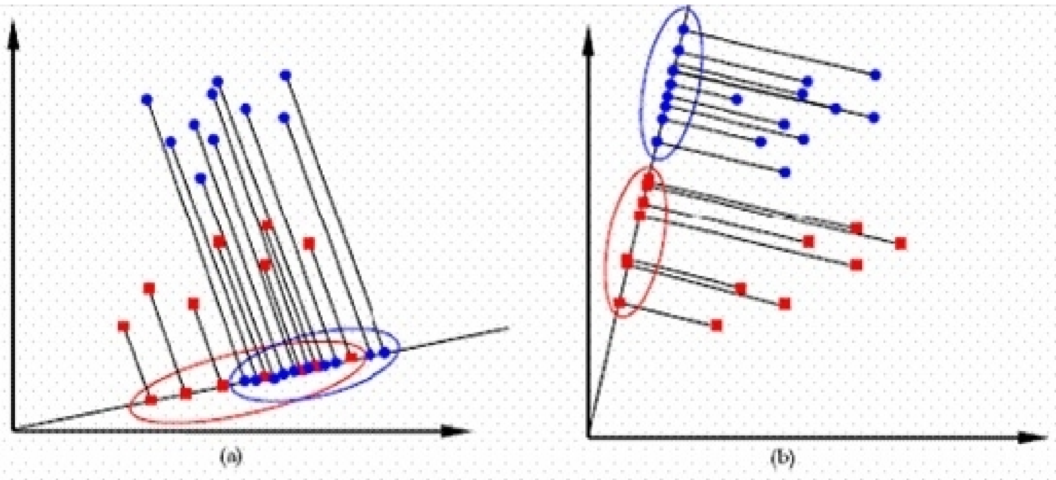


FIGURE 3.7: Illustrates (a) overlapping of features (pixel intensity values) of between-class (red dotted point) (S_B) and within-class (S_W)(blue dotted points) of face image database, (b) depicts the maximum separation between-class (S_B) and within-class (S_W) of face image using Fisher-LDA technique.

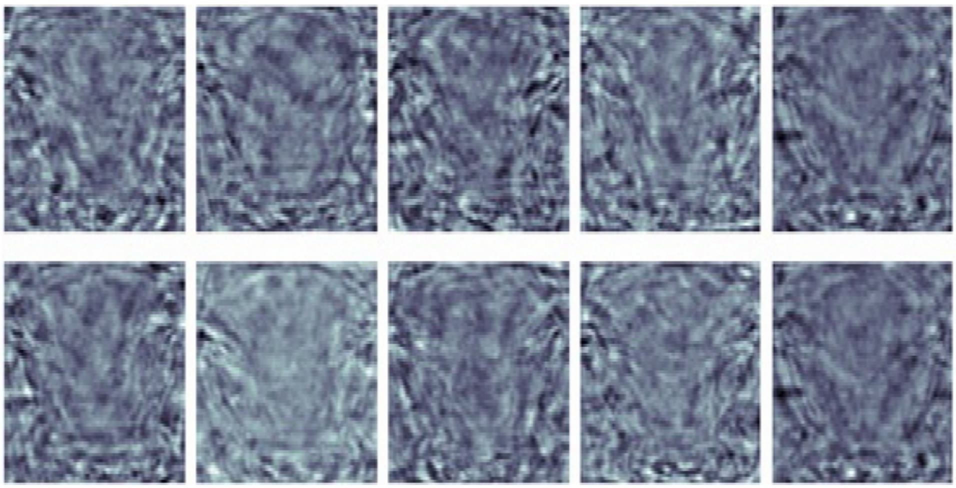


FIGURE 3.8: Illustrates the computation of Fisher values of cattle face images from database.

