Chapter 4

Automatic Identification of Cattle based on Muzzle Point Pattern

This chapter explores the effectiveness of the proposed novel hybrid texture feature extraction approach that resulted from extracting the texture features of muzzle point image pattern of cattle for identification of individual cattle.

Cattle identification is an important problem for association of breeds, registration of cattle, traceability, health management of animals, and verification of false insurance claim of cattle throughout the world. To solve these major problems, the muzzle point image of cattle is taken as a biometric identifier for identification of cattle. In this chapter, a hybrid texture feature extraction method is proposed. The proposed approach extracts the prominent texture features of the muzzle point image pattern to identify and classify the individual cattle to solve problems of cattle identification using a low cost camera.

4.1 Introduction

The development of effective animal recognition-based systems for tracking of animals, rare and endangered species needs unbiased and accurate information on their life history and study population ecology [68] [69].

Available identification methodologies of Capture-Mark-Recapture (CMR) are applied to identify species or individual animal. However, these approaches are not suitable to give accurate performance. Therefore, it attracts the multidisciplinary researchers, scientists, engineers, ecologists, and biologists to perform in depth study for designing and development of animal biometrics-based recognition systems. The recognition systems are applied for tracking, monitoring, management of individual animal over time to answer the questions related to individual growth, survival, dispersal and reproductive strategies of animals [40] [156].

Animal biometrics is an emerging research field for representation and detection of phenotype appearances and visual features of species or individual animal. It has a wide range of applications, including identification, classifying species, tracking animal from birth to the end of the food chain, and understanding animal critical disease trajectories and population patterns.

The classical animal identification techniques, such as marking the animal's body, using permanent identification which are used to identify the animals. The permanent identification techniques mainly include ear-tagging based marking scheme, embedding of microchips, freeze-branding, ear-tipping and notching based marking techniques for identification of individual animal or species. For example, Capture-Mark-Recapture (CMR) is one of the permanent animal identification technique, where animals are physically marked or tagged with artificial marking schemes [198].

Efficient identification of individual cattle based on artificial marking technique, embedding microchips or ear-tags have been an essential operation for Radio Frequency Identification (RFID) systems. However, collecting all embedded tags in a large-scale system through a handheld RFID reader, is a big challenge to perform for accurate identification of cattle. These marking techniques need better management and practical implementation during reading or scanning of embedded tags or microchips in the body of individual animal [7]. These approaches are known to be at least obtrusive for efficient and accurate identification of individual animal with the large number of false matching values [199]. The computer vision, pattern recognition, animal biometrics-based recognition systems and efficient techniques are used to overcome these major limitations in the field of cattle recognition.

Computer vision and animal biometrics are the emerging research field for identification of individual cattle in the livestock monitoring [9] [166]. The animal biometrics has provided a better platform for design and development of quantified methodologies for recognition, representation, and detection of visual appearances of different species. It also identifies the species based on its behavioral characteristics, morphological image patterns, and biometric characteristics [99].

For example, SLOOP [53] is an animal biometrics-based recognition system for recognizing the different species or individual, based on their visual features, phenotype appearances and morphological image patterns [99].

Other examples, iconic coat patterns (joint stripe markers on zebra coat pattern) [111], spot point pattering on cheetahs or tiger [170], the facial image of animals [59] and muzzle point image pattern [9] of cattle are unique and immutable first animal biometric characteristics for recognition of individual animal [197].

The classical animal recognition approaches are intrusive for varying degrees of species and inefficient for implementing the enormous population of animals. Thus, there is a need to explore the alternative approach for cattle recognition that mitigates the major challenging problems for monitoring and tracking of animals across the world. It also provides efficient solutions to traditional animal recognition based systems and classical livestock framework based systems. Therefore, animal biometrics offer a new paradigm to design and develop a non-invasive, cost-effective, robust and automatic recognition system for the identification, and verification of individual animal using their unique and immutable primary biometric characteristics.

Currently, deploying animal biometrics-based recognition systems into computerized systems faces major challenges with respect to identification accuracy and the system's robustness. According to the literature, it is found that animal movements cannot be easily controlled. Therefore, addressing the current challenges, facing biometrics-based cattle recognition systems, would eliminate several problems inherent to the classical cattle identification methods and RFID-based animal monitoring.

Baranova et al. [11] studied the dermatoglyphics about the granule, ridges, and vibrissae from the various cattle breeds. They have concluded that the muzzle point image pattern of livestock breeds has unique and discriminatory biometric characteristics. These biometric characteristics-based features are immutable for identification of individual cattle.

The biometric characteristics of the muzzle point image consist of two feature patterns include bead pattern and ridge pattern used for recognition of individual cattle [130]. These feature patterns are graphical feature pattern. The basic structure and arrangement of texture features are the non-uniform representation of the bead pattern. The structure formation of bead pattern is similar to island structure [131]. On the other hand, the ridge feature pattern contains a unique and immutable biometric pattern. The shape of ridge pattern is similar to rivers. The ridge pattern separates the bead patterns in the muzzle point images.

The bead and ridge pattern constituent the minutiae points by joining the ridge terminations and bifurcations in the muzzle point images. Thus, the recognition of muzzle point image of cattle is similar to recognition of minutiae points in the human fingerprint [140] [189]. The bead and ridges feature patterns play a significant role in recognition of individual cattle [10] [140]. Based on biometric characteristics of muzzle point image, cattle recognition system provides efficient, cost-effective, and suitable biometric identifiers for identification of missed or swapped animal. It is also helpful for verification of false insurance claims, tracking, and reallocation of cattle at the slaughterhouses. The proposed cattle recognition system also provides a way to control and outbreaks of critical diseases in the large population of livestock throughout the world [109].

The different organizations (*e.g.*, food safety and world animal health) have formally recognized the significant values of the development of animal identification and traceability systems. They further actively promoted for biometrics based recognition systems [9] [10]. Such animal biometrics-based recognition system provides (a) controlling the widespread of diseases by identifying and detecting infected animals, (b) reducing losses of livestock producers by controlling the diseases, and (c) decreasing the government cost by the control, intervention, and eradication of the outbreak [5] [125] [126].

To the best of our knowledge, muzzle point image pattern of cattle is suitable, and the most discriminatory primary biometric characteristics for the recognition of individual cattle [140] [130]. This chapter explores the effectiveness of muzzle point image feature for recognition of cattle. Further, a hybrid texture feature based extraction method is proposed to extract the texture feature of muzzle point image pattern for recognition and classification of individual cattle.

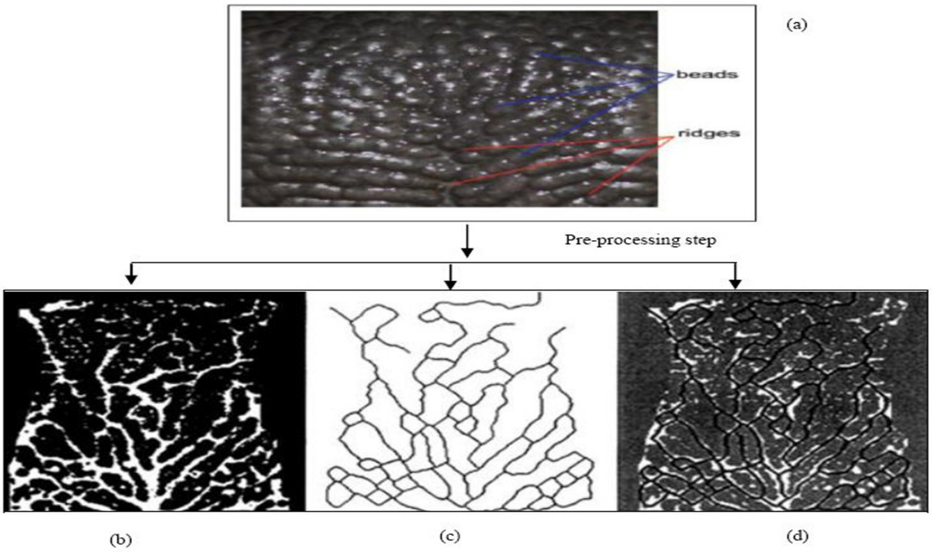


FIGURE 4.1: Illustrates the pre-processing of beads and ridges from the original muzzle point image: (a) input muzzle image, (b) blurred muzzle point image pattern, (c) perform the pre-processing steps to find out the beads, and ridge from the muzzle point images, and (d) shows the filtration process of overlapping region between beads, and ridges pattern.

4.2 Motivation

The motivation of proposed muzzle point recognition approach is to achieve higher resilience towards classical animal recognition based systems and livestock management systems. The proposed cattle recognition approach introduces recognition algorithm for identifying individual cattle, which is automatic and non-invasive approach for recognition and verification of individual cattle. Only a few researchers in cattle biometrics have been done and proven that muzzle point image pattern is the first biometric features for recognition of cattle.

In the available literature, the authors and researchers have done identification of individual cattle based on captured image of muzzle print of cattle [10]. The muzzle print images were captured manually on $A-5$ paper with blue ink. After the acquisition, captured images of muzzle print are required to be converted into 500 dot per inch (dpi) image resolutions to maintain the better image quality for processing and extraction of salient set of features of muzzle print images of cattle [140]. In current state-of-the-art methods, cattle are only recognized based on manually captured images of muzzle print of cattle [9]. The identification of cattle based on captured muzzle print image on $A-5$ paper reported more number of False Acceptance Rate (FAR) is high in cattle recognition.

This chapter explores the effectiveness of a novel cattle recognition system that is resulted from the extraction of discriminatory features (bead and ridges pattern) of muzzle point image pattern of cattle using hybrid texture feature extraction algorithms. The recognition system performs the automatic recognition and classification of individual cattle based on captured muzzle point images using the low-cost digital camera. The pre-processing of muzzle point image pattern, and extraction of the bead, and ridges as texture features shown in FIGURE (4.1), respectively.

•Research contributions:

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

- In this chapter, a hybrid texture feature extraction based approach is proposed for the recognition and classification of cattle based on their muzzle point image pattern as a primary animal biometric characteristics.
- In the proposed approach, the pre-processing and enhancement techniques are applied to enhance the low quality of muzzle point images by reducing the noise and other artifacts from the captured muzzle point image database using filtering process. Therefore, Contrast Limited Adaptive Histogram Equalization (CLAHE) [206] technique is utilized for the enhancement process of muzzle point images.

