Deep Learning Framework for Recognition of Cattle using Muzzle Point Image Pattern

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Deep learning framework for recognition of cattle using muzzle point image pattern

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A B S T R A C T

Animal biometrics is a frontier area of computer vision, pattern recognition and cognitive science to plays the vital role for the registration, unique identification, and verification of livestock (cattle). The existing hand-crafted texture feature extraction and appearance based feature representation techniques are unable to perform the animal recognition in the unconstrained environment. Recently deep learning approaches have achieved more attention for recognition of species or individual animal using visual features. In this research, we propose the deep learning based approach for identification of individual cattle based on their primary muzzle point (nose pattern) image pattern characteristics to addressing the problem of missed or swapped animals and false insurance claims. The major contributions of the work as follows: (1) preparation of muzzle point image database, which are not publically available, (2) extraction of the salient set of texture features and representation of muzzle point image of cattle using the deep learning based convolution neural network, deep belief neural network proposed approaches. The stacked denoising auto-encoder technique is applied to encode the extracted feature of muzzle point images and (3) experimental results and analysis of proposed approach. Extensive experimental results illustrate that the proposed deep learning approach outperforms state-of-the-art methods for recognition of cattle on muzzle point image database. The efficacy of the proposed deep learning approach is computed under different identification settings. With multiple test galleries, rank-1 identification accuracy of 98.99% is achieved.

1. Introduction

Animal biometrics is an emerging research field of computer vision, wildlife science, and pattern recognition [1]. Animal biometrics-based recognition system develops quantified and efficient recognition methodologies for representing extracted visual features, detecting discriminatory features for identifying the phenotypic appearance of species or analysis of individual animal's behaviours based on its morphological image pattern and animal biometric characteristics. The phenotypic presentations consist of the composite of an organism's observable morphological features [1,2].

Animal biometrics-based recognition system is a pattern recognition system. The recognition system extracts the prominent animal biometric features from the morphological image, biometric characteristics and phenotypic appearances of different species or individual animal.

In animal biometrics, identification of cattle based on biometric features has been one of the current and future research frontiers in the modern livestock for registration, tracking and breed associations of cattle.

Based on available literature, animal identification methodologies can be categorized into following groups: (1) permanent recognition method, (2) semi-permanent recognition method, and (3) sketch pattern-based marking recognition approach [1,2,5]. The permanent recognition method includes the making based animal identification schemes. These marking schemes are as ear-tattoo-based identification

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techniques, embedded of microchips-based marking approach invasive, hot-iron and freeze branding of livestock. The ear-tattoos-based animal marking schemes are the manual marking technique to identify the massive number of livestock animal's herds and other species. The sketch patterning-based marker methods are not used to identify the solid colour breeds of livestock (especially cattle breeds).

The ear-tattoos-based marking techniques are highly applicable for tracking and identification of several cattle breed associations such as Brown Swiss, Red Poll, and Milking Shorthorn breed associations [5,6]. The distinct artificial marking techniques, such as embedding of microchips, ear-tattooing and hot-iron techniques are required for identifying individual cattle, but these techniques give the defects on the cattle [6,7].

On the other hand, the collar-id and ear-tagging based identification techniques are the examples of semi-permanent animal identification approaches for identification of individual animals [8,9]. According to authors Wardrope [6], Johnston and Edwards [10], the ear-tagging based verification and identification techniques are not competent to identify individual cattle. The monitoring and tracking of individual cattle based on embedded unique tag numbers can be easily lost.

The ear-tagging based techniques suffer from the major problems for verification and identification of animals. These major problems of ear-tagging based techniques are mainly-(1) integrated labels in the ear-tags can vanish easily (2) different integrated labels can also be eventually damaged and (3) the ear can gradually be corrupted due to long-term usage [6–10].

The sketch based patterning techniques perform the design and different patterning of different colour on the body of livestock. The sketch patterning and design-based techniques depend on individual drawing skills. The major problem of patterning technique is that it lacks standards [7]. Due to the enormous amount of human resource requirements, the classical animal identification approaches need more cost for the tagging of cattle's ear. The ear-tagging based systems suffers from the venerability loses due to duplication, fraudulent and forged of embedded standard ear-tags [2,3,5,12]. The embedded RFID chips based techniques are also applied for the identification and tracking of individual cattle. However, the implementation and management of RFID protocol, RFID-chips, and scanners at various checkpoints have been reported the major challenging problems for monitoring of the massive number of livestock animal and other species throughout the world [12].

1.1. Motivation

Towards successful operation of any farm, an effective livestock management is essential. Efficiency, affordability, and scalability of livestock management and solutions play a significant role in the modern farm houses. As the number of farms decreases in the country, but the numbers of livestock on each increases every year. Dairy livestock needs better monitoring for breed associations, milking, health monitoring of animals, weighting and other activities. Therefore, the ability to reliably tracking and identifying individual animal in herds is an important for cattle registration and recognition.

The cattle recognition using manual identification approaches has been a major problem for breeding association, registration and health monitoring of the livestock (especially for cattle) in the classical animal identification systems, livestock based monitoring frameworks, and non-biometrics-based capture- recapture marking methodologies [3,4].

The classical animal identification framework and identification paradigm provides non-invasive technique for identification of individual cattle in the heard. The non-invasive identification techniques such as visible ear tagging based identification, freeze brandings, marking the animal body with hot-iron, embedding of microchips are applied for cattle registration. Moreover, the labelled ear-tags with RFID devices have been also incorporated for cattle identification. The labelled ear-tags are scanned electronically because of cost, and most ear-tags use low-frequency (LF) RFID. Therefore, the RFID scanner systems must be deployed within a few inches of the labelled ear-tags. The users (e.g., farm workers, parentages, owners of cattle and others) require operating the scanned devices by personal with every animal for reliable scanning of embedded ear-tags.

The RFID based ear-tagging of individual cattle has been widely adopted throughout the world. For example, dairy farms in the Europe, USA, and Asian countries are more reluctant to perform the identification of cattle so due to costs of the ear-tags, and the lack of national standards.

In the classical animal identification approaches, animal recognition and livestock framework-based systems provide manual procedures or methods for verifying the registered (e.g., insurance animal) and imposter animal based on registered unique ear tag numbers of livestock, embedded number in hot iron, and marked number in the ear-tattoos on body surface of animal. The embedded unique numbers can be easily duplicated, and forged for creating the false registered number. The users (parentage, owners and others) claim number of false insurance claims by replacing the previous registered unique number. In the available literature, the classical animal recognition and livestock framework based systems cater the manual methods for verifying the registered (e.g., insurance animals by government and insurance provider organizations) to find the imposter animals. These recognition systems use the manual approaches such as ear tags, hot iron, and ear tattoos. Therefore, classical identification methods are unable to provide the satisfactory level of security for owners and verification of cattle breed associations in the farmhouses throughout the world.

Animal biometrics-based cattle recognition system gives the efficient methodologies for registration of livestock animals using its biometric features. The cattle recognition system also caters the better method for monitoring, and traceability of individual cattle in the farmhouses [2,4]. Moreover, the recognition system plays a vital role in the verification of false insurance claims and registration of livestock, tracking, breeding monitoring, and breeds production. Nowadays, non-registration and the massive number of livestock animals are transported across the border, and cattle recognition system provides efficient methods to stop the kind of activities of border transfer of livestock animals for slaughterhouses [5,6].

Currently, deep learning approach is an emerging field of computer vision for detection and representation of phenotypic appearances and visual biometric feature of species and individual animals. Deep learning has gained more attention as of the most powerful approaches for the feature extraction and representation of different species or individual animal in the recent years [7–9]. With efficient learning capacity for feature representations, the deep learning based learning frameworks are used to learn the extracted sets of biometric feature of species for the representations and identification [10,11]. The different layers of the deep learning framework are used to model and represent the complex data variations for animal recognition [12,13].

The well-developed deep learning approaches and frameworks are applied to propose a cattle recognition system to solve the above issues by learning the muzzle point feature its representation and classifiers jointly for a particular task tasks [14,15].

In this paper, we address the problem: how to recognize cattle based biometric feature characteristics of muzzle point image pattern (nose image pattern) using deep learning-based recognition approaches? To address this problem, we use a 30 megapixel camera for capturing the image of muzzle point pattern of cattle.

The muzzle point image pattern consists of rich and dense texture features. The proposed cattle recognition system recognize the cattle based on texture feature of muzzle point image. The system uses the deep learning based recognition frameworks.

The cattle recognition system captures the image of muzzle point pattern (nose pattern) of cattle. After that, the captured image of muzzle point pattern are pre-processed using the low pass filtering technique to remove the noises and other artefacts from the captured muzzle point image database. The texture features are extracted from the muzzle point image database. The extracted features are classified using deep learning approaches to identify the individual cattle.

Based on overall observations and our acknowledgment, there are no such animal biometrics-based recognition and verification systems present in animal biometrics literature or public domain to cater the better methods for identification and registration of cattle based on primary biometric characteristics.