3.4.1.3 Independent Component Analysis

Independent Component Analysis (ICA) [18] is a generalized learning technique of PCA [179]. It minimizes both second-order and higher-order dependencies in the input features

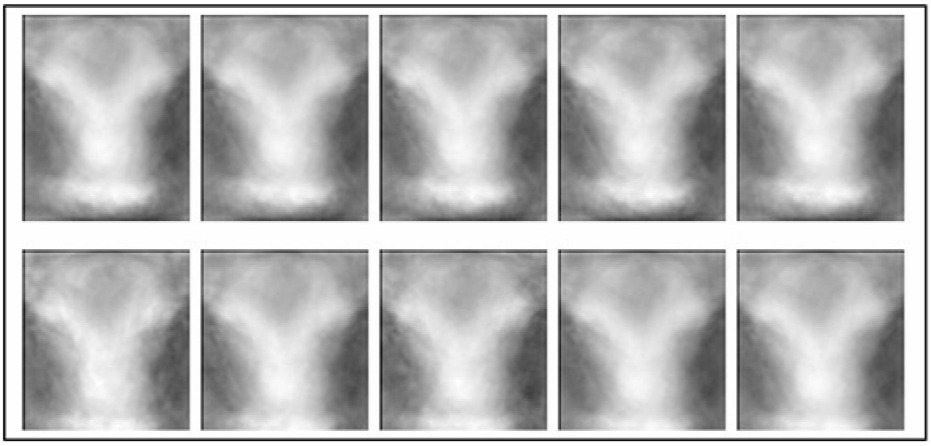


FIGURE 3.9: Reconstruction of Fisher face of cattle face images using LDA supervised learning technique.

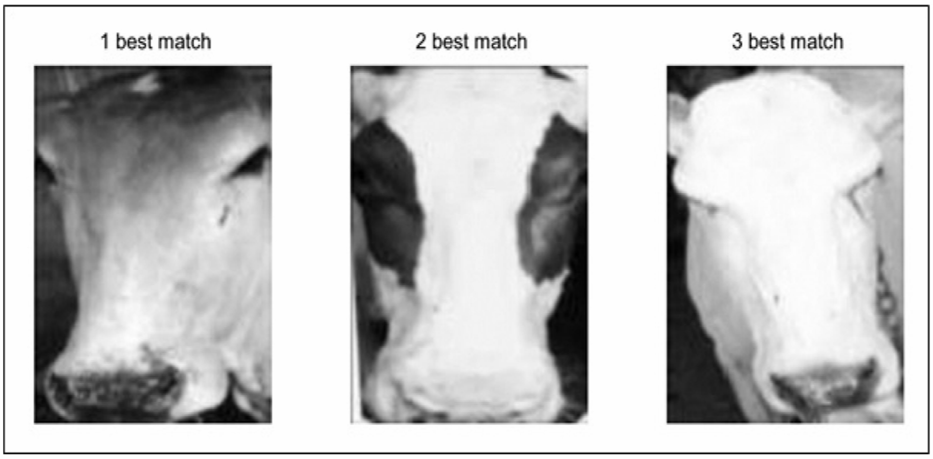


FIGURE 3.10: Illustrates the matching of best three matches of individual subject(cattle) face image by using LDA supervised learning algorithm after the reconstruction of Fisher face value of cattle face images from database.

and attempts to find the basis along which the features (data) (when projected onto them) are statistically independent [18] [110]. Independent Component Analysis (ICA) [18] is a generalized learning technique of PCA [179]. It minimizes both second-order and higher-order dependencies in the input features and attempts to find the basis along which the features (data) (when projected onto them) are statistically independent [18] [110].

3.4.1.4 Candid Covariance Free-Incremental-PCA

Candid Co-variance free Incremental PCA (CCIPCA) [194] is appearance based image analysis and representation technique. It computes the principal components (Eigen-vectors) of the face image of cattle incrementally without estimation of the covariance matrix of the facial feature of cattle. Therefore, CCIPCA learning technique is called co-variance-free-Incremental-PCA [179]. It is motivated by the concept of statistical efficiency with the smallest variance given the observed data [194].

3.4.1.5 Incremental-Linear Discriminant Analysis

Incremental-Linear Discriminant Analysis (I-LDA) is an incremental learning technique. It is supervised learning approach for recognition and classification of objects [21].

LDA technique computes the set of feature Fisher discriminatory criterion to maximize the ratio of the inter-class scatter matrix, and the total scatters matrix of face image database of cattle [60].

The incremental-LDA technique is applied to extract the discriminating features of face images of cattle during training and testing phase of the proposed cattle recognition based framework. The Incremental-LDA technique computes the principal components of the face image database. It updates the computed scatter matrices of the face image of cattle. The discriminant components of feature vectors are efficiently determined from the updated feature model of face images based on variance criterion of principal facial components. Therefore, Incremental-LDA technique is accurate as well as efficient in both time and memory. The benefit of the proposed approach over other LDA method is that the proposed approach lies in its ability to handle large data sets with many classes [102] efficiently.