- The image segmentation algorithms are essential for partition the muzzle point images into required distinct regions of bead pattern, and ridges pattern. The muzzle point images consist of rich texture information (feature) and different color based discriminating texture features. After the pre-processing phase of muzzle point images, color K-means clustering, watershed segmentation and texture feature based segmentation techniques are examined and applied for the segmentation of muzzle point image pattern to segment the images into distinct Region of Interest (ROI) for extraction of texture features from the muzzle point image database of cattle.

- After segmentation of muzzle point images, the discriminatory features are extracted from the muzzle point images using texture feature extraction approaches. The texture feature extraction approaches are Haralick texture features technique, Morphology and shape based features, Histogram of Oriented Gradient (HOG), Wavelet feature, color -based Feature, Tamura feature, Law Texture Energy (LTE), Speeded Up Robust Features (SURF), Local Binary Pattern (LBP), and Fuzzy-LBP for muzzle point image pattern of cattle database for recognition and classification of cattle.

- The extracted texture feature are encoded into a corresponding feature vector through encoding process for the complete representation of the feature in the feature space. Finally, K-nearest neighborhood (K-NN) [144] [145], Fuzzy-K-NN [97], Radial Basis Probability Network (RBPNN) [92], Probabilistic Neural Network (PNN) [169], Decision Tree (DT) [160], Gaussian Mixture Model (GMM) [204], Multi-layer Perceptron (MLP) [157], and Naive Bayes based [96] classification models are applied to classify, and identify the individual cattle based on extracted muzzle point image features.

- A database of muzzle point image pattern of 500 cattle (subjects) is prepared with the 20-megapixel camera from the Department of Dairy, and Husbandry, Institute of

Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U.), Varanasi-India-221005. The size of the database is 5000 muzzle point image pattern (i.e., 500 subjects $\times$10 muzzle images of each cattle).

4.3 Material and Methods

This section deals with the details of database preparation and description of muzzle point image of cattle using digital camera and characteristics of captured muzzle point images. The captured muzzle point images are used as the input image in the proposed cattle recognition system for automatic recognition and classification of cattle. The detail of preparation and description of cattle database is given in the next subsection.

4.3.1 Database Preparation and Description

The database of muzzle point image was prepared using a 20-megapixel camera to capture the images from the Department of Animal Husbandry and Dairy, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U), Varanasi, India-221005.

The preparation of the muzzle image database of cattle has been done in two different sessions under different unconstrained environments. The size of muzzle point image database is 5000 (*e.g.*, 500 subjects $\times$ 10 images per subjects, and each image is 200 $\times$ 200 pixel). Some samples of muzzle point images from the cattle database are shown in FIGURE (4.2). Based on the observation of muzzle point image pattern from the 500 cattle breeds, no one of the pairs of image pattern has the similar pattern of muzzle image of cattle beads. Each muzzle point image pattern has unique ridges and bead pattern as distinguished biometrics features in the muzzle images [131]. The beads and ridges pattern of muzzle point image of cattle are shown in FIGURE (4.3), and FIGURE (4.4),

TABLE 4.1: Detail the muzzle point image pattern 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

FIGURE 4.2: Some muzzle point image patterns of cattle from database.

respectively. Table 4.1 illustrates the composition of the muzzle point images of cattle for the experiment in this chapter.

4.4 Proposed Approach

This section presents in detail the various steps of proposed hybrid texture feature extraction approach for cattle recognition with detail description of the individual step.

A cattle recognition based biometric system is essentially a pattern recognition system. It captures biometric data of an individual animal. The cattle recognition system extracts the salient set of biometric feature set from the data after pre-processing and segmentation of captured images. It performs the comparison between test (query) feature set against

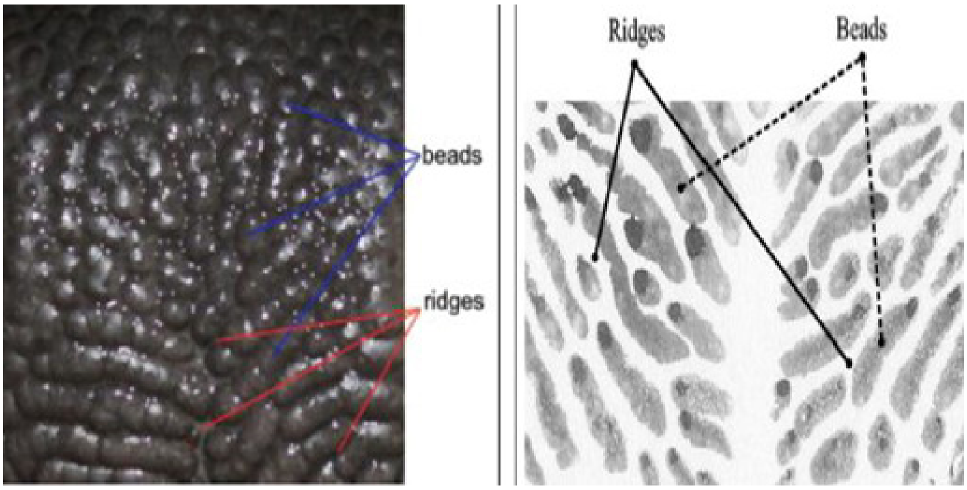
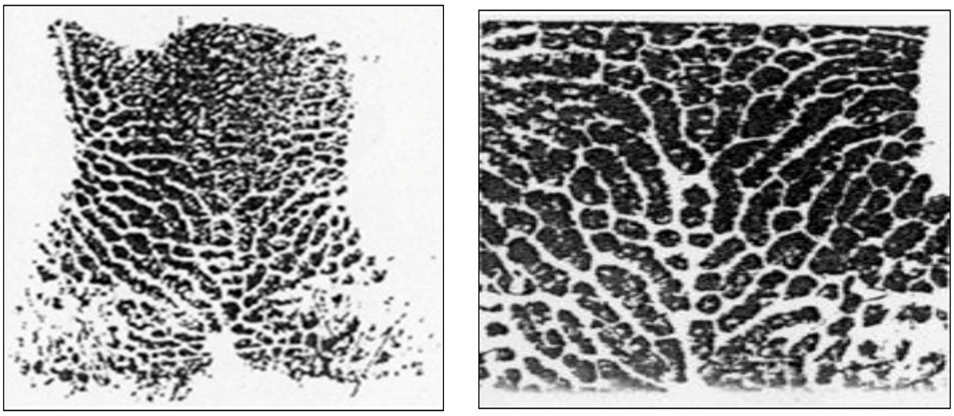


FIGURE 4.3: Beads and ridges of the muzzle point pattern of cattle from database.



(a) (b)

FIGURE 4.4: Illustrates the images of muzzle point patterns of cattle used in the calf registration (a) at the age of 2 months for advanced calf registration, (b) illustrates registration of cattle using muzzle images at the age of 14 months.

the feature set(s) stored in the database and executes an action based on the result of the comparison for recognition of animal. The cattle recognition system consists of four main modules. The modules of cattle recognition system are (1) pre-processing and enhancement of muzzle point images (2) segmentation of muzzle point images to find the region of interest (ROI), (3) feature extraction and quality assessment of extracted features using statistical analysis, and (4) finally classification, and recognition of cattle based on extracted texture features of muzzle point image pattern of cattle. The schematic description of each step for cattle identification and classification is shown in FIGURE (4.5).

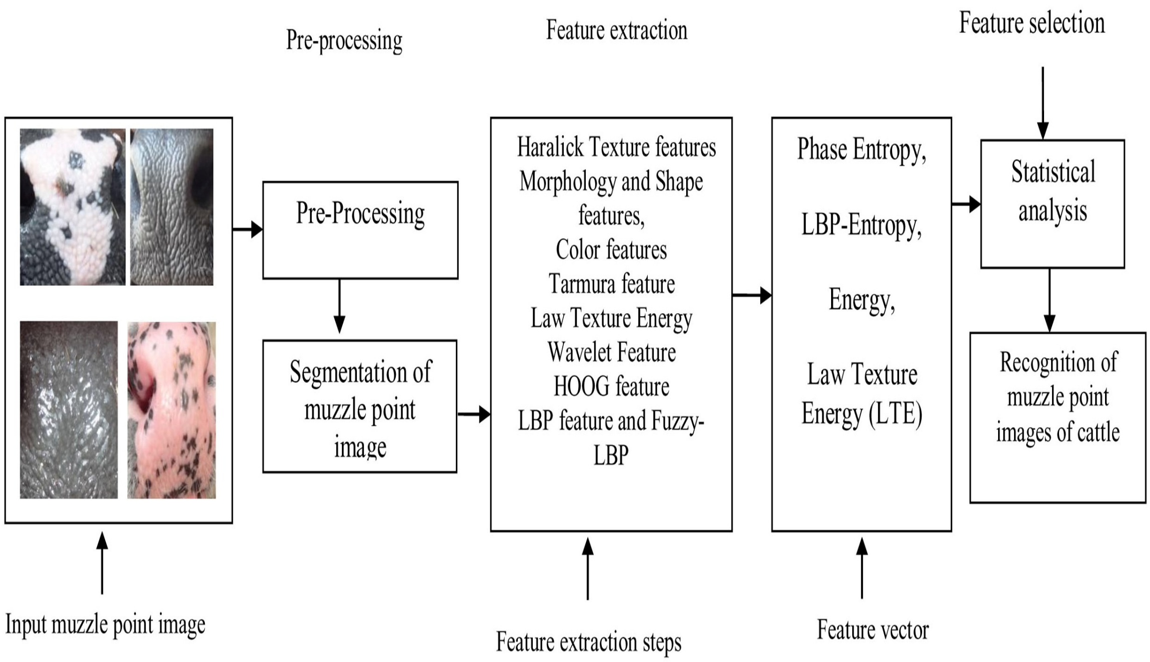


FIGURE 4.5: Block diagram of the proposed automatic recognition system of cattle based on muzzle point image pattern.

4.4.1 Pre-processing of Muzzle Point Image

The pre-processing is a mandatory step for feature extraction and matching process for recognition of objects. The objective of the pre-processing step is to mitigate the noise, and other artifacts, such as gray scaling, and cropping of muzzle point images. The pre-processing of muzzle point image pattern, and extraction of beads, and ridges as texture features shown in FIGURE (4.1), respectively.