1.2. Research contributions

Following are important contributions of this research:

1. The unique and immutable bead and ridge pattern as biometric characteristics of muzzle point image of cattle leads to interesting challenges for an animal biometrics-based recognition system for cattle identification. Considering the non-intrusive nature of muzzle point biometrics pattern, this research explores the new possibility of determining the unique identity of individual cattle using deep learning approaches. Motivated from animal biometrics research across multiple domains and interdisciplinary researches, we discuss the major challenges and opportunities of the cattle recognition system. For recognition of individual cattle, novel deep learning based representation frameworks and matching schemes are proposed in this paper. It is customized towards recognition of cattle and yields current state-of-the-art results.
2. In this paper, a novel deep learning-based stacked denoising auto-encoder framework is used to encode and decode the extracted set of salient texture feature of muzzle point image of cattle for recognition of individual cattle.
3. The deep learning framework-based approaches are suitable to address the significant variations of muzzle point images of cattle in the unconstrained conditions due to low illumination, body dynamics and blurred images due to the head movement and body dynamics of cattle, and the poor image quality of muzzle point images. We proposed a Convolution Neural Network (CNN) and Deep Belief Network (DBN) deep learning approaches to learn the muzzle point texture feature of cattle for better representation into different deep neural network layers with deep learning framework.
4. A deep belief network (DBN) is the graphical deep learning model is used to learn the extracted features of muzzle images for hierarchical representation of the training datasets by stacking of Restricted Boltzmann Machines (RBMs) based classification technique for classification and identification of cattle. It is trained in a greedy manner for learning of feature extraction and representation from the given large unlabelled image database and updating the loss function of DBM by including low rank regularization. Finally, a multilayer deep learning neural network has been used as classifier to achieve the identification decision for cattle.
5. A database of muzzle point image of cattle over 5000 images pertaining to over 500cattle is contributed to the research community in the animal biometrics. To the best of our knowledge, this is the largest muzzle point image dataset publicly available for research on cattle recognition. Moreover, the performances of existing handcrafted texture feature extraction technique and appearance-based feature extraction and representation algorithms systems are compared and evaluated the experimental results across various gallery sizes of muzzle point images on a standard identification settings and benchmark.

The remaining parts of the paper are as follows: Section 2 illustrates the literature review in the direction of cattle recognition. Section 3 provides the database preparation and description of muzzle point images of cattle. Section 4 detailed the proposed deep learning based recognition system of cattle followed by the feature extraction and representation of muzzle point image features using deep learning approaches. Stacked Denoising Auto-encoder is presented in Section 5. Section 6 provides the Pre-Training and generalizability of proposed model in brief. The experimental results and brief analysis of the work is reported in Section 7. Further, it includes the performance evaluations and comparative analysis of proposed approach. Finally, the conclusions and future directions are provided in Section 8.

2. Related work

In this section, we have provided the literature review of cattle using various computer vision and animal biometrics approaches for identification of individual cattle. Off late the animal biometrics-based recognition systems have received significant attentions due to more proliferation for recognition, detection, tracking, and monitoring of different species or individual animal [1,2]. These animal biometrics-based recognition systems identify the individual animal or species using its physical visual features (e.g., facial images), morphological image pattern, and biometric characteristics of animals. The permanent animal recognition techniques provide the safety by recognizing the animal using ear-tattoos, ear-tip or notches, freeze-branding, hot iron around animal's neck and embedded microchips, electronic devices, sensors, and RFID-transponders [3–5].

For example, ear tagging, and ID-collar-based recognition techniques are semi-permanent based recognition approaches for the identification of individual cattle [5,6]. However, the embedded label of ear-tags can be lost quick. The ear-tagging systems include only the various kinds of metal clips and plastic labels or tags. However, these ear-tags can cause different types of infections and critical diseases to animals after these embedding of these tags in the body of the animal or other species.

The ear-tagging and collar-ID based approaches are susceptible to damage, duplication, losses, un-readability, and fraud of ear-tags. Therefore these methods are not fit for long-term usages [6]. While in temporary recognition based methodologies, it recognizes the individual animal by utilizing the sketch patterning-based techniques. For example, paint or dying and RFID based animal recognition with embedded transponders or sensors in their body are temporary identification methods [7–11].

Based on the available classical identification techniques, the RFID-based animal identification process is one of the most promising for cattle or other livestock animals. According to the author Baranov et al. [16], the muzzle dermatoglyphics (i.e., ridges, granola, and vibrissae) from various races are different. In a similar direction, Mishra et al. [17] proposed a method for identification of individual cattle using beads and ridges pattern.

Minagawa et al. [18] introduced a framework for the cattle identification using muzzle print images. The muzzle print images were captured on A-5 paper with black ink and evaluated performances of proposed approach using filtering techniques. For analysis of muzzle print image, the authors applied the binary transformation processes and morphological approaches (i.e., thinning operation). They have reported the Equal Error Rate (EER) of 0.419, respectively.

Barry et al. [19] proposed a technique for recognition of cattle using muzzle print image similar to Minagawa et al. [18]. They have done experimentation to evaluate the performance of proposed approach. They have reported the 241 False Non-Match Rates (F NMR) over 560 Genuine Acceptance Rate (GAR), and 5197 false matches over 12,160 impostors matching closely with the same value of EER of 0.429, respectively.

Awad et al. [20] proposed a cattle recognition framework using SIFT descriptor approach to localize and detect the interesting points in the muzzle print images for the identification of cattle database is 90 muzzle images ($6 \times 15 = 90$).

In the similar direction, the author of [21] proposed a matching refinement technique in Scale Invariant Feature Transform (SIFT) descriptor approach for the recognition of cattle on the database of 160 muzzle print images. They have computed the matching scores of the key points of muzzle impact images by applying matching refinement technique in SIFT key point localization and detection approach. However, the matching refinement approach has had the performance compared to the original SIFT approach with the value of EER being equal to 0.0167 [23].

In the same direction, Tillett et al. [22] used the image processing and computer vision based techniques for the recognition and analysis of the behaviour of pigs. Pigs are identified in surveillance video by tracking and detecting their movements.

Kumar et al. [23] proposed a framework to determine the individual cattle identity based on their face image. They have evaluated the performance proposed system using extracted features.

Recently, author Tharwat et al. [24] proposed a muzzle image based cattle recognition approach using local texture descriptor based technique such as LBP texture algorithm for the extraction of local texture features from the muzzle print images. The RANdom SAmple Consensus (RANSAC) approach is utilized to mitigating the outliers from the muzzle image which is incorporated in the SIFT algorithm for the improvement of reliability and robustness of their proposed identification approach for cattle. The six images for each subject (cattle) are used as training muzzle images in the experiment, and the total size of the database is 90 muzzle images (6 × 15 = 90). They achieved more than 90% accuracy of cattle recognition. The major shortcoming of this proposed approach is to take more processing time during recognition of livestock (cattle).

3. Database preparation and description

To the best of our knowledge, there is no publicly available muzzle point image pattern database that can be applied to evaluate the current state-of-the-art based recognition and classification algorithms or develop new algorithms for recognizing and verifying the muzzle point image pattern of cattle. Inspired from the classical animal recognition systems and its failures, there is a need to develop an automatic, non-invasive and robust animal biometric systems for identification of cattle, therefore, we prepare a database of muzzle point image pattern of cattle using a 30-megapixel camera from the Department of Dairy and Husbandry, Institute of Agricultural Sciences (I. A. S), Banaras Hindu University (B.H.U), Varanasi, India-221005. Some sample of muzzle point image pattern of cattle is shown in Fig. 1.

The database contains images of muzzle point pattern in the form of various covariates, such as low illumination, poor image quality, pose variation due to body dynamics and head movement images (shown in Fig. 2). From these muzzle point images, we manually filtered the covariates images along with blurred and low illumination muzzle point images [23]. In total, muzzle point image pattern database of cattle, therefore, the database consists of 500 muzzle point images about 500 subjects. The extraction of discriminatory texture muzzle point features (bead and ridge pattern is shown in Fig. 2.

3.1. Biometric characteristics of muzzle point image pattern of cattle

For identification and traceability of animals, smart devices (e.g., smart phone, digital camera, smart watches, and distributed embedded smart camera) are gaining diverse proliferation due to the wide range of applications and uses. It is becoming a good platform for sensing the multimedia data, computing, and communication. For identification of individual cattle using proposed cattle recognition system, a 30-megapixel camera is used to capture the muzzle point image of cattle.

The recognition of animals is very similar to the identification of minutiae points in the human fingerprint. The motivation of this the research works for cattle recognition is that the muzzle point image pattern of cattle consists of rich dense texture feature. The muzzle point image pattern of cattle consists of two discriminatory features-(1) beads image feature pattern (2) ridge image feature pattern of muzzle point image of cattle. The bead image features are the prominent set of texture features pattern. It consists of anon-uniform image pattern in the muzzle point images of cattle. The bead and ridge feature pattern of the muzzle point image of cattle are shown in Fig. 3 and Fig. 4, respectively.