As Incremental-PCA technique incrementally updates the Eigenaces of muzzle point images of cattle, the weights for previously trained face images become invalid due to the Eigenspace in which they reside has been changed. Consequently, the previously trained face images must be kept and reprojected into the updated Eigenspace. Therefore, Incremental-PCA learning-based algorithm requires far less memory to update the Eigen values and is often faster with a slight degradation in accuracy for cattle identification.

Similar to Incremental-PCA [179], the essence of Incremental linear discriminant analysis is incremental-based learning technique for updating the Fisher discriminant values (Eigen-decomposition) into the between-class and within- classes of cattle face images. Therefore, identification accuracy of Incremental-LDA method yields lower than the Incremental- LDA-LiBSVM classification technique. It is in terms of the more incremental updating of the between-class (S_B) and within-class (S_W) scatter matrices of face images of cattle.

3.4.2 Experimental Protocol and Analysis

In this subsection, experimental protocol and experimental analysis are given in detail. The performance evaluation of proposed framework based cattle recognition system is evaluated to identify the individual cattle based on their face image database.

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 $20,00 = 500 \times 4$ images) and the remaining $30,00 = 500 \times 6$ images were used as probe/testing the proposed cattle recognition system. The training and testing partitioning of the given database were performed by using 5-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. The identification accuracies of cattle identification are reported and summarized in the given Table 3.2, Table 3.3, and Table 3.4, respectively. Table 3.2, Table 3.3, and Table 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.

All the experimental results are presented in the form of Cumulative Match Characteristic (CMC) [24] 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 showed in FIGURE (3.11), FIGURE (3.12), and FIGURE (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 is 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 [20]. 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 (ICA) recognition method [110] 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 facial images compared to PCA [179] and LDA techniques [18].

The performance of PCA [179], LDA [60] and ICA [21] algorithms, amplified by increasing the level of Gaussian smoothing levels are shown in FIGURE (3.11). Figure 3.12 demonstrates CMC curve for identification accuracy of cattle face based on Table 3.2. It illustrates that the Incremental–Support Vector Machine (I-SVM) [172] algorithm yields identification accuracy of 95.87% with respect to others. Identification accuracy of Independent Candid Covariance Incremental PCA (IND-CCIPCA)[60] increases slowly with increasing each smoothed level of Gaussian Pyramid due to the number of chosen Eigen faces decreases at each level.

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

GL	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

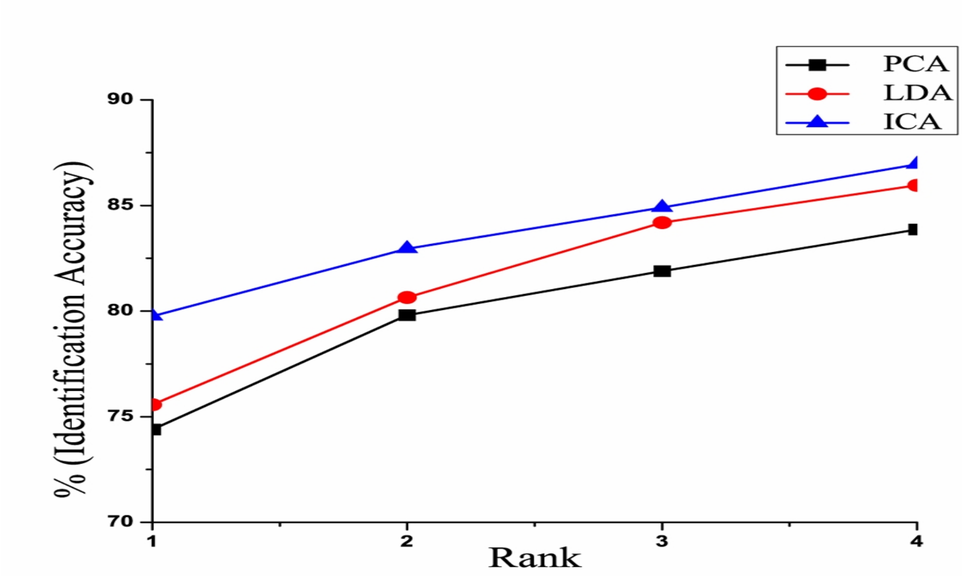


FIGURE 3.11: Illustrates the identification accuracy (%) of PCA, LDA and ICA techniques for recognition of cattle.