On the other hand, the primary objective of the enhancement algorithms is to improve the quality of captured muzzle images of cattle before extracting texture features of muzzle point images for better representation and matching of features in the feature space. Because, the muzzle point images of cattle are captured from the low illumination, poor image quality and blurriness due to head movement and body dynamics of cattle in the unconstrained environments. Few muzzle point images are obtained from the low illumination and record minor handshakes of dairy staff members associated with hand motion. For mitigating the problem of low image quality, poor illumination, and blurriness, the data pre-processing algorithm uses the mean value of N muzzle image of captured database.

In the proposed approach, the motivation behind applying the pre-processing and enhancement techniques is to enhance the low quality of muzzle point images by reducing the noise and other artifacts from captured muzzle point image database. Therefore, Contrast Limited Adaptive Histogram Equalization (CLAHE) [206] technique is applied for the enhancement process of muzzle point images. After enhancement process, color K-means segmentation algorithm is applied to find the region of interest from the input image of muzzle point [144] [203].

Figure 4.6 illustrates the pre-processing process of muzzle point image pattern of cattle. After pre-processing steps, segmentation algorithms are applied to segment the muzzle point images into different segments. The each segment is employed to find the Region of Interest (ROI) from the segmented muzzle point images. The segmentation of muzzle point image is illustrated in brief in the next subsection.

4.4.2 Segmentation of Muzzle Point Image

The image segmentation algorithms are essential for partition the muzzle point images into required distinct regions of beads, and ridges pattern. The muzzle point images consist of rich texture information (feature) and different color based discriminating texture features. After the pre-processing phase of muzzle images, color feature-based clustering [38] and texture based segmentation algorithms [128] are examined and applied for the segmentation of muzzle point images.

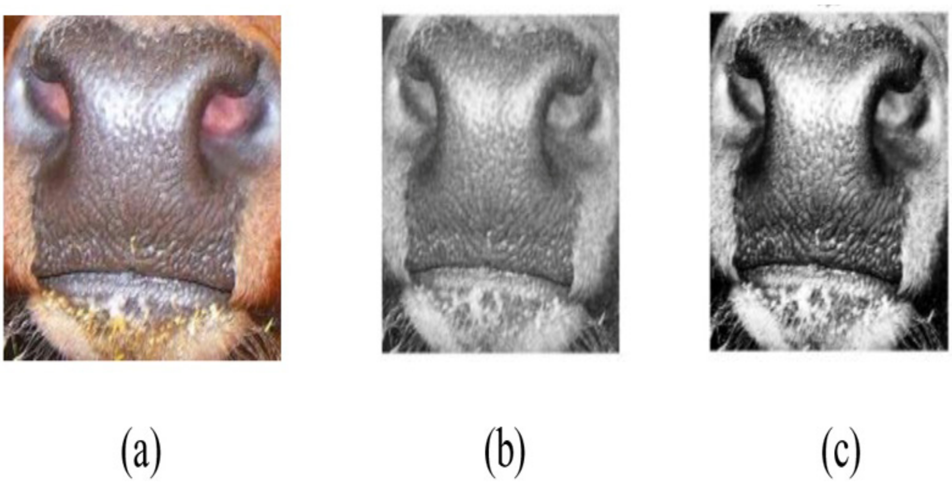


FIGURE 4.6: Illustrates pre-processing:(a) original muzzle point image, (b) blurred image, and (c) enhanced muzzle point image.

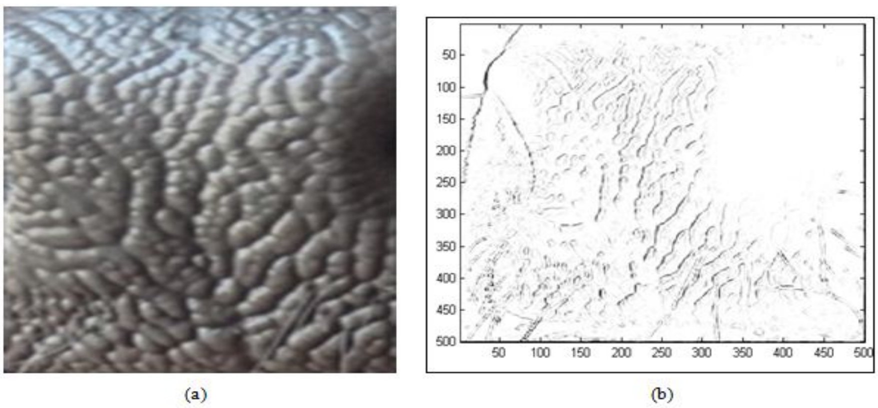


FIGURE 4.7: Illustrates (a) original muzzle point image, and (b) segmentation of muzzle point image pattern.

The main motive to apply the texture-based segmentation and color-based segmentation algorithms are to preserve relevant and discriminatory information of muzzle feature sets for the recognition and classification process. Therefore, color K-means clustering and texture feature-based segmentation algorithms are applied to segment the muzzle point images into distinct Region of Interest (ROI) for extraction of texture features from the muzzle point image database of cattle [168] [128]. The segmented muzzle point image pattern is shown in FIGURE (4.7).

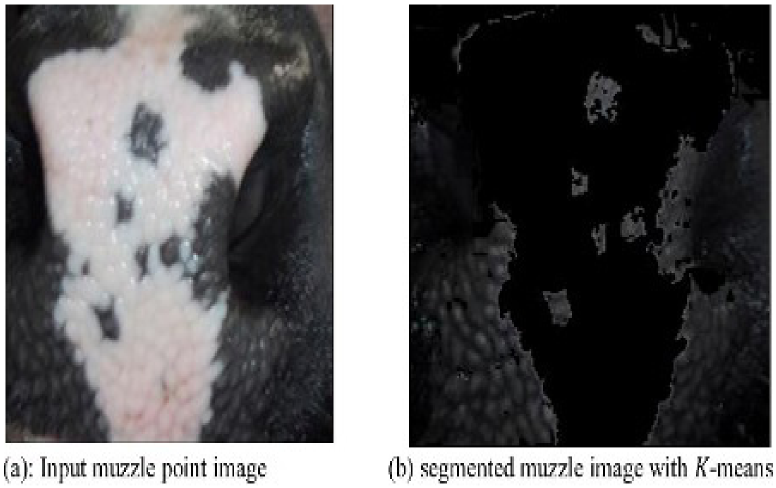


FIGURE 4.8: Illustrates (a) original muzzle point image pattern, (b) segmented muzzle image with color K-means based segmentation approach.

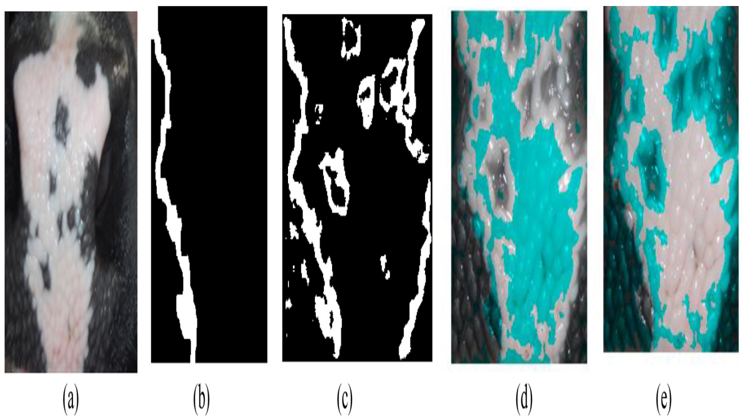


FIGURE 4.9: Illustrates segmentation of muzzle point image pattern: (a) original muzzle images, ground truth, and ((b)–(e)) illustrates the find out a ROI using texture segmentation algorithm.

The segmentation of muzzle point images of cattle with ground truth, and Region of Interest (ROI) based segmentation of muzzle point image pattern using color-based K-means clustering, and texture segmentation algorithms are shown in FIGURE (4.8), FIGURE (4.9), and FIGURE (4.10).

The segmentation algorithms partition the input images into multiple segments and find ROI from each segmented muzzle point images. However, the segmentation algorithms depend on the type of essential discriminating features to be preserved, and extraction of

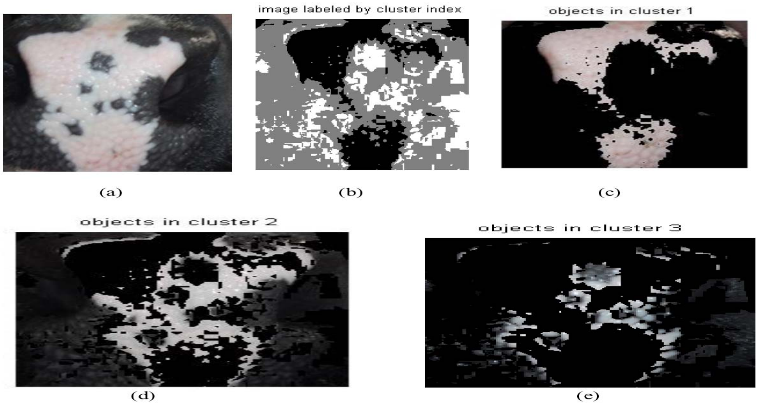


FIGURE 4.10: Illustrates the segmented muzzle point image pattern using K-means colour cluster based segmentation algorithms.

discriminatory information from particular ROI of segmented muzzle point image pattern. The motivation to apply the clustering algorithms is that it preserves the distinct and discriminatory features from the muzzle point images. The segmented muzzle point image pattern is shown in FIGURE (4.7).

Figure 4.10 illustrates the segmented of muzzle point image pattern using K-means color cluster algorithm, shown in FIGURE (4.10) ((a)–(e)) for clusters $n = 3$ (*i.e.*, cluster-1, cluster-2, and cluster-3, respectively). The segmentation of original muzzle image, Figure (4.10)(a). FIGURE (4.10)(b) illustrates the labeled muzzle point images by using cluster index, and FIGURE (4.10) ((c)–(e)) presents beads and ridge of muzzle point image as required features in the cluster-1, cluster-2, and cluster-3, respectively.