The ridges features are the uniform image pattern. It is similar to ridges of the human fingerprint images. The texture feature contains the discriminatory patterns as bead pattern and ridge pattern for cattle recognition. The recognition of cattle based on muzzle point image is similar to recognition of human fingerprint recognition. Therefore, in this research, we proposed a novel approach for recognition of cattle based on muzzle point image characteristics which start with selecting texture rich feature of the muzzle point image database of cattle using deep learning convolutional neural network (CNN) architecture which is a combination of Stacked Denoising Sparse Auto-encoder (SDSA) and

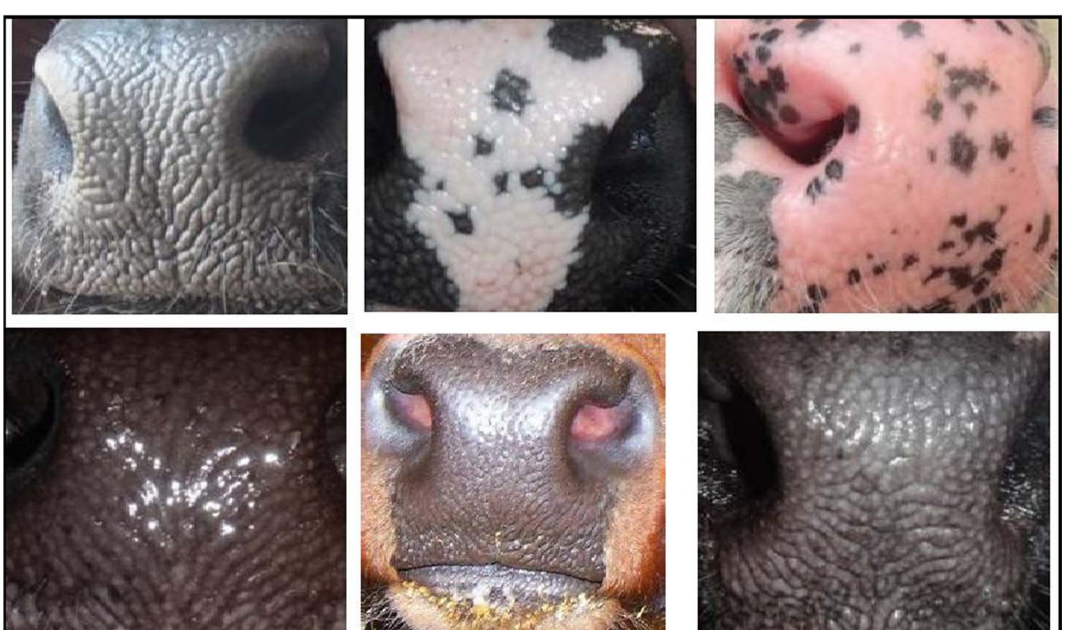


Fig. 1. Some muzzle point images of cattle from database.

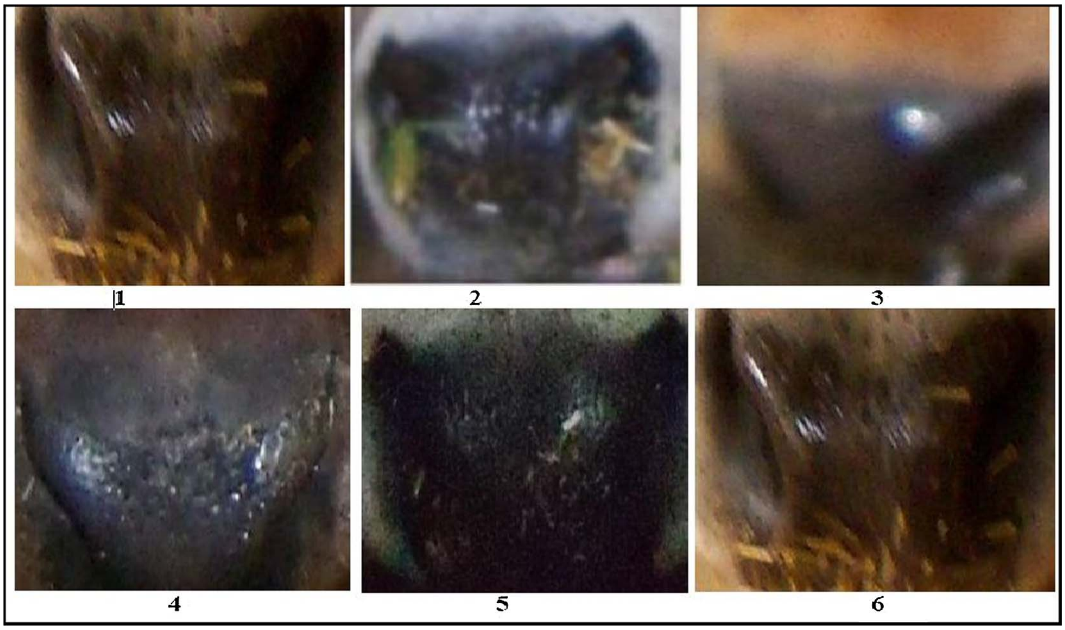


Fig. 2. Illustrates the blurred muzzle point images in (1, 2, 3 and 6) and images (4 and 5) shows poor illumination.

Deep Boltzmann machine (DBM) learning techniques.

4. Proposed system

A deep learning based framework is used in the proposed cattle recognition system for identification of cattle is depicted in Fig. 6.

The proposed cattle recognition system takes the captured muzzle point image pattern of cattle. The captured images of muzzle point pattern consist of rich dense texture feature of muzzle point image. Therefore, the texture feature of muzzle point image are extracted and encoded using the deep learning frameworks and the existing hand-crafted texture feature extraction and appearance based feature representation techniques. The appearance based feature extraction and representation algorithms are unable to perform the recognition of cattle based on low illumination, poor image quality, and blurred image of muzzle point of cattle which are captured in the unconstrained environment. Therefore, texture feature descriptor techniques are utilized for uniquely identification of individual cattle in this work.

The proposed cattle recognition system is used to learn the discriminatory set of extracted muzzle point image features for better representation with limited training database. The basis of the proposed approach includes muzzle point texture feature pattern of cattle for recognition of cattle. The muzzle point features consist of two prominent sets of feature known as bead and ridge features. The features are extracted and represented using proposed deep learning approaches such as convolution neural network, deep belief network frameworks. The extracted set of salient muzzle point features of cattle are encoded using stacked denosing auto-encoder technique for better feature representation in feature space.

The salient set of extracted muzzle point feature of cattle is

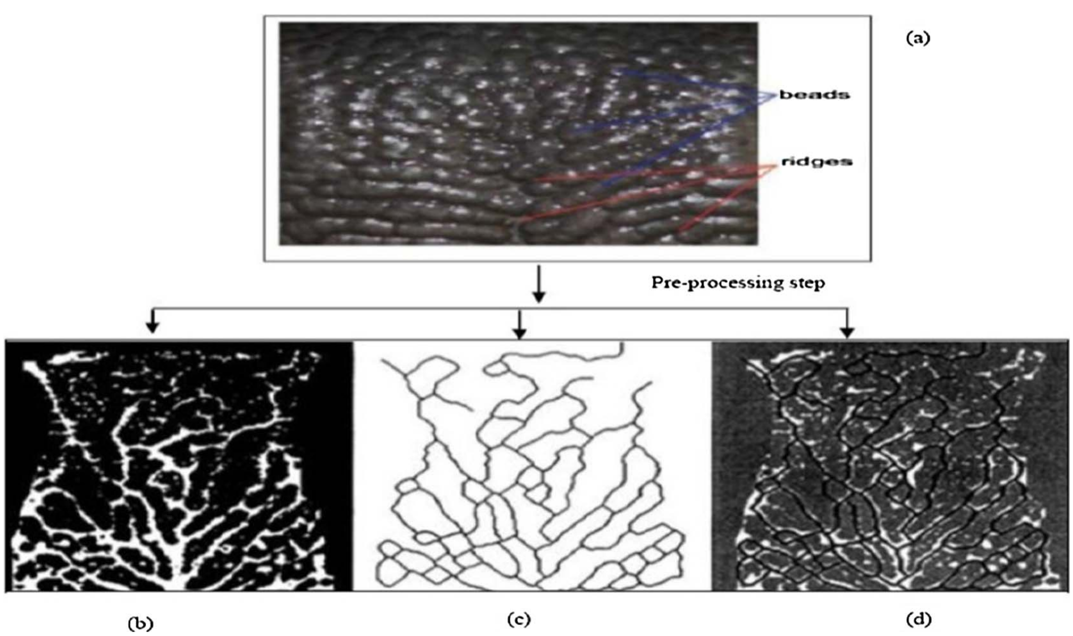


Fig. 3. Illustrates the pre-processing process (a) muzzle point image (b) filtration of discriminatory features (beads and ridges) (c) shows the removal of background (d) find out the ridges and bead features from the overlapped features.

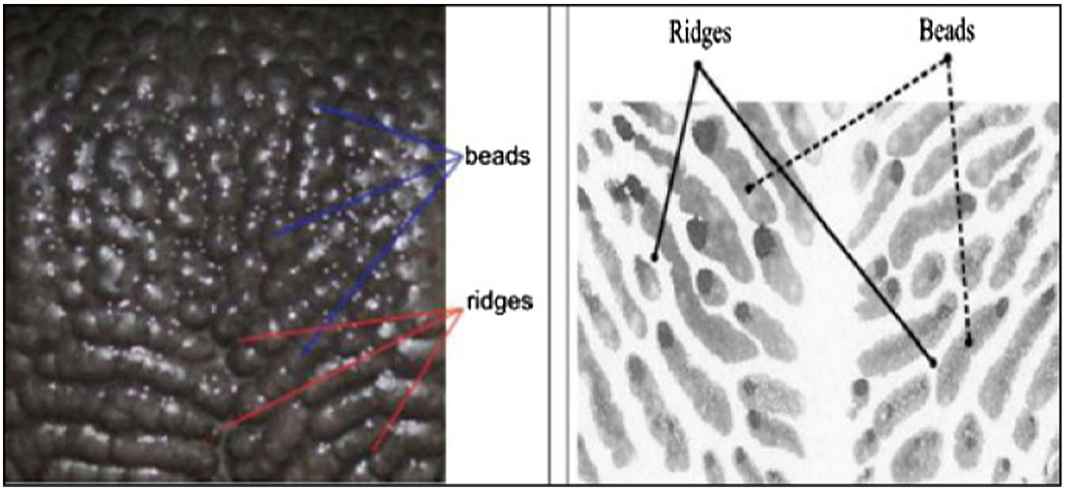


Fig. 4. Illustrates the extraction of discriminatory feature (bead and ridge pattern) from muzzle point image.

classified by deep learning based Restricted Boltzmann Machines (RBMs) classification framework is trained in a greedy manner for learning of feature extraction and representation from the given large unlabelled muzzle point image database and updating the loss function of DBM by including low rank regularization. Finally, a multilayer deep learning neural network has been used as classifier to achieve the identification decision for cattle.