TABLE 3.3: Identification accuracy (%) of face images of cattle based on Batch-CCIPCA, ICA, Ind-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA and PCA-LiBSVM

GL	Batch-CC	ICA	Ind-C	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

Where GL = Gaussian Level, Batch-CC = Batch-Candid Co-variance free Incremental PCA (CCIPCA), PCA-L = PCA-LiBSVM, Ind-C = Independent-CCIPCA

The CMC curve of recognition accuracy of PCA [179], LDA [18] [21] and ICA [110] face recognition algorithms for cattle is shown in FIGURE (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 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%) than LDA recognition approach (92.87 %) 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% the recognition 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.

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 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 Co-variance free Incremental PCA (Ind-CCIPCA) technique provides 52.25% (shown in FIGURE (3.12)).

TABLE 3.4: Identification accuracy (%) of face images of cattle using Batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms

GL	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

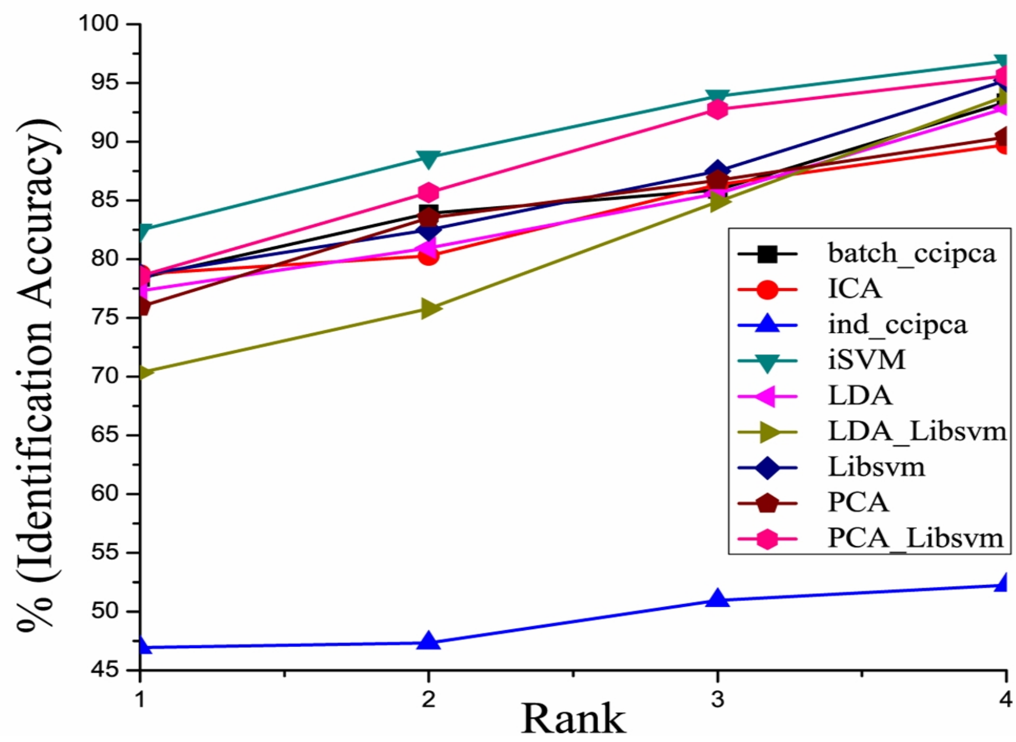


FIGURE 3.12: Illustrates the CMC to show recognition accuracy of cattle face image based on Table3.3

Table 3.4 illustrates the identification accuracy of cattle recognition based on face images using the Batch-Incremental Linear Discriminant Analysis (Batch-ILDA), Candid Co-variance 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. In the given Table 3.4, 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, therefore, 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-LiSVM 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-LiSVM (94.44%). It is also shown that the ILDA-LiBSVM method achieves more identification accuracy than PCA and ICA technique.

The Candid Co-variance 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. 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 FIGURE (3.13)).