4.4.2.1 Minima Selection and Region Merging

The watershed segmentation algorithms are applied to partition into regions of the object in given image [184]. 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 over-segmentation. Hence, a dynamics algorithm has been applied with texture segmentation technique for the selection of discriminatory minima

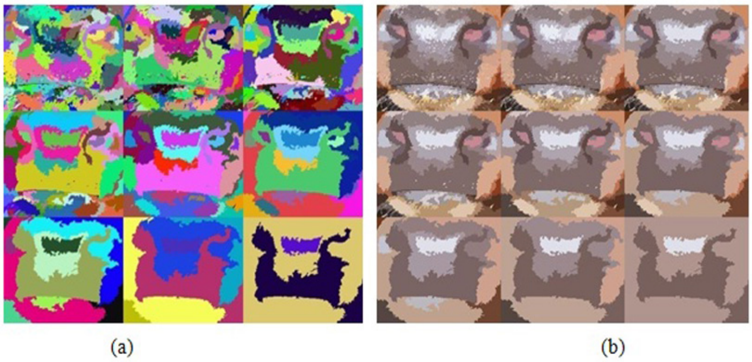


FIGURE 4.11: Illustrates of the watershed based segmentation: selection of region of interest (ROI) from the muzzle point image pattern database.

value based on suppression of irrelevant minima gradient values and preserve the rest feature values of muzzle point images in this chapter [185]. These values are used to initialize the markers for the selection of watershed region(*e.g.*, region of interest) from muzzle point images [65]. The dynamic algorithm mitigates the over segmentation problem by reducing the insufficient minima of partitioned ROIs of muzzle images pattern into different classes [186].

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:

1. In the merging procedure, it applies a strategy to 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.

2. 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 is shown in FIGURE (4.11).

4.5 Feature Extraction and Matching

The feature is an important characteristics to encode the given image pattern into set of discriminatory measurable information or values [53]. The feature extraction is a step to extract the feature from image pattern in the proposed cattle recognition approach [138]. It is responsible for texture analysis, and classification of image pattern based on discriminating set of features.

The eventual objective of this section is to articulate extraction of feature vector from each image of muzzle point pattern database of cattle. After pre-processing, and segmentation of muzzle point images, texture features are extracted from the muzzle point image [200].

The muzzle point image consists of rich texture features in the form of bead pattern and ridge pattern as mentioned above section. Therefore, eight texture feature extraction techniques have been applied to extract the texture features of the muzzle point image pattern. After segmentation of muzzle point images, texture features of muzzle image pattern (*e.g.*, rich texture information, and distinct features such as, beads, and ridges pattern) are extracted using texture feature approaches.

The eight texture feature based extraction techniques are illustrated namely, Haralick texture features method [75] [76], morphology based features [46], shape based features [163], Histogram of Oriented Gradient (HOG) features [43], Wavelet feature [181], Color based features [38], Tamuras feature [51], Laws Texture Energy (LTE) [150], Local Binary Pattern based texture feature extraction [142], and Fuzzy-Local Binary Pattern (Fuzzy-LBP) [86].

TABLE 4.2: Illustration of various texture features extracted from the muzzle point image pattern and their ranges.

Features	Number of features	Range
Haralick texture features [75] [76]	22	F1-F22
Morphology and shape feature[46]	10	F23-F32
Histogram of Oriented Gradient (HOG)[43]	36	F33-F69
Wavelet feature [181]	32	F70-F102
Color features[38]	06	F103-F109
Tamuras feature [51]	03	F110-F112
Law Texture Features [150]	16	F113-F129
LBP Features [142], and FLBP [86]	56	F-130-F186

The ranges of extracted sets of texture feature are shown in Table 4.2, which illustrates the distribution of muzzle texture feature type, and the number of the feature are selected for the identification and classification of muzzle point image. Finally, classification is performed on the extracted texture features of muzzle point images for identification of cattle. In this chapter, K-nearest neighborhood (K-NN) [144] [145], Fuzzy-K-NN [97], Radial Basis Probability Neural Network (RBPNN) [92], Probabilistic Neural Network (PNN) [169], Decision Tree (DT) [160], Gaussian Mixture Model (GMM) [204], Multilayer Perceptron (MLP) [157], and Naive Bayes based [96] classification models have been applied to classify, and identify the individual cattle based on their extracted muzzle point image features. The extracted texture feature are encoded into a corresponding feature vector through encoding process for the complete feature representation in the feature space. The encoding of texture features of muzzle point images of cattle is discussed in the next subsection.

4.5.1 Encoding of Texture Features of Muzzle Point Images

A feature extraction and representation descriptor is essentially a well-defined function that converts an input image or image regions into a corresponding feature vector through encoding process. The encoding of extracted features is done by applying LBP based descriptor technique in this chapter [142]. The extracted muzzle point image features are invariant to monotonic changes in the intensity in the gray level domain. However, variations in the pixel intensity in a given muzzle image are solved by appearance-based recognition algorithm due to low illumination conditions, and another outdoor environment. Therefore, local features are extracted, and encoded by its descriptors with size 8×8 (e.g., descriptor window size) from the neighbor pixel of given images. The length of extracted feature vector is known as the scale of a feature descriptor. The LBP and fuzzy-LBP [86] texture feature algorithms are applied to extract the local texture features from the muzzle images, extracted texture features are encoded to obtain a descriptor for better representation and recognition of cattle.

In the available literature, the most of the research works on texture classification, and recognition of objects apply the hard assignment, and quantization. For this purpose, however, defined assignments can lead to a quantization and reconstruction of error space during classification, and recognition in the feature space [60]. A soft quantization technique has been applied to represent the distribution of extracted texture feature of muzzle point image using supervised Fisher Linear Discriminant Analysis (FLDA) technique to maximize the ratio of the determinant of between-class (S_B), and within-class (S_W) of muzzle image database for the classification of extracted texture features [18].

In this chapter, Gaussian Mixture Model (GMM) has been applied to Fisher feature vectors of muzzle images for the derivation of a probabilistic representation of these texture features in the feature space. FLDA extraction and representation technique [60] provided a fixed length and compact representation of muzzle image feature from a set of the arbitrary number of local texture features of muzzle point image pattern for recognition of cattle.

The main objective is to perform the encoding of muzzle texture feature using FLDA technique [37]. It captures the most significant differences between-class (S_B) and within-class (S_W) of muzzle point images using first, and second order statistical based probabilistic distribution of extracted features of muzzle image pattern [37] [182]. The computed differences of the higher order statistics based muzzle point feature sets are chosen to learn the proposed recognition system for the accurate classification, and recognition of individual cattle as compared to other available encoding algorithms, such as histograms, kernel code book [37] [71] [182].

The Fisher vector formulation is given in the Equation (4.1). Moreover, detailed discussion about Fisher vector formulation, and detail analysis can be found in the references [161], [147]. The distribution of local features are modeled using GMM classification model is defined as follows (shown in Equation (4.1)):

$$p(d|\theta) = \sum_{k=1}^{K} p(d|\mu_k, \sum_k)\pi_k \tag{4.1}$$

Where, $p(d|\mu_k, \sum_k)$ is a multivariate Gaussian distribution with mean μ_k, co-variance matrix $\sum_k$ (assumed to be diagonal) π_k is the mixing coefficient of the Gaussian component, and $\theta = (\pi_1, \mu_1, \sum_1 \ldots, \pi_K, \mu_K, \sum_K)$ is the vector of the parameters for model. Here K is the total number of Gaussian components assumed to be present while modeling the feature distribution. The parameters of GMM classification model are learned using Expectation Maximization (EM) [133] technique to encode the muzzle texture features from the training sets.

Furthermore, LBP texture descriptor algorithm has been applied to extract the texture feature of muzzle point images for classification and recognition of cattle. As mentioned

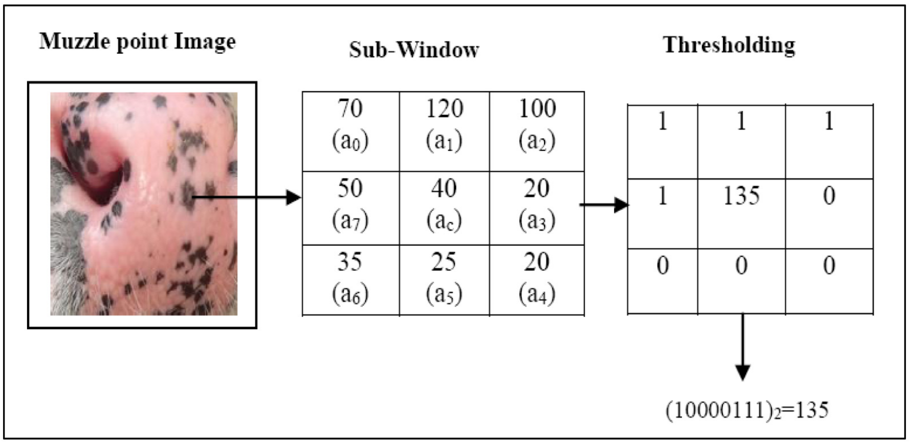


FIGURE 4.12: Illustration of LBP binary codes obtained by comparing centre pixel (thresholding) with its neighboring pixels and transform into decimal code.

previously, the muzzle image database of cattle is captured from the unconstrained environments. The unconstrained environments are low illumination, poor image quality, and blurriness of image due to head and body movement of cattle; the LBP texture feature descriptor technique is applied to extract and encode the texture feature from these images to improve the recognition rate of proposed system. LBP descriptor technique is faster to compute the texture features, and robust to blurriness, pose, and poor illumination changes in the muzzle point image of cattle database.

The computation of texture feature vector using LBP texture descriptor technique corresponds to gray level of the center pixel (c), and presents to gray level of the p equally spaced pixels on the circle of radius R ($R \geq 0$), where $c = (1, 2, \cdots, N)$. The binary code generation of LBP texture descriptor technique for muzzle point image pattern is shown in FIGURE (4.12), respectively.

After that texture feature extraction algorithms which are applied to extract and encode the texture features from each segmented muzzle point images of cattle. Finally, extracted features of muzzle images are classified using different classification models to recognition the cattle based on muzzle point image features. The classification of extracted texture feature is illustrated in the next section.

4.6 Classification

To establish the classification of a given probe image (query image), the multi-class classification models are used to classify the feature vectors of muzzle pointimage using K-nearest neighborhood (K-NN) [144] [145], Fuzzy-K-NN [97], Radial Basis Probability Neural Network (RBPNN) [36] [92], Probabilistic Neural Network (PNN) [169], Decision Tree (DT) [160], Gaussian Mixture Model (GMM) [204], Multilayer Perceptron (MLP) [157], and Naive Bayes based [96] classifier models. The brief descriptions of these classification techniques are stated as follows:

4.6.1 K-nearest neighbour (K-NN) Classifier

The K-nearest neighbor (K-NN) [144] is a classification technique. The feature vector is assigned to the class. For K-NN classification, the numbers of nearest neighbor (K) set to 5, and Euclidean distance-based similarity matching matrix and the *"nearest"* rule to decide how to classify the probe images (testing) is used [145].