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

The purpose of animal biometrics-based cattle recognition system is to provide the efficient methodologies for registration of livestock animals using its biometric characteristics such as muzzle point image pattern (nose image pattern) and face image biometric features. The cattle recognition system also caters the better method for cattle monitoring, and traceability of individual cattle in the farmhouses. Moreover, cattle recognition system also plays a vital role in the verification of false insurance claims and enhance the breeding associations, and breeds production. Nowadays, massive numbers of non-registered livestock animals are transferred across the borders for slaughterhouses. The cattle recognition system can perform the accurate verification of registered and non-registered cattle to stop these activities of border transfer of livestock animals for slaughterhouses.

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

4.1. Pre-processing and enhancement

In this subsection, we have applied various image pre-processing techniques to mitigate the noises from captured muzzle point images. The fundamental problems involved in the acquisition of images of cattle are (a) little illumination and (b) poor image quality. The capture muzzle point images from the unconstrained environments are transformed into greyscale images to mitigate the artefacts and noises from muzzle point images [25].

After the pre-processing, the transformed images are enhanced by contrast limited adaptive histogram equalization (CLAHE) based image processing technique. It improves the contrast between patterns of muzzle point images. Moreover, CLAHE enhancement technique over amplifies the distinct noises in approximately similar regions of interest in muzzle point image pattern [25].

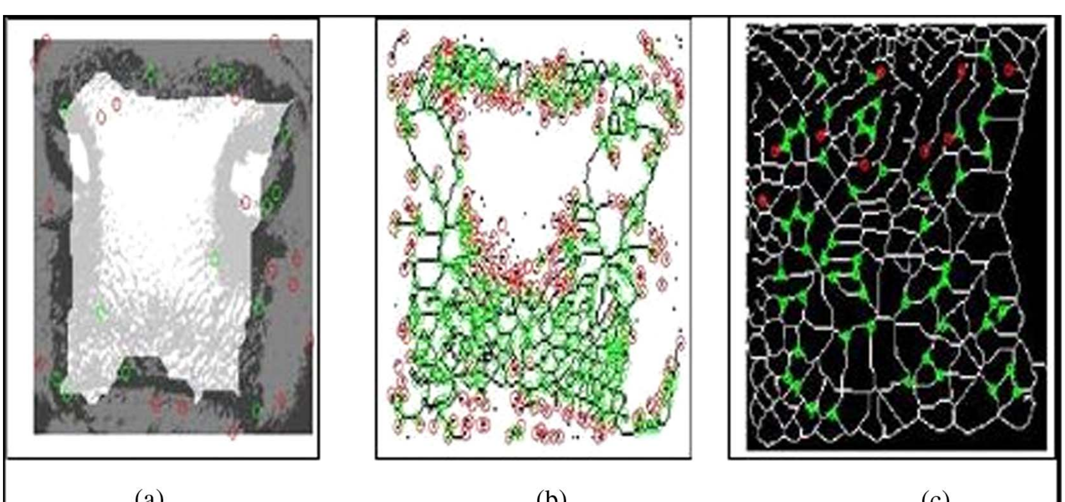


Fig. 5. Illustrates the segmentation of muzzle point images: (a) illustrates the region of interest (ROI) of muzzle point images, (b) ridge bifurcation (green colour) and ridge termination (red colour) are extracted from ROI and (c) suppression of irrelative feature information.

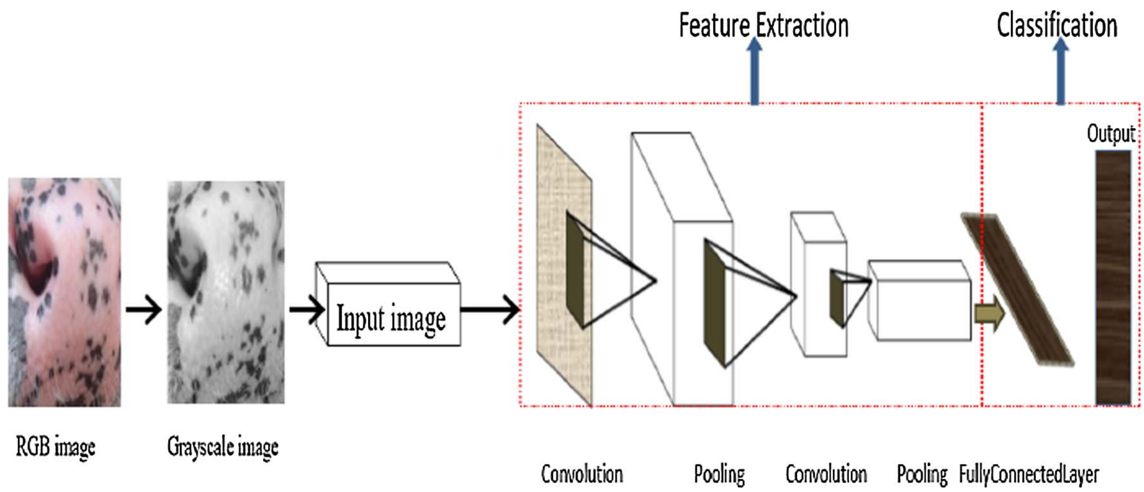


Fig. 6. Block diagram of proposed deep learning based framework for cattle recognition.

4.2. Feature extraction and representation of muzzle point image

The proposed system consists of a deep learning framework for the learning and representations of the extracted sets of discriminatory texture and holistic features of the muzzle point image pattern (as shown in Fig. 5). Since the proposed recognition system is used as the general in nature. It is explained using different deep learning architectures: Convolutional Neural Network (CNN) [26,27], Deep Belief Network (DBN) [28–30] and Stacked Denoising Auto-encoders (SDAE) [31,32]. The following subsection first explains the basics of CNN, DBN, and SDAE auto-encoder techniques followed by the proposed cattle recognition system with multiple neural networks [13].

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

4.3. Convolution neural network

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

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

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

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

$$Y^{j(r)} = f\left(C^{j(R)} + \sum_i K^{ij(R)} * (X^{i(R)})\right) \tag{1}$$

In the Eq. (1), $(*)$ denotes the convolution operation. (X^i) and (Y^j) represent the (i^{th}) input and the (j^{th}) output in the CNN, respectively. The softmax () as a non-linear activation function is chosen in the proposed approach. The softmax () activation function provides a feature gradient at the final layer of a network used as for classification. Where(R) depict a local region in the defined layers where assigned weights are shared between the layers.

The prepared database is captured from unconstrained environments, such as low illumination, the poor image due to blurriness, and head movement, body dynamics of cattle. To handle this problem, we have applied the Convolution Neural Networks (CNNs) [8,9], for automatically learning of extracted discriminatory muzzle features.

In the fully-connected layers, the input muzzle images are depicted as a vertical line of neurons. The proposed recognition system gives the input pixels of muzzle point images to a layer of hidden neurons. For each local receptive field, different hidden neurons are chosen in the first hidden layer.

After that, we start the local receptive field over by one pixel to the right (i.e., one neuron), to connect to a second hidden neuron and so on, to building up the first hidden layer. As mentioned in the above section, each hidden neuron has a bias weight (C^j) and (5×5) weights connected to its local receptive fields. For training, we have chosen the same (5×5) weight matrix and bias weight (C^j) for each of the (24×24) hidden neurons shown as follows:

$$\sigma\left(b + \sum_{l=0}^{l=4} \sum_{m=0}^{m=4} w_{l,m} \times (a_{j+l,k+m})\right) \tag{2}$$

In other words, for the (j^{th}) layers, output of (k^{th}) hidden neuron is given in Eq. (2). Where$(\sigma)$is the neural activation sigmoid function. (C^j) is the shared weight value for the bias $w(l,m)$. It is a (5×5) matrix of shared weights. Finally, we use (x) and (y) to denote the input activation at position (x,y). The first two convolution layers are followed by max-pooling layer for feature reduction and increasing their robustness to distortions of muzzle point image pattern.

B. **Max-pooling layer:** The max-pooling layer is applied in the proposed approach for selection of the maximum values of every (2×2) grid in the muzzle point feature map. This procedure units directly outputs the maximum activation in the input region (as shown in Eq. (3))

$$P(s) = Y^i_{j,k} = \underbrace{\max}_{1 \leqslant p,q \leqslant s} (x^i_{(j-1).s+m,(k-1).s+n}) \tag{3}$$

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

4.4. Classification of features using deep belief network and restricted Boltzmann machines

A Deep Belief Network (DBN) is the graphical deep learning model which is applied to learn the extracted sets of extracted features of muzzle point image pattern for hierarchical representation using the training detains the training phase of the proposed system [28,29]. DBN learning framework is proposed by stacking of Restricted Boltzmann Machines (RBMs) learning techniques. It is trained in a greedy manner for classification of extracted features. The main motivation to apply the RBM a deep learning technique is that it is extremely useful for unsupervised learning of the feature extraction and representation of muzzle point image which is taken from the given large unlabeled muzzle point image database.