PCA learning method separates pairwise linear dependencies between the pixel value of cattle face images. The objective to apply PCA technique is to perform the computation of covariance matrix of the pixel intensity values of cattle face image database. Therefore, representations of extracted discriminatory features of cattle face images [21]. 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 [18]. 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 PCA technique [179] has been applied to generate new dimensions (*e.g.*, Eigen-vectors) 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.

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 technique [179] given recognition accuracy of 83.86% for face recognition of individual cattle. PCA-LiBSVM technique [35] [179] 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 Eigen-face values of the cattle face images. Similarly, the LDA-LiBSVM [35] [18] classification technique has provided the relatively better recognition rate of 93.91% which is higher than LDA face recognition technique [18] at each smoothed levels of Gaussian pyramid of cattle face database.

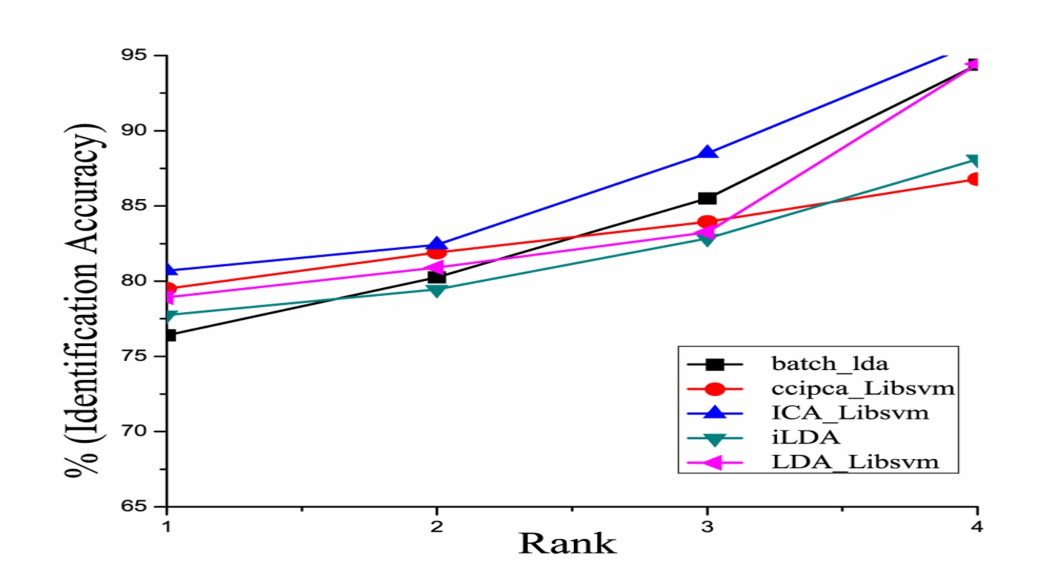


FIGURE 3.13: CMC to show identification accuracy of Batch–LDA, CCIPCA-LiBSVM, ICA-LiBSVM, I-LDA and LDA-LiBSVM for cattle face (based on Table 3.4).

The CMC curve for recognition accuracy of ICA-LiBSVM [110] technique is shown in FIGURE (3.13) It yields recognition accuracy of 95.87% on the starting smooth level of Gaussian pyramid on the accuracy of other recognition and representation algorithms. After the first level, the performance of recognition and representation algorithms decreases due to the selection of a minimum number of facial features of cattle.

The recognition accuracy of LDA-LiBSVM [18] [35] method is higher than Batch-LDA, CCIPCA-LiBSVM [194] Incremental-LDA [194] and PCA-LiBSVM techniques [35] [179] because LDA-LiBSVM technique predicts the sets of feature of the same class of cattle face image which are close to each other. It minimizes intra-class variance and maximizes inter-class variance within/ between gray scales assigned to black and white pixel classes.

3.5 Summary

In this chapter, 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 face image of cattle. Therefore, the proposed approach provides an affordable, non-invasive, efficient cattle recognition system for the for 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".

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) [110] algorithm provided the recognition accuracy of 86.95% at the starting smoothed level of Gaussian pyramid of cattle face image database. The PCA-LiBSVM [35] [179] and ICA-LiBSVM [18] [35] 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 $\times$ 10 image of each subject) illustrates that face recognition for cattle is feasible.

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 an important insight in the identification of cattle based on their facial images [30] [109] [166].

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 non-invasive way if the performances of automatic best matching algorithms are satisfactory.