4.6.2 Fuzzy K-Nearest Neighbour Classifier

The fuzzy K-nearest neighbor (Fuzzy K-NN) is a classification approach which allocates a fuzzy class membership to a sample vector rather than assignment of the vector to a general class [97].

4.6.3 Radial Basis Function Neural Network Classifier

In radial basis probabilistic neural network based classification technique, distances from the test feature vector to the training feature vectors are determined by the first neural network layer known as radial basis layer [36]. The next layer is a competitive layer. It sums up the distance vectors for each input classes and generates a vector of probabilities considered as its output [92]. Furthermore, the *complete transfer functions* are exploited in this layer which then chooses the maximum of these probabilities to evaluate the class of the test data [36] [92].

4.6.4 Decision Tree Classifier

Decision Tree (DT) is ensemble-based classification technique for classifying data [160]. It consists of a set of nodes and edges which organized in a hierarchical tree. A set of rules for the different classes is derived from the tree that is constructed using the input features from the training data [160]. These rules are used to classify and predict the class of the test (query data).

4.6.5 Gaussian Mixture Model Classifier

A Gaussian mixture model (GMM) is a parametric-based probabilistic model that assumes all the data points. The data point is generated from a combination of a finite number of Gaussian distributions with unknown parameters [204]. The GMM classifier model uses the maximum likelihood algorithm for fitting GMM to the training datasets. The trained GMM classifier has been evaluated on test data [204].

4.6.6 Probabilistic Neural Network Classifier

Probabilistic neural network (PNN) [169] is a classification technique based on neural network. It works like feed forward neural network, and it is derived from the Bayesian network and statistical algorithms known as Kernel Fisher Discriminant analysis (KFDA) [103]. The motivation behind to apply the PNN [169] based classifier technique is because of it faster, and yields accurate classification rate as compared to the well know back-propagation paradigm [157].

4.6.7 Multilayer Perceptron Classifier

The Multilayer Perceptron (MLP) [157] is a feed-forward neural network based classification technique for classifying and analyzing images patterns. It has been used an extensively in classification and regression analysis of data. It consists of multiple layers of simple, two states sigmoid processing elements or neurons known as nodes that interact using weighted connections. A general principle for the Multilayer perceptron can be found in [157].

4.6.8 Naïve Bayes Classifier

The Naive Bayes is a simple probabilistic technique [96] for constructing classifiers based on Bayes' theorem with strong (naive) independence hypothesis between the extracted sets of input features of given database, where (X) is defined as the feature space. The classifier models that assign class labels, to problem instances, represented as vectors of feature values (D) [96].

4.7 Classifier Tuning Strategy

This section presents in detail the tuning strategies of classification models to classify the extracted texture feature of muzzle point images of cattle database. The extracted texture features of muzzle images are classified by using multi-classification techniques.

For the evaluating the performance of proposed recognition system, the classification models among the above seven are selected by same training and testing feature sets (data). To achieve higher recognition accuracy the parameters of the different classifiers (as mentioned above) are tuned with the proposed system. In this work, K-NN [145], and fuzzy classifiers [91] have provided the better classification results as compared to other classification models. The classifier models have performed the better recognition of cattle by classifying features of extracted muzzle images pattern of cattle.

The fuzzy classifier strategy is applied to train the classification models using fuzzy inference system. The fuzzy inference system consists of conditional if-then rules that illustrate a relationship between the input and output fuzzy sets. The different clusters are set fixed using defined radii in the fuzzy inference system [91]. To cluster the extracted texture feature of muzzle images the radii are defined as a vector that provides the center range of inferences in each of the feature space, and to be supposed as feature sets which are assigned within a defined unit feature space area (hyper box).

The range of suitable radii values of clusters is taken a range of $0.2-0.5$, where, radii $(r) \in (0.2 \leq radii \leq 0.5)$. The selection of range values play an important role to find the large clusters of extracted texture muzzle features from the muzzle point images. In this chapter, a radii (r) value is chosen to 0.50 for the classification of texture features of muzzle point and depth analysis. The input membership function has been selected as the Gaussian distribution function. The linear function is decided as output membership function for the fuzzy-k-NN classification model.

In the case of PNN classifier [169], all biases layers in radial basis neural network are first initialized to $\sqrt{lg(0.05)/s}$, where, s is a spread constant in the radial basis functions of PNN [169]. In this experiment, the maximum classification accuracy has been obtained by setting the value of spread constant (s) = 0.50.

Furthermore, for K-NN classifier [203] strategy, the value of K is varied from the 2 to 6 in this experiment. However, at $K = 2$, K-NN classifier yields the maximum classification accuracy for identifying cattle using of muzzle point image, the distance between different classes is evaluated using classical Euclidean distance technique. The majority rule is used for classification [48]. That is, a sample point is assigned to the class the majority of the (K) nearest neighbors are from [105].

In the case of GMM classification technique [204], the centers of clusters are initialized to 5 for all the respective groups of muzzle point image database. In the DT classifier [160], the parent node and leaf node values should be tuned. The parent and leaf node values are 10 and 1 respectively to give a higher accuracy.

Naive Bayes is a probabilistic based classification technique. It is applied for analysis of extracted features which are supposed to be independent to give the class of muzzle images database. Therefore, a Naive Bayes based classification technique [96] selects a small number of parameters that are required to be estimated for the classifying the texture feature of muzzle point pattern with small estimator variance (*e.g.*, one-dimensional kernel density estimation with Gaussian distribution) (shown in Equation (4.1)).

4.7.1 Statistical Analysis

In this subsection, statistical measures are performed to analyze the statistically significant analysis of extracted texture features of muzzle images [129]. The statistical measurement-based techniques provide a way to check and validate the significant of extracting texture features whether a given set of texture features has unique capability among labeled classes (feature sets) or not [52].

For validation of texture features, classical statistical inference based technique, such as One Way Analysis of Variance (ANOVA) [129] test has been performed to test the statistical significance of extracted texture features (data) [52]. It is one of the well-established statistical tests for comparison of more than population means of feature vectors [52] [129].

ANOVA test considers the variation (*e.g.*, variance) within the set of feature groups, and translates that variation (*e.g.*, differences) between the groups, doing same way, taking this into consideration, this procedure provides more meaningful information about how many subjects (groups) belongs to the same group or not [183].

Finally, action has taken into consideration for the final decision which is based on observed differences. The observed differences are high which indicates that the extracted sets of features of muzzle point image pattern are more statistically significant for the classification, and recognition of cattle [52].

4.7.2 Performance Evaluation

After the statistical measurement of extracted texture of muzzle image using Analysis of Variance (ANOVA) [183]. Test performance evaluation has been performed after computations of variations between the set of features of inter-class (S_W) (within class), and intra-classes (between classes) (S_B) of muzzle image database.

When variations between the classes of texture features were found to be relatively high as compared to variation of within-class (S_W) of muzzle feature, then ANOVA [52] test was taken under consideration of statistically validate the significant of data. The data validation and analysis reported that higher value of (F) or low value of (p), statistical parameters showed that extracted sets of texture features of muzzle point image pattern are statistically significant for classification and recognition of individual cattle [183]. Therefore, values of (F) and (p) are calculated from the extracted texture feature in this experimentation. Computed values of (F) and (p) are shown Table 4.3. The statistics parameters (F) and (p) are defined as follows:

A. F- Statistics Parameter

F- statistics 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 parameter-based is simply 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 ridges pattern information in the muzzle point images) are scattered from the mean value of extracted features (shown in Equation (4.2)).

$$F = \frac{Between - classes)(S_B)variation}{Within - class(S_W)variation} \tag{4.2}$$

The calculation of variation for Between-class (S_B) and Within-class (S_W) of extracted muzzle point image are given as follows:

$$Between - classes)(S_B)variation = \sum_{i=1}^{K} N_i \frac{(\mu^{'} - \mu)}{(K-1)} \tag{4.3}$$

$$Within - class(S_W)variation = \sum_{i=1}^{K} \sum_{j=1}^{N_i} \frac{(\mu^{'}_{(i,j)} - \mu_i)}{(K-1)} \tag{4.4}$$

Where $\mu^{'}_{i}$, N_i and μ are defined as sample mean of extracted feature set ofi^{th} group/class of cattle (shown in Equations (4.3) and (4.4)), total number of the muzzle point images of cattle database, and overall mean of cattle muzzle point image database, respectively. $(\mu'_{(i,j)})$ depicts the j^{th} observation in the i^{th} out of K class of extracted set of muzzle point feature of cattle database.

B. p-statistics-based parameter

p-statistics-based parameter determines whether any of the differences between the means are statistically significant, compare p-statistics-based parameter to evaluate the significance of the extracted set of muzzle point features of cattle database based on the defined hypothesis. The defined significance level (α) is applied to validate the classification and identification of cattle based on extracted features as follows:

1. If p-value $\leq \alpha$, no all of the classes of extracted feature set of muzzle point images are equal.
2. If the p-value is larger than the significance level (α), the enough evidence is available to reject the defined hypothesis and the mean of overall database of cattle muzzle point images are equal.

In this chapter, 186 texture features are extracted from the cattle database of muzzle image pattern [166]. The extracted texture features from the muzzle point images resulted in a (p)-value which is less than 0.0001 (shown in Table 4.3). The (p) statistics based-value indicates the extracted features are statistically more significance for the classification, and identification of individual cattle based on extracted texture features of muzzle point images [183].

The composition of prepared muzzle point image database from four cattle breeds (races) are illustrated in Table 4.1. The classes of muzzle point image database are equivalent to cattle breeds. The number of group for muzzle point images is defined as a subset from the whole muzzle point image database.

Before, the extraction of texture features of muzzle point images, initially, cattle database of muzzle point images has been divided into three classes, known as (A), (B), and (C) classes. The database size of each set (A), and (B) classes is 2000 muzzle point images, 200 subjects $\times 10$ images of each subject, and class C consists of 100 images of muzzle point pattern (e.g., 100 subjects $\times 10$ images of each subject) with size 200×200 pixels.

The characteristic of class (A) muzzle images is manifested with poor illumination of 2000 muzzle pattern images pattern, set B holds blurriness and pose variation based co-variate 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.