For the classification, the logistic regression classifier is used based on $h(l)$ (the last hidden layer of DBN learning model). This step is similar with the using the weights (w) and hidden layer biases which is generated with the unsupervised training for initialization of the weights of a Multilayer Perceptron Layer (MLP) neural network. The training of the proposed deep DBN learning model is shown in Fig. 7. In this approach, the DBN learning model is applied by constructing the multiple RBM models. The RBM classification is stacked on top of layers. Each layer consists of multiple nodes which feed into the next layer [30].

The basic working model of Restricted Boltzmann Machines (RBMs) framework for cattle recognition is that a Deep Belief Network (DBN) deep learning framework is used for extracting and learning the extracted set of texture features of muzzle point images. The DBN is the graphical deep learning model which is used to learn the extracted features of muzzle images for hierarchical representation of the training datasets by stacking of Restricted Boltzmann Machines (RBMs) classification technique for classification and identification of individual cattle based on extracted muzzle point features.

5. Stacked denoising auto-encoder

Stacked Denoising Auto-encoder (SDAE) is encoding technique to encode and decode the extracted features [31]. In this paper, Stacked Denosing Auto-encoder (SDAE) deep learning technique is applied to encode and decode the extracted texture feature extraction of muzzle point image pattern of cattle and encoding the extracted set of features for better feature representation in feature space.Stacking denoising auto-encoders is applied to initialize the deep network. It works in much the same way as stacking the RBMs models in deep belief networks. The stacking of denoising auto-encoder is chosen such that the output layer of the first auto-encoder operates as the input layer of the second auto-encoder. The two fundamental components of an auto-encoder are mainly - (1) the encoder and (2) decoder. An encoder maps the input (X) to the hidden layer nodes using deterministic mapping function $(f\colon h = f(X))$ (shown in Eqs. (4) and (5)).

$$f = G\theta X = s(w.\,X + \Delta) \tag{4}$$

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

$$Y'' = G'\theta' f = s(w.\,X' + \Delta') \tag{5}$$

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

A decoder maps the hidden nodes back to the original input space through another deterministic mapping function $(G_{W',b'})$. For real-valued input, by minimizing the reconstruction error $(f_{ae} = \|X - Y''\|_F^2)$. The parameters of auto-encoder and auto decoder can be learnt for recognition of cattle. The parameters are optimized by utilizing the unsupervised training data. Then the output of the hidden layer is used as the feature for image representation. The auto-encoders is arranged to form an underground network by nursing the latent representation (output code) of the denoising auto-encoder found on the layer below as input to the current layers [32].

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

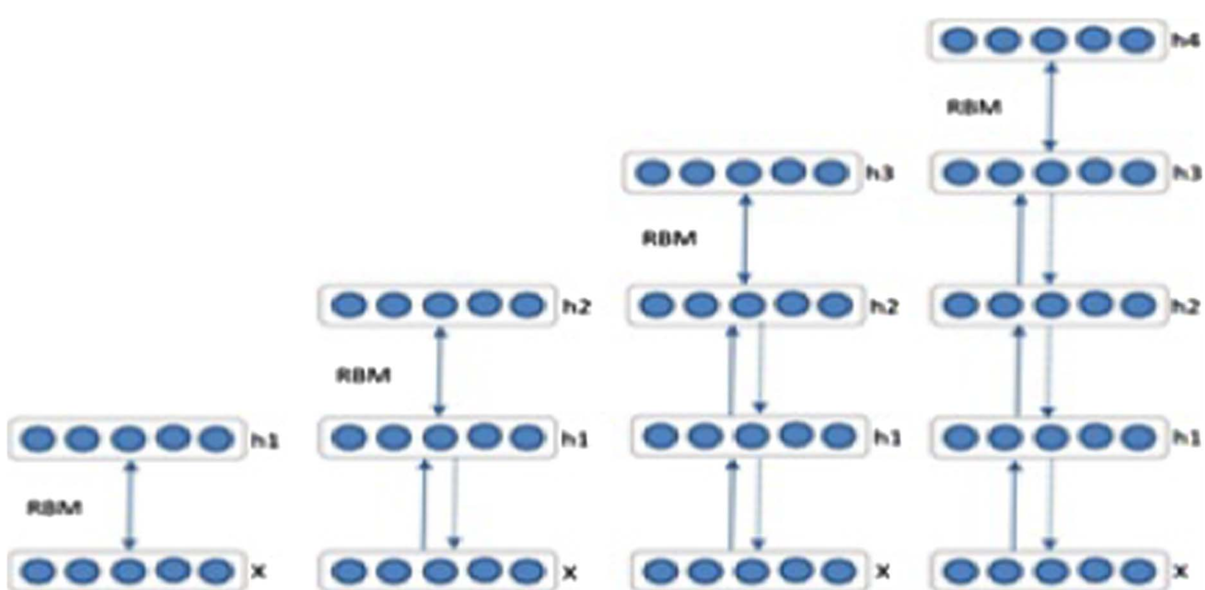


Fig. 7. Illustrates the architecture of DBN learning model composed of 4 stacked RBM classification approaches.

unsupervised pre-training of stacked denoising auto-encoder architecture is performed one layer at a time. Each layer is trained as a denoising auto-encoder by mitigating the error in reforming its input (which is the output code of the previous layers). Once the first (K) layers are trained, we can train the $(K+1)$. The layer because we can now calculate the code or latent representation from the layer below. The non-linear mapping function $(f_{W,b})$ is applied for vectorized input image (X) and the hidden representation (Y) is calculated as follows (shown in Eqs. (6), (7) and (8), respectively):

$$Y = f_{W_{ij},b}(X) = S(W_{ij}.\ X + b) \tag{6}$$

Where $S(\cdot)$ denotes the sigmoid activation function and W and b are the weight matrix and bias of the mapping function and W_{ij} represents the weight of the connection from the (i^{th}) input node to the (j^{th}) hidden node. The decoder maps the learnt features to the data space, using the following Eq. (6). A reconstruction step (GW',b') is implemented on the lower dimensional mapping (y) as follows:

$$(GW',b') = (Y'') = S(W'.\ Y + b') \tag{7}$$

In the Eq. (7), W' represents the weight matrix. W_{ij} shows the weight function of the connection from the (i^{th}) hidden node to the (j^{th}) decoder output node, and b' presents the bias constraint of mapping function. Next, we have evaluated loss function of an auto-encoder as follows (show in Eq. (8)):

$$f_{ae} = \|X - Y''\|_F^2 = \|X - S(W'S(WX+b)+b')\|_F^2 \tag{8}$$

The stacked denoising auto-encoder is a nonlinear auto-encoder for representation of extracted feature which is different from PCA [33], and Linear Discrimination Analysis (LDA) [34] techniques. It has been decided that training an auto encoder is to reduce reconstruction error by maximizing a lower bound on the mutual feature between input layer representation and the learned representation [28,29]. We added the sparsity constraints for further boost the ability of auto-encoder for representation of extracted muzzle point images in proposed deep networks. The proposed deep learning approach enhances the generalization of auto-encoder by training with locally corrupted inputs of muzzle point image pattern.

In denoising auto-encoder, input (X) is first corrupted by some predefined noise, for example, Additive Gaussian noise $(\widetilde{X}|X \sim N(x,\sigma^2 I))$, masking noise (a fraction of X is forced to 0), or salt-and-pepper noise (a fraction of X is forced to be 0 or 1). Fig. 8(a) and (b) represents the 20% and 30% corrupted muzzle point images for better representation of extracted muzzle point images. We have applied the Rectified Linear Unit (ReLU) activation function in all the encoder layers of proposed cattle recognition system. For supervised fine-tuning, a softmax (0,) activation based layer with 35 nodes has been incorporated on top of each stacked denoising auto-encoders. The four dropout [7] modules are applied in between layers to prevent over fitting. We have chosen the dropout probability as 0.35.

6. Pre-Training and generalizability of proposed recognition model

In this subsection, pre-training of a proposed deep learning recognition model is illustrated in detail. Deep learning architecture needs the massive amount of datasets for the training the proposed models because the optimization functions are formulated to diminish the training error of the proposed model. The proposed design tends to learn maximum information from the given muzzle point image dataset.