One of the most significant advantages of dividing the prepared database of muzzle point images of cattle into three classes (e.g., (A), (B), and (C) classes of muzzle point images) is to perform the depth level analysis of extracted features by maximizing the ratio between–class (S_B), and minimizing the within–class (S_W) scatter feature matrix. The minimization strategy yields computation of discriminatory sets of features of muzzle images for the improvement of classification, and recognition of cattle based on muzzle image pattern. The variations of significant texture features of muzzle image are shown in Table 4.3. The division of classes of muzzle point image database of cattle is shown in FIGURE (4.13).

In Table 4.3, some short notations are used as, HF= Haralick features, LTE = Laws Texture Energy, LBP = Local Binary Pattern, HOG = Histogram of Oriented Gradient, and FLBP = Fuzzy Local Binary Pattern.

Where $N_1 = e^{+18} \pm 9.7511 \times e^{+18}$, $N_2 = e^{+019} \pm 2.2334e^{+019}$, $N_3 = e^{+019} \pm 2.7006 \times e^{+019}$, $N_4 = 009 \pm 1.1345 \times e^{+009}$, $N_5 = e^{+9} \pm 6.1147 \times e^{+8}$, $N_6 = e^{+009} \pm 1.7594 \times e^{+9}$, $N_7 = e^{+9} \pm 6.0847 \times e^{+8}$, $N_8 = e^{+9} \pm 4.9497 \times e^{+8}$, $N_9 = e^{+9} \pm 7.1588 \times e^{+8}$, $N_{10} =$

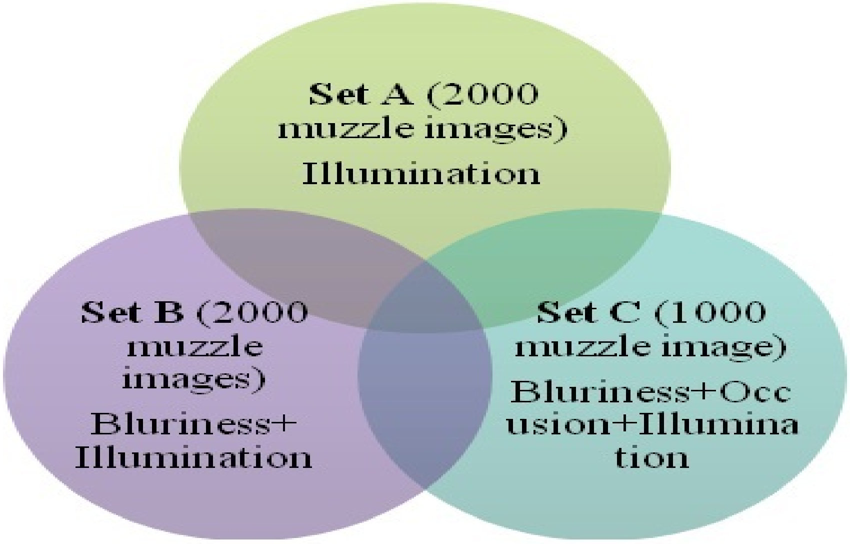


FIGURE 4.13: Distribution of classes of muzzle point image pattern database under different conditions.

TABLE 4.3: Summary statistics (mean ± standard deviation) of few extracted texture features of muzzle pattern of set A, B, and C groups.

F	class A	class B	class C	F-vale	P-value
HF	$7.1133N_1$	$1.8778N_2$	$2.1482N_3$	10.4606	≤ 0.0001
LTE1	1.9634e+N_4	$1.6626N_5$	$3.2373N_6$	16.2052	≤ 0.0001
LTE 2	$1.0628N_7$	$1.1165N_8$	$1.3241N_9$	1.9141	≤ 0.0001
LTE 3	$2.4890N_{10}$	$1.2204N_{11}$	$3.3821N_{12}$	24.5293	≤ 0.0001
LTE 4	$1.6038N_{13}$	$1.0689N_{14}$	$2.0546N_{15}$	13.8461	≤ 0.0001
LTE 5	$1.5785N_{16}$	$1.2408N_{17}$	$1.7115N_{18}$	4.30460	≤ 0.0001
LTE 6	$1.4530N_{19}$	$7.9325N_{20}$	$1.5152N_{21}$	11.4587	≤ 0.0001
LBP 1,8 entropy	2.0290 ± 0.4720	1.1916 ± 0.3442	2.1978 ± 0.5986	55.7414	≤ 0.0001
LBP 1 ,8 energy	0.3992 ± 0.1506	0.6764 ± 0.1066	0.3630 ± 0.1817	59.3935	≤ 0.0001
LBP 2, 16 entropy	2.3655 ± 0.5837	1.2949 ± 0.3692	2.4472 ± 0.6627	60.6534	≤ 0.0001
LBP 2, 16 energy	0.3826 ± 0.1564	0.6722 ± 0.1064	0.3612 ± 0.1777	60.5802	≤ 0.0001
LBP 3, 24 entropy	2.5046 ± 0.6359	1.3285 ± 0.3789	2.5079 ± 0.6736	62.1876	≤ 0.0001
LBP 3,24 energy	0.3855 ± 0.1542	0.6719 ± 0.1053	0.3726 ± 0.1696	60.8724	≤ 0.0001
HOG feature	2.4956 ± 0.6459	1.3385 ± 0.3889	2.5079 ± 0.6936	63.1876	≤ 0.0001
Fuzzy-LBP	2.5146 ± 0.6369	1.3285 ± 0.3799	2.5079 ± 0.6756	62.1376	≤ 0.0001

$e^{+9} \pm 1.4208 \times e^{+9}$, $N_{11} = e^{+9} \pm 6.7234 \times e^{+008}$, $N_{12} = e^{+9} \pm 1.5850 \times e^{+9}$, $N_{13} = e^{+8} \pm 8.1916 \times e^{+7}$, ${}_{N}14 = e^{+8} \pm 4.2658 \times e^{+7}$, $N_{15} = e^{+8} \pm 1.0112 \times e^{+8}$, $N_{16} = e^{+8} \pm 7.7265 \times e^{+7}$, $N_{17} = e^{+8} \pm 4.8826 \times e^{+7}$, $N_{18} = e^{+8} \pm 8.5985 \times e^{+7}$, $N_{19} = e^{+9} \pm 8.9512 \times e^{+8}$, $N_{20} = e^{+8} \pm 5.5436 \times e^{+8}$, $N_{21} = e^{+9} \pm 6.7139 \times e^{+8}$.

4.8 Experimental Results and Discussion

This section provides details about the database, experimental results, experimental protocols, and obtained results. Furthermore, the experimental results are analyzed and compared with that of other classification models. The simulation of the proposed framework was performed via the Intel Core i5-4210U CPU running at 1.70 GHz, and 200 Giga Byte of RAM.

The size of a database of muzzle point images is 5000 (*e.g.*, 500 $\times$ 10 subjects (cattle) images per subjects). The size of each muzzle image is 400$\times$ 400 pixels. For evaluating the performance of the proposed system, experimental results were conducted on 5000 muzzle images database of cattle. Firstly, 5000 muzzle images ware segmented into three classes, such as *A*, *B*, and *C* classes of cattle database. The size of each class is 2000, 2000 (2000 = 200 $\times$10 images of each subjects), and 1000 (e.g., 1000 = 100 $\times$ 10 images of each subjects) muzzle point images of cattle.

In feature extraction phase, eight texture feature extraction techniques are applied for the extraction of texture features from three classes of muzzle point images after preprocessing and segmenting muzzle point images. The texture features are extracted using eight texture feature techniques namely Haralick texture features (gray level texture features)(F1-F22), Morphology and shape features (F23-F32), Histogram of Oriented

Gradient (HOG) (F33-F69), wavelet features (F70–F102), color based features (F103-F109), Tamura's features (F110-F112), and Law's Texture Energy (F113-F129) features, Fuzzy-Local Binary Pattern (FLBP), and LBP (F130-F186) based texture features.

Finally, a 2D-matrix of 5000 $\times$186 texture feature matrix was constructed using all the extracted set of texture features, where 5000 are the number of muzzle point images pattern in the cattle database and 186 are the total number of extracted texture features from the muzzle point image database. Furthermore, texture features are extracted from muzzle point images which are low illuminated, poor quality, blurred during head movement of cattle for depth level analysis and better recognition, and classification of individual cattle.

The recognition accuracies are calculated by sample images of muzzle pattern of cattle. The database of muzzle point images are divided into two phases: (1) training phase and (2) testing phase for training and testing of proposed system. For training phase, six muzzle point images randomly selected for training purpose from class/group (A), (B), and (C) of muzzle point images for training the system and remaining muzzle point images were used for the testing process.

For class-A (200 cattle), the size of sample images is 25, 40, and 135. For Class-B (200 Cattle), the size of sample images is 60, 60, and 80. For Class-C (100 cattle), the size of sample images in the class-C is 20, 30, and 50, respectively. For testing phase, the unknown test muzzle image is matching with stored trained muzzle point images of cattle using similarity matching score technique.

The training and testing partitioned database of muzzle point images is performed five-fold cross-validation to test the classification models and compute the recognition accuracy by classifying the extracted set of muzzle texture features. In this experiment, K-nearest neighborhood (K-NN) [144] [145], Fuzzy-K-NN [97], Radial Basis Probabilistic

Neural Network (RBPNN) [36] [92], Probabilistic Neural Network (PNN) [169], Decision Tree (DT) [160], Gaussian Mixture Model (GMM) [204], Multilayer Perceptron (MLP) [157], and Naive Bayes based [96] classifier techniques are applied to evaluate the recognition accuracy by classifying the extracted set of features of muzzle point for cattle recognition.

4.8.1 Experimental Analysis

In this section, all the experimental results are systemically presented with their detailed analysis. The experimental results of cattle recognition are summarized in Tables 4.4 and 4.5, respectively. Table 5 illustrates the performances of different classification algorithms along with their comparative recognition accuracy.

In Table 4.4, first three columns present the recognition accuracies from the class (A) of muzzle point image pattern. The second columns and third columns present the recognition accuracy by classifying the extracted texture features of muzzle point images of class (B), and (C), respectively. It is clearly shown the evident that K-NN classification technique yields the better accuracy by classifying extracted features of muzzle point of individual cattle as compared to other classification algorithms.

Based on the observations of experimental results, the K-NN [144] [145] classification technique has yielded the classification accuracy of 95.82% to classify, and recognize individual cattle. The Fuzzy-K-NN [97], Decision Tree (DT) [160], Gaussian Mixture Model (GMM) [204], Probabilistic Neural Network (PNN) [169], Multilayer Perceptron (MLP) [157], and Naive Bayes based [96] classifier models yield the recognition accuracy of 94.85%, 75.54% (from the class (A)), 79.45% accuracy from the class (B), and 85.76% recognition accuracy from the class (C).

TABLE 4.4: Recognition Rate (%) for (A, B and C classes) of muzzle point pattern, each groups have different cases (muzzle images pattern).

Recognition accuracy (%)									
Classification	Class A (200)			Class B (200)			Class C(100)		
Images	50	50	100	50	50	100	30	20	50
RBPNN[36]	88.75	86.26	88.25	74.36	74.36	76.65	85.27	87.98	87.98
NaiveBayes [96]	63.21	63.21	77.32	64.67	75.65	73.84	63.92	74.83	71.84
FuzzyKNN [97]	92.75	92.75	94.56	86.25	83.25	90.73	74.35	75.45	76.26
KNN[145]	95.82	93.82	96.74	96.34	91.72	92.85	85.62	85.83	89.95
MLP[157]	62.63	62.47	67.84	72.33	71.37	77.93	68.73	70.92	74.43
DT[160]	78.47	73.23	75.54	70.41	72.45	79.45	81.47	82.68	85.76
PNN[169]	92.63	92.63	94.56	90.42	90.42	94.88	78.42	79.62	79.68
GMM[204]	70.25	73.25	77.63	82.74	82.25	85.67	72.74	79.65	84.47

While Gaussian Mixture Model (GMM) [204] based classifier yields the accuracy of 77.63%, 85.67%, and 88.47% to classify the individual cattle from the group (A), (B), and (C), respectively. Moreover, Probabilistic Neural Network (PNN) [169] based classifier provides the accuracy of 94.56%, 94.88%, and 79.68%from the classes (A), (B), and (C) to recognize the cattle, while Multilayer Perceptron (MLP) [157] classification technique achieved the classification rates of 67.84%, 77.93%, and 74.43% from the classes (A), (B), and (C), respectively. The Naive Bayes based [96] 77.32%, 73.84%, and 71.84% recognition rates of muzzle images pattern for recognizing the individual cattle.

The classification accuracy of the K-NN [145] classifier among all classifiers such as, fuzzy K-NN [97], Radial Basis Probabilistic Neural Network (RBPNN) [36] [92], DT [160] [97], GMM [204], and PNN [169] classification models yield the maximum classification accuracy of 96.74%. Therefore, K-NN classifier has also been chosen for classification of the extracted features to recognize individual cattle.

The recognition rate of the muzzle point pattern of cattle from different classes is shown in Table 4.5. The recognition rates (%) of categories of cattle bread ((A), (B), and (C)) have been considered in the different cases based on sample images of muzzle images database of cattle.The class-A, class-B, and class-C of cattle pieces of bread consist of 200, 200,

TABLE 4.5: Recognition rate (%) for (A, B, and C) groups of muzzle point pattern, each groups have different cases(muzzle images).

Recognition accuracy (%)									
Classifiers	Class A (200)			Class B (200)			Class C(100)		
	25	40	135	60	60	80	20	30	50
RBPNN[36]	64.25	68.78	72.65	69.96	71.46	72.95	78.84	74.68	87.68
NaiveBayes [96]	60.35	64.78	68.82	70.47	72.55	73.94	66.92	68.83	70.80
FuzzyKNN [97]	79.85	85.93	93.88	83.95	85.75	87.68	72.89	74.93	77.96
KNN[145]	75.32	76.63	78.84	66.47	73.89	75.59	74.43	79.93	82.25
MLP[157]	51.37	57.67	63.84	65.33	69.87	72.93	64.73	67.92	72.84
DT[160]	69.76	72.67	78.64	75.45	76.35	78.75	82.87	83.58	84.86
PNN[169]	56.73	58.76	62.95	66.97	70.82	73.68	63.72	65.84	69.90
GMM [204]	70.75	72.43	74.40	69.72	72.56	78.86	72.43	79.65	84.47

and 100 muzzle point images of cattle. For evaluating the classification accuracy, each class is divided into different sub-class with various sample images of cattle.The size of sample images of class-A is 25, 40, and 135 respectively. The size of sample images of class-B is 60, 60, and 80, respectively. Finally, the sample size of images for class-C is 20, 20, and 50 to validate the classification accuracy for identification of individual cattle.

The experimental results are done to evaluate the performance of cattle recondition under different scenarios such as, rotation, and occluded (horizontally and vertically occluded part) of muzzle images for the recognition and classification of cattle, which is illustrated in subsections 4.8.2, and 4.8.3, respectively.

4.8.2 Recognition of Muzzle Point Images under Different Rotations

In this subsection, we have performed the experimental results of muzzle pattern recognition of cattle based on different orientations of muzzle images, and tested against different orientation during the testing phases. The muzzle images patterns are rotated in the following angles: (0°, 45°,90°, 135°,180°, 225°, 270°, and 315°). The images of muzzle

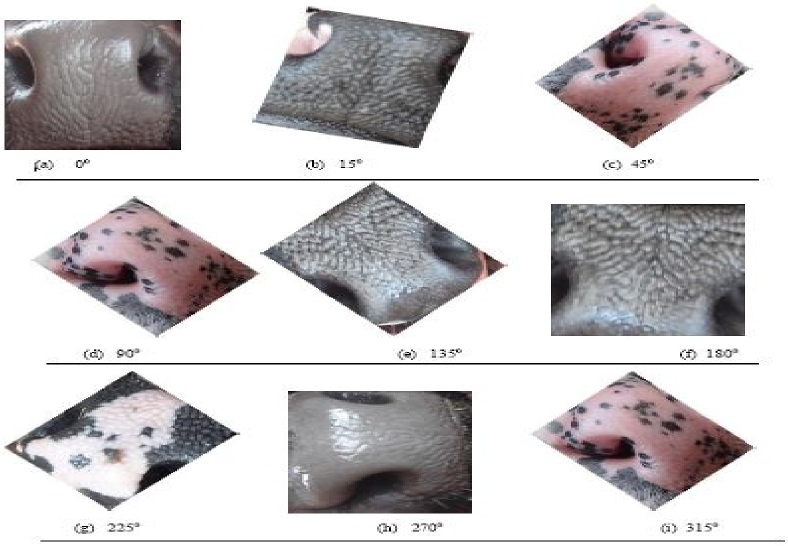


FIGURE 4.14: Sample images of muzzle point pattern are rotated with different angles (0°, 15° 45°, 90°, 135°, 180°, 225°, 270°, 315°).

TABLE 4.6: Recognition Rate for (A, B, and C) classes of muzzle point pattern, each class have different subjects (number of images muzzle images).

Recognition accuracy (%)									
Classification	Class A(200			Class B(200)			Class C(100)		
Angles	0°	15°	45°	90°	135°	180°	225°	270°	315°
Subjects	50	50	100	25	50	125	20	30	50
RBPNN [36]	81.75	84.96	86.25	70.36	72.86	74.65	78.27	76.98	78.98
NaiveBays [96]	65.87	67.58	70.45	74.39	76.55	78.94	70.72	73.63	75.92
FuzzyK-NN [97]	85.75	87.65	89.56	84.25	83.75	82.73	74.35	72.67	76.66
K-NN [145]	92.82	93.87	90.74	92.34	90.95	91.97	84.87	85.83	88.95
MLP [157]	62.73	64.47	67.84	72.33	73.97	75.93	68.73	70.92	70.94
DT [160]	78.47	73.23	75.54	70.41	72.45	79.45	81.47	82.68	84.89
PNN [169]	90.73	92.89	94.56	89.42	91.72	92.88	78.42	79.42	81.78
GMM [204]	69.75	70.25	71.63	73.42	76.25	78.47	68.74	71.98	72.87

point pattern, and recognition rate are shown in FIGURE (4.14). The recognition rate(%) of individual cattle by classifying different classifiers are given in Table 4.6.

TABLE 4.7: Recognition Rate (%) for (class-A (Bottom Occluded images), B, and C ((Top Occluded images(B+C)) groups of muzzle point image pattern, each groups have different cases.

Recognition Accuracy(%)								
Classifiers	(Class-A)				classes(B+C)			
Images	50	50	50	50	75	75	75	75
NaiveBays [96]	95.85	97.75	98.56	88.95	89.25	94.73	74.35	76.26
KNN[145]	92.78	94.87	96.84	97.34	98.85	96.65	85.82	91.82
PNN[169]	97.86	98.57	97.45	89.39	94.55	99.94	89.72	94.72

4.8.3 Recognition of Muzzle Point Image of Cattle between Different Occlusion

In this section, experimental results and analysis are performed on the muzzle images. The muzzle point images are partially occluded (*e.g.*, percentage (%) of occluded part of a muzzle image pattern). These occluded muzzle point images are consider to evaluate the performance of proposed approach and to investigate whether proposed texture feature extraction approach is robust against the occluded muzzle point images pattern for recognition of individual cattle. The recognition of cattle based on muzzle point images under different under occlusion classes are divided according to occluded parts (bottom part and vertical part of muzzle images in the given percentage) are shown in Table 4.7.

In this experiment, we have used 60% of the total database images of muzzle point for training process, and remaining muzzle point images in testing process of occluded muzzle images (different occluded percentage (%), and sizes) shown in FIGURE (4.15). After that, we applied the occluded images for the testing to classify individual cattle using muzzle images. The result of this experiment is shown in Table 4.7 .