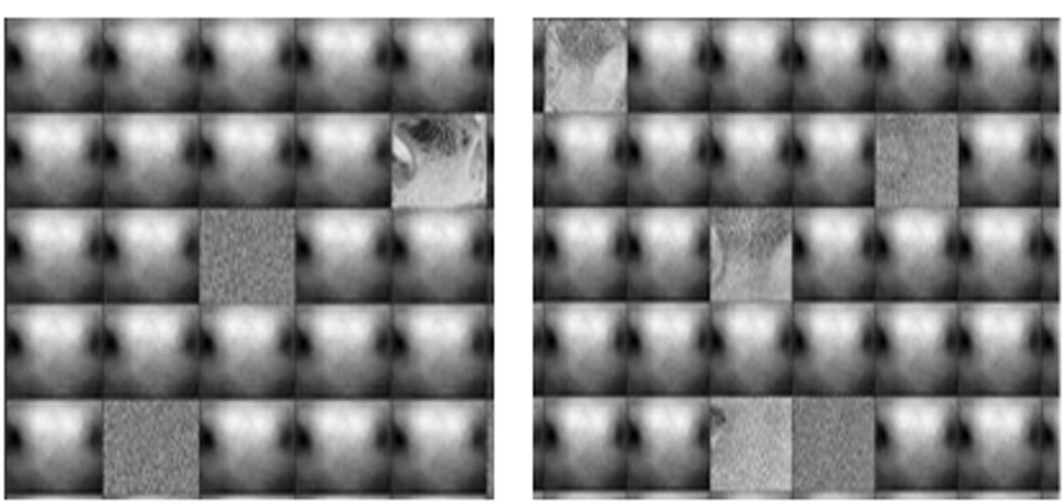
The second major challenge is generalizability [28–30]. It provides a method to train the model which can improve the generalizability without reducing the power of the proposed deep learning model. It is accomplished by including a penalty variable to loss function, known as the regularizer function.

The primary objective to apply the regularization is to provide the better representation of the information in the feature space to avoid over-fitting of a given problem, and yield to a solution faster by offering ancillary features.

The pre-training of each auto-encoder is implemented in greedy fashion one layer at a time. Each layer of an auto-encoder is trained by lessening the rebuilding of its input. The performances of the above three frameworks over a set of test images using the features obtained are calculated, individual, and the one which gives relatively better performance is employed for the recognition purpose. The various identification settings and standard protocols are used for evaluating the experimental results of proposed system and existing handcrafted texture feature descriptor techniques. The experimental results and discussion of proposed system is illustrated in the next section.

7. Experimental results and discussions

In this section, we have performed the experiments to compute the effectiveness of the proposed deep learning approach for the recognition of cattle using muzzle point image pattern. The comparison with existing benchmark algorithms (texture feature descriptor technique, appearance based feature extraction and representation, and learnt feature techniques) is accomplished to evaluate the identification



(a) (b)

Fig. 8. (a) Illustrates 20% corrupted images of muzzle point pattern (b) shows the 30% corrupted muzzle point images using stacked denoising auto-encoder.

accuracy in multiple identification settings.

For performance evaluation of experimental results, the database of muzzle point image pattern is segmented into following phases: (1) training phase and (2) testing phase. In the training phase, 100 muzzle point images (10 cattle (subject) ×10 image of each subject) are utilized to train the proposed deep learning approach. In the testing phase, 400 testing pairs (40 cattle (subject ×10 image of each subject)) of muzzle point image pattern in each fold are used to test the probe images.

The deep learning based framework demands the massive amount of database to train the proposed network. Despite, the size of muzzle point image database is 5000 images which are a relatively smaller image database. It is not satisfactory to adequately train a deep belief network or a stacked denoising auto-encoder. Therefore, a transfer learning approach is applied for the fine tuning the weight between the input and hidden layer and determined the pre-training the proposed deep learning approach.

7.1. Performance evaluations

The proposed deep learning based approach for cattle recognition is motivated by the observation that the muzzle point image pattern of cattle consists of rich and dense texture features in the form of bead and ridges pattern. The bead and ridge pattern of muzzle point image are salient biometric features for cattle recognition.

Moreover, it is challenging to restrict the body movement due to head movement and unconstrained environments during the data acquisition of cattle.

During data acquisition, the unconstrained environments such as low illumination, poor image quality, and blurriness due to head movement are also the biggest problems for recognition of individual cattle, implying that appearance based feature extraction and representation algorithms may not yield good results.

On the other hand, local feature based feature extraction and representation algorithm can provide good results. The hypothesis is that feature (information) content present in the muzzle point image pattern varies with unconstrained environments for cattle.

To efficiently extract and encode texture features of muzzle point image pattern of cattle, local feature descriptor techniques must be used. In this paper, the bead and ridges texture features are extracted from the muzzle point image pattern of cattle database using the handcrafted texture feature descriptor techniques. The handcrafted texture descriptor features and learnt features techniques used for feature extraction and representation. These approaches are mainly Local Binary Pattern (LBP) [35], Circular-LBP [36], Scale Invariant Feature Transform (SIFT) [37], Dense-SIFT [37], Speeded Up Robust Feature (SURF) [38], and Vector of Locally Aggregated Descriptors (VLAD) techniques [39]. The computation of features and encoding of the local binary pattern based feature, SIFT and SURF feature of muzzle point image is shown in Figs. 9 and 10, 11, 12, and 13 respectively.

Moreover, the appearance based feature extraction, and representation methods, and learned feature based techniques are used for the evaluation and comparison of the experimental results of proposed approach.

For comparative analysis, we have also applied the appearance based face recognition and representation approaches, such Principal Component Analysis (PCA) (Eigen-values) [33], Linear Discriminant Analysis (LDA) [40], Kernel-LDA [41], and Direct-LDA [42] for the evaluation of experimental results. Dense-SIFT (DSIFT) feature descriptor technique is applied to extract the set of key points of muzzle point images. These key points are distributed at regular intervals on a uniform grid. In each grid (cell), the discriminatory key-points are selected from a descriptor of length n × 16, where n is the number of orientations.

For the evaluation of performance, we have performed the three experiments to evaluate the effectiveness of the proposed approach and compare with existing benchmark texture descriptor technique and appearance based feature extraction and representation algorithms in multiple identification settings. In this section, we have illustrated the detail evaluation of the experimental results of cattle recognition as follows:

7.1.1. Experiment 1: Accuracy analysis of different state-of-the-art deep learning approaches

Muzzle point images of 100 cattle (subject) are randomly chosen for training the system and the remaining muzzle point images corresponding to 400 (cattle) are used for testing with 1, 2, 3, and 4 images per subject in the gallery. The least one shot similarity based matching scores are obtained per subject. It is used as the similarity match score. Further, all the experimental results are reported with five-times random sub sampling based cross validation technique. The identification experiments are performed and the results are reported in terms of rank-1 identification accuracy along with Cumulative Match Characteristics (CMC) curves as follows:

- The experimental results are also analyzed with varying gallery sizes and summarized in Tables 1 and 2. The experimental results are also depicted in Figs. 14 and 15, respectively. With the proposed deep learning approaches, such as CNN, SDA and DBN yield 75.98%, 88.46%, and 95.99% identification accuracy for identification of individual cattle, respectively.
- The proposed approach has two components: (1) learning the robust texture feature of muzzle point image feature for representation and learning the distance learning based metric with One-Shot Similarity (OSS) based similarity matching techniques.
- For evaluation of effectiveness of both the components of proposed approach, we tactically replaced one component at a time with existing descriptors or matchers (Chi-square (χ^2) based dissimilarity

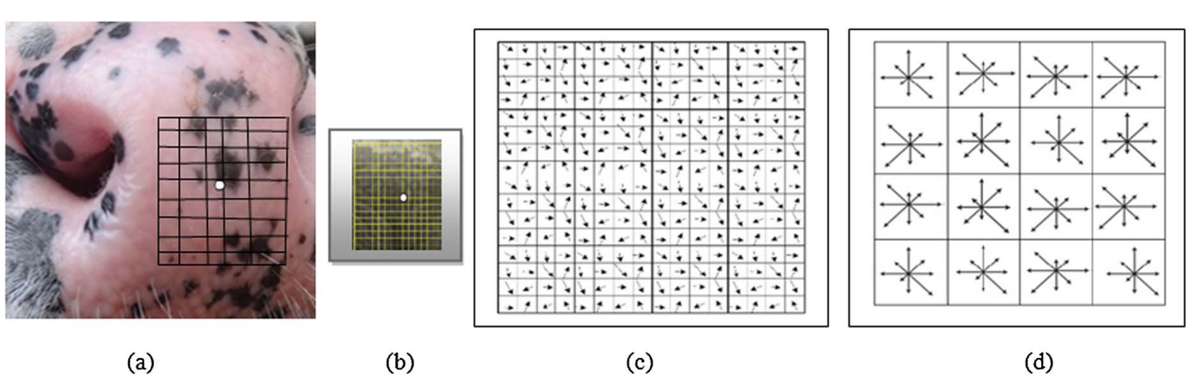


Fig. 9. Illustrates the SIFT keypoint descriptor: (a) input muzzle point image (b) A SIFT descriptor of the size (m × n) is chosen from muzzle point image, (c) selection of 16 × 16 pixel orientations, (d) 4 × 4 cells descriptor with 8 pixel orientations are chosen. The size of single SIFT keypoint descriptor is 4 × 4 × 8 = 128 element.

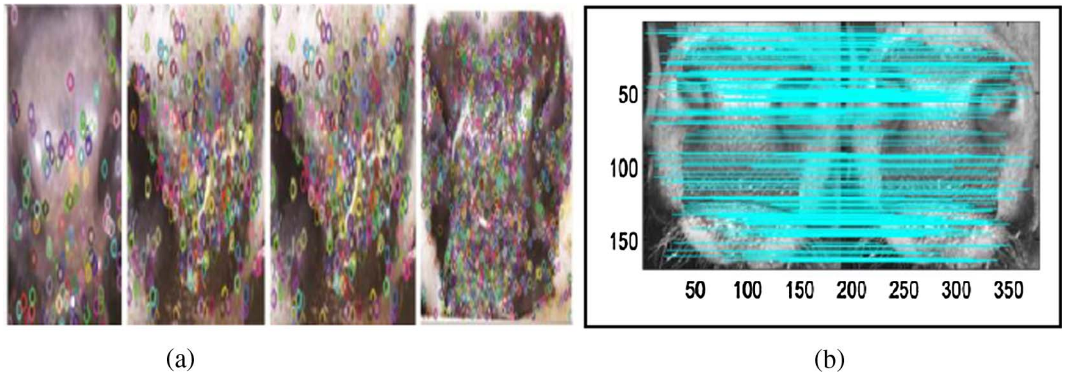


Fig. 10. Illustrates (a) the process of SIFT keypoint localization; detection and (b) matching of test muzzle point image with stored muzzle point image using SIFT keypoint descriptor.

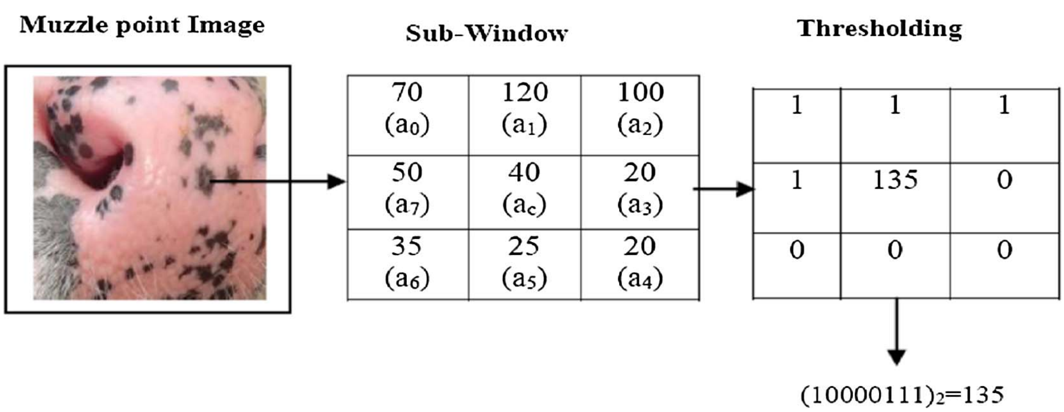


Fig. 11. Illustrates the extraction and encoding of local binary pattern based descriptor features from the muzzle point image pattern.

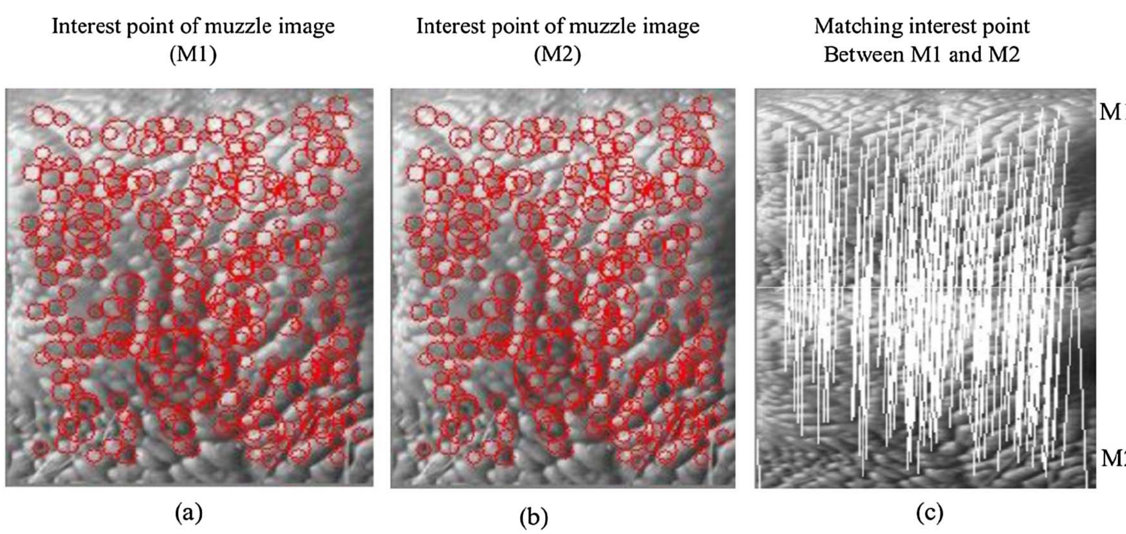


Fig. 12. Illustrates the process of building of SURF descriptor: (a)-(b) shows the detection of keypoints in the muzzle point images (c) matching of muzzle point images based on keypoint SURF descriptor with size (for a neighborhood of size 6s where s is scaling parameter of wavelet responses in horizontal and vertical directions.

matching technique) and compared the experimental results with four gallery muzzle point images per subject (cattle).

- As shown in the Table 1, it can be observed that with increasing the number of muzzle point texture feature of cattle database per subject from one to four, the identification performance of deep learning framework using the DBN learning technique provides the highest identification accuracy for identification of individual cattle. Table 1 illustrates the average identification accuracy based on individual patches of the muzzle point image pattern of cattle for recognizing individual cattle.
- Identification accuracies using the proposed deep learning framework are calculated by considering different number of muzzle point image features amongst the calculated ones. It can be observed that with the increase in usage of number of texture features of muzzle point image pattern of cattle, the identification accuracies are gradually increasing in all the three deep learning algorithms (as shown in Table 2). This explains the importance of all the muzzle point image features.

As explained earlier, as the number of features is increasing, the identification accuracies are gradually increasing but at every instant DBN technique provided the good experimental results amongst the

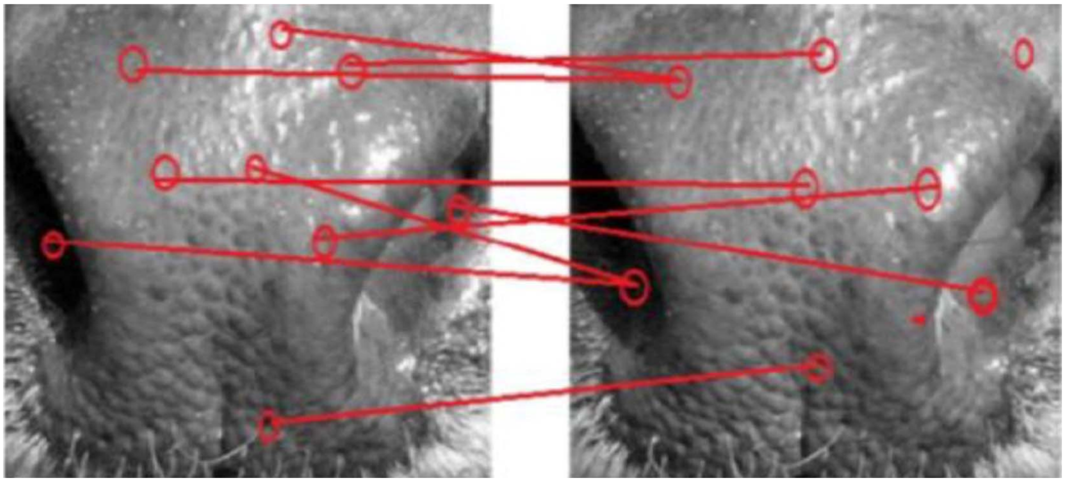


Fig. 13. Matching of keypoints of muzzle point images using SURF descriptor.

Table 1
Illustrates the identification accuracy (%) of CNN, SDAE, and DBN deep learning approaches.

S. No.	Proposed approach	Identification accuracy (%)
1	CNN	75.98
2	SDAE	88.76
3	DBN	95.99

Table 2
Identification accuracy (%) of CNN, SDAE and DBN deep learning approaches.

Number of feature sets	Identification accuracy (%)		
	CNN	SDAE	DBN
50	63.75	67.75	65.95
100	67.98	68.65	69.85
150	73.85	71.96	75.85
200	76.75	76.92	77.94
250	79.98	78.67	82.99
300	82.99	85.98	86.92
350	86.75	89.79	94.75
400	95.98	96.92	98.99

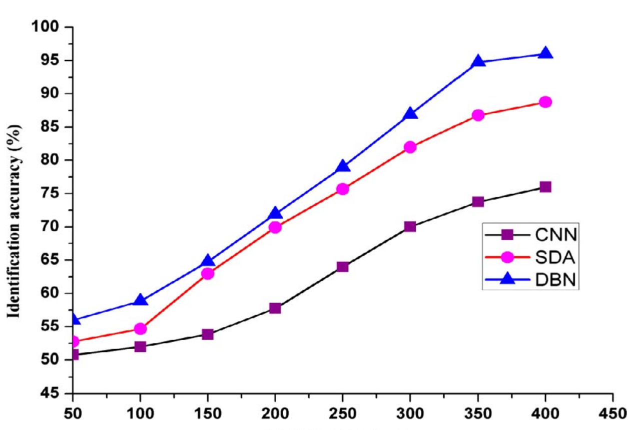


Fig. 14. CMC curve illustrate the identification accuracy vs. number of muzzle point features.

three deep learning approaches. This is can be seen in Fig. 14.