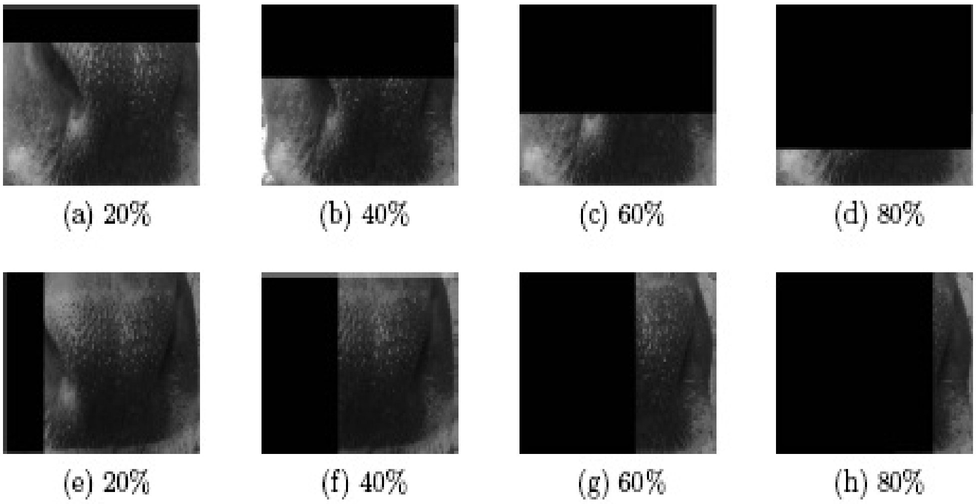


FIGURE 4.15: Samples of occluded muzzle images,top row (a, b, c, d) represents bottom(horizontal) occlusion, bottom row (e, f, g, h) represents top (vertical) occlusion.

4.9 Discussion

In this chapter, we have demonstrated the comparative study of experimental results for identifying, and classifying individual cattle using proposed approach. The summary of identification, and classification techniques for cattle based on their muzzle images pattern with their accuracy have been shown in Table 4.8. The proposed approach extracts the discriminatory set of muzzle point features to classify and recognize individual cattle. The size of a database of muzzle point images is 5000 (*e.g.*, 500 $\times$ 10 subject's (cattle) images per cattle).

For evaluating the performance of the proposed approach, the experimental results have been conducted on 5000 muzzle images database of cattle. Firstly 5000 muzzle images ware segmented into three classes, such as (A), (B), and (C) classes of cattle database. The size of each class is 2000 , 2000 (2000 = 200 $\times$10 images of each subjects), and 1000 (e.g., 1000 = 100 $\times$10 images of each subjects) muzzle point images of cattle. The texture features are extracted by hybrid texture feature extraction techniques from muzzle point image cattle database.

In feature extraction phase, eight texture feature extraction techniques and hybrid texture feature extraction are applied for the extraction of texture features from three classes of muzzle point images after the pre-processing and segmenting muzzle point images. The texture features are extracted using eight texture feature techniques namely, Haralick texture features (gray level texture features)(F1-F22), Morphology and shape features (F23-F32), Histogram of Oriented Gradient (HOG) (F33-F69), Wavelet features (F70-F102), Color based features (F103-F109), Tamura's features (F110-F112), Law's Texture Energy (F113-F129) features, Fuzzy-Local Binary Pattern (FLBP), and LBP (F130-F186) based texture features.

A 2D- matrix of 5000 $\times$186 texture feature matrix was constructed using all the extracted set of texture features, where 5000 are the number of muzzle point images pattern in the cattle database and 186 are the total number of extracted texture features from the muzzle point image database. The texture features of muzzle point images are extracted from low illuminated, poor quality, blurred muzzle point images due to head movement, and body dynamics of cattle for depth level analysis and better recognition, and classification of individual cattle.

Finally, the extracted set of discriminatory features are classified by using classification techniques such as K-NN [203], Fuzzy-KNN [97], Decision Tree [160], PNN [169], Radial Basis Probabilistic Neural Network (RBPNN) [36], Multilayer perceptron [157], and Naive Bayes [96] to classify the extracted muzzle features.

The K-NN [203] and fuzzy K-NN [97] classification methods yield the recognition accuracy of 96.74%, and 94.56%, respectively. It can be observed from the comparative experimental results that none of the previously proposed approaches using texture feature based techniques yields better results as compared to recognition of cattle using muzzle point image pattern.

In this chapter, the performance of the proposed method has been compared quantitatively with current state-of-the-art methods viz. recognition method used by Tharawat et al. [177], Minagawa et al. [130], and Barry et al. [15], Noviyanto et al. [140], Awad et al. [10], Noviyanto et al. [140].

The author, Tharawat et al. [177] proposed a technique for the recognition of cattle using Local Binary Pattern (LBP) descriptor technique for the classification of the cattle breeds (races) using local features of the muzzle print image pattern in the Table 6.7.

Minagawa et al. [130], proposed a method for cattle identification based on muzzle pattern. The proposed approach for livestock identification begins by a rectangular cropping of the downside of the muzzle print pattern image. It started from the minimum line between nostril borders. A noise filtering process has continued the identification process by applying the low pass filtering techniques, however, unfortunately, the research paper has not given any detail explanation clearly about the filtering technique that has been used for the filtering process. Moreover, a ridge thinning method has been applied to extract the joint pixels as the discriminatory features. The joint pixel values are from two muzzle print images of cattle is overlaid. Two joint pixel values are correctly matched if both muzzle print images are in a range of a 11×11 pixel region centered in the joint pixels of muzzle print images. It has been taken as the ground truth. The extracted features of common pixel values of muzzle print images are classified and recognized using unsupervised learning Principal Component Analysis (PCA) based on the co-occurrence feature matrix of beads features for calculation of eigenvalues for cattle recognition and yield recognition rate of 30–40%.

In the similar direction, Barry et al. [15] has also proposed a cattle identification method for beef cattle based on muzzle print image pattern. Unlike Minagawa et al. [130] and Barry et al.[15] have applied bead pattern of muzzle point images as the features for identification of beef cattle. In the proposed approach, two steps are involved for identification of individual cattle. The first step is applied to cater the normalization orientation and segmentation of captured muzzle print images of cattle. Barry [15] applied feature (information) only in the middle part of the muzzle print image pattern. The muzzle print image has been rotated so that the minimum line between nostril borders is in parallel with horizontal line. The region of interest of muzzle print images is a rectangular area which is cropped by manual procedures with d=0.8d size centered in the minimum line between nostril borders of cattle. The d defined as the distant of minimum line between nostril borders.

Noviyanto et al. [141] proposed a method using Speeded Up Robust Feature (SURF) from the muzzle print images of cattle for identification of individual cattle. A uniform-SURF (U-SURF) approach was used to identity the eight animals, using 15 print images each cattle. The size of muzzle print image database of cattle is 120 muzzle print images. The experimental setup and validation protocols include 10-times validation to validate the experimental results. 10 muzzle-print images were used in the training phase, and the other 5 images were applied as input sample images for identification of individual cattle. The proposed approach achieved the maximum identification accuracy of 90% under rotation conditions. In the similar direction, Noviyanto et al. [140] proposed a technique for refinement of matching in SIFT descriptor based approach for identification of cattle and reported the minimum Equal Error Rate (EER) value of 0.0167. This EER value was less than obtained EER values of original SIFT technique.

In Awad et al. [10], the authors proposed a method using Scale-Invariant Feature Transform (SIFT) algorithm for identification of individual cattle. The proposed approach is

TABLE 4.8: Summary of identification and classification techniques based on muzzle images pattern used in the literatures and experimental results of proposed approach.

Refs.	Images	Features	Recognition	Accuracy (%)
[10]	15	SIFT	SIFT+RANSAC	93.33%)
[15]	100	Beads	EDT	45%
[30]	30	LBP	RASL+WLBP	95.3%
[41]	50*	PCA	PCA+ICA	96%)
[101]	12	Face	ANMA	80%
[130]	43	Beads	PCA	30-40%
[141]	15	SURF	Eigen face	90%
[140]	48	muzzle	SIFT	0.0167 (EER)
[177]	217	LBP	LDA, SVM	89%
Prop.approach	5000 MP	PHy	K-NN,Fuzzy-KNN	96.74%,94.56%

combined with a Random Sample Consensus (RANSAC) technique to mitigate the noises from very low–quality images, blurred, and poor quality of muzzle print images of cattle, and in doing so the authors improved the identification accuracy using the previously collected muzzle print images of cattle database. In this experiment, seven muzzle print images of each cattle were interchanged between the enrollment phase and the identification phase. After that the similarity scores between all of muzzle print images were evaluated to create a similarity matching score matrix with a dimension of 105×105. The proposed approach obtained 93.30% recognition accuracy under these condition with (FMR = 6.6%) on 105 images from 15 cattle animal.The comparative analysis of experimental of current state-of-the-art methods is shown in Table 4.8.

In the Table 4.8, various notations are used as Prop.= Proposed approach, MP = muzzle point image pattern, PHy = Proposed Hybrid texture feature approach, EQT = Euclidean distance based matching technique, ANMA = Associate Neural Memory Algorithm, WLBP = Weber's Local Binary Pattern Descriptor)+ RASL + Chi square distance, RANSAC = RANdom SAmple Consensus algorithm, SIFT = Scale Invariant Feature Transform, SURF = Speeded Up Robust Features, SVM =Support Vector Machine, PCA = Principal Component Analysis, ICA = Independent Component Analysis, LBP = Local

Binary Pattern, 50* = 50 sheep images.

4.10 Summary

In this chapter, a hybrid texture features extraction approach is proposed for recognition, and classification of individual cattle based on muzzle point image pattern. The proposed approach operates on the texture feature vectors obtained from the 5000 images of muzzle image pattern using eight texture features approaches and perform classification, and recognition of cattle. The proposed approach yields the better recognition accuracies of 94.5%, and 96.74% by classifying the extracted texture features of muzzle point images by applying K-NN, and Fuzzy-K-NN classification techniques. This research work illustrates a current state-of–art approach for the recognition, and classification of individual cattle in the animal biometrics, pattern recognition, and computer vision.

The proposed hybrid feature extraction based automatic recognition of cattle based on muzzle point image pattern extracts texture features from the different classes such as, *A*, *B*, and *C* of muzzle image database. The experimental results indicate that the proposed approach succeeds in efficiently utilizing a feature representation of input data to perform the accurate classification, and recognition of muzzle point pattern recognition for individual cattle.

From the experimental evaluation on a database of 5000 muzzle point image pattern of cattle (*e.g.*, 500 cattle (subjects) $\times$ 10 images of each subject), and their qualitative, and quantitative analysis, it can be concluded that the proposed hybrid texture features approach is performing better in comparison to other cattle recognition technique. It illustrates that the automatic recognition of cattle is feasible using muzzle point image pattern as primary animal biometric characteristics. It is also capable of alleviating the problems associated with covariates of muzzle images due to low illumination, poor image quality, and pose variation due to head movement of cattle.

The proposed approach can provide the better solutions to problems of registration, missed, swapped, false insurance claims, and traceability of cattle in the traditional animal recognition based methodologies, and livestock framework based systems.