The identification accuracy of DBN is higher as compared to convolution neural network and stacked denoising auto-encoder based deep learning approaches for recognition of individual cattle. The deep

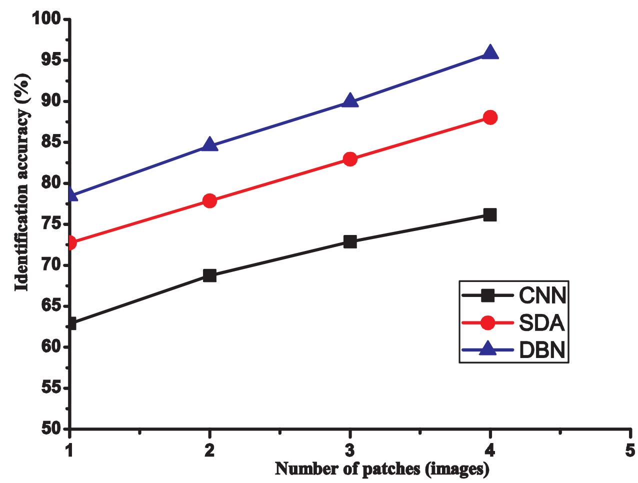


Fig. 15. CMC curve illustrate the identification accuracy vs. number of patches (images).

learning based DBN approach yields 98.99% of identification accuracy for identification of cattle.

It is observed that the identification accuracies of the three deep learning frameworks are gradually increasing with the increase in the number features of selected patches from the muzzle point texture features. After the selection of 400 numbers of features from each patch (size: 200 × 200 pixels), deep learning algorithms provide the robust representation of muzzle point features in the different layer of the proposed framework.

When the size of each patches of muzzle point images are reduced, the selected discriminatory set of the muzzle texture feature has also reduced, therefore, we have selected the 400 number of features as better muzzle point feature sets from the extracted patches. This shows us that all the patches of muzzle point image pattern have been calculated collectively to describe and represent the discriminatory set of muzzle point features to the best extent than a set of few patches (as shown in Table 1 and Table 2, respectively).

7.1.2. Experiment 2:Average accuracy analysis with standard deviation of existing handcrafted texture feature and representations

In this section, we have evaluated the performance of the existing handcrafted texture feature and representation algorithms.

- We have also applied the handcrafted texture features based representation algorithms for evaluations of experimental results for identification of cattle. The experimental results are summarized in

Table 3
The experimental results are reported in terms of average accuracy with standard deviation over 10-fold cross-validation for Existing Handcrafted Texture Features based methods.

Existing Handcrafted Texture Features based method	Methods	Number of muzzle point images per subject (cattle) in gallery			
		1	2	3	4
	LBP + χ^2	72.84 (0.8)	73.52 (0.83)	73.76 (1.23)	74.97 (1.2)
	Circular-LBP	73.87 (1.5)	76.5 (1.83)	78.96 (1.56)	79.87 (2.2)
	SIFT + χ^2	67.98 (1.2)	69.97 (1.2)	70.97 (2.2)	72.85 (1.3)
	Dense-SIFT + χ^2	69.75 (2.6)	71.84 (2.6)	73.98 (1.4)	75.89 (1.65)
	SURF	75.48 (0.9)	78.99 (1.5)	85.49 (1.3)	89.76 (1.43)

Table 3, respectively.

- In Table 3, the existing handcrafted texture feature based descriptor algorithms such as Local Binary Pattern (LBP) and Circular-LBP (Circular-LBP) feature descriptors provide the rank-1 identification accuracy of 72.84 ± 0.80% to 74.97 ± 1.2 and 73.87 ± 1.5 to 79.87 ± 2.2, respectively with 4 muzzle point images of cattle as gallery image per subject (cattle).
- The SIFT feature descriptor techniques such as SIFT and Desne-SIFT (D-SIFT) yield identification accuracy of 69.75 ± 2.6 to72.85 ± 1.3 and 69.75 ± 2.6 to 75.89 ± 1.65, respectively.
- The evaluation of the experimental results, we performed the testing of muzzle point images multiple in the gallery. During the experimental results on every test muzzle point images, we have calculated the least distance matching scores for every subject.
- The matching score values are used for evaluation of the experimental results. The experimental results illustrate that even with multiple gallery muzzle point images, the identification accuracies are reported in the increasing order however, the performance leaning remains the same.
- The better performances of texture feature based descriptors algorithms are attributed to spatial collation in regional blocks that is able to good deal with the covariates, such as pose due to head movement, body dynamics, poor image quality and low illumination.
- Vector of Locally Aggregated Descriptors (VLAD) [39] is a feature extractor learning based descriptor algorithm. It extracts visual information (features) the training datasets [39].
- As illustrated in given Table 4, the better recognition accuracy is achieved with OSS [43] (SVM [44] classification model) for this representation when the gallery consists of four images per cattle subject, with rank-1 accuracy of 45.98 ± 0.8% to 59.64 ± 1.12% and VLAD + LDA + SVM technique yields 50.76 ± 1.6% to 67.98 ± 1.17%, respectively.
- Based on overall performance of the existing handcrafted feature descriptors techniques, SURF descriptor provides better identification accuracy of 75.48 ± 0.9) to 89.76 ± 1.43, respectively because the detection of the SURF descriptor compute the discriminatory keypoints of muzzle point image pattern efficiently in the different scales (vertical and horizontal scale of wavelet responses) as compared to SIFT and Dense-SIFT approaches.

Table 4
The experimental results are reported in terms of average accuracy with standard deviation over 10-fold cross-validation for texture holistic features based recognition algorithms.

Existing Learnt Feature based method	Methods	Number of muzzle point images per subject (cattle) in gallery			
		1	2	3	4
	VLAD + LDA + (OSS)	45.98 (1.5)	49.89 (1.47)	53.94 (1.22)	59.64 (1.12)
	VLAD + LDA + SVM	50.76 (1.6)	54.92 (1.27)	58.74 (1.02)	(1.17)

7.1.3. Experiment 3: Average accuracy analysis with standard deviation of appearance based face recognition algorithms

Features of muzzle point images were extracted using the appearance based feature extraction and representation approaches, such as PCA, 2-D PCA, LDA, and its modified LDA version (e.g., Kernel-LDA, Direct-LDA) algorithms, respectively. As shown in Fig. 2, following operations are applied to perform matching of extracted set of features and representation of muzzle point texture feature for identification of individual cattle:

- Principal Components Analysis (PCA) technique is used to perform the dimensionality reduction of extracted feature of muzzle point image database. PCA technique compute the on the feature space. Principal components corresponding to 99% Eigen-values in the PCA subspace are retained.
- The extracted texture features are classified is using supervised learning Linear Discriminant Analysis (LDA) technique.
- The Cosine similarity matching based method, One-Shot Similarity (OSS), distance learning based metric technique are used for the similarity matching score after matching a pair of samples (muzzle point image patterns of cattle).
- After that the similarity matching scores are measured. The identification accuracies of cattle are shown in Table 5. Based on observation of Table 5 it is shown that the Kernel-LDA and Direct-LDA techniques provide 60.89 ± 1.87% to 68.97 ± 1.28% and 63.77 ± 1.79 to 69.97 ± 1.33, identification accuracies for cattle recognition.
- On the other hand, texture feature descriptor techniques, such as SURF, LBP, Circular-LBP, SIFT, Dense-SIFT and VLAD are handcrafted existing features based descriptors for the better representation of muzzle point features for identification of individual cattle. The LBP and Dense-SIFT descriptor algorithms illustrate the low recognition accuracy as compared to VLAD + LDA with One-Shot-Similarity (OSS) and VLAD + LDA with Support Vector Machine (SVM) techniques for identification of individual cattle using their primary muzzle point image pattern. The learnt feature descriptor techniques, such as VLAD + LDA + OSS and VLAD + LDA + SVM technique yield 60.89 ± 1.5% to 59.64 ± 1.12% and 50.76 ± 1.6 to 67.98 ± 1.17 identification accuracy, respectively.

The capture muzzle point image database has several significant challenges due to the unconstrained environment, such as poor illumination, image quality, low contrast, and blurred. Therefore, existing feature extraction and representation algorithms are unable to perform identification of cattle using muzzle point images. The learning-based

Table 5
The experimental results are reported in terms of average accuracy with standard deviation over 10-fold cross-validation on holistic features based recognition algorithms.

Holistic Feature based Methods	Methods	Number of muzzle point images per subject (cattle) in gallery			
		1	2	3	4
	PCA	65.89 (1.67)	68.95 (1.83)	69.86 (1.23)	70.97 (1.2)
	2D-PCA	67.89 (1.84)	69.65 (1.63)	73.86 (1.51)	75.67 (1.45)
	LDA	69.96 (1.98)	72.91 (1.64)	73.48 (1.43)	74.99 (1.37)
	Kernel-LDA	60.89 (1.87)	65.65 (1.73)	67.86 (1.57)	68.97 (1.28)
	Direct- LDA	63.77 (1.79)	65.96 (1.63)	68.96 (1.53)	69.97 (1.33)

Table 6
Comparison of our proposed approach with the literature.

Authors	No. of images (Muzzle print images) and cattle	Technique used	Identification accuracy (%)
Noviyanto et al. [4]	80 images	SURF + kappa statistic + Eigen-face Algorithm	89.30%
Minagawa et al. [18]	43 muzzle print images using ink	PCA + Eigen-values based approaches	30%
Barry et al. [19]	29 cattle breeds	Eigen-value + Segmentation based technique	98.50%
Awad et al. [20,50]	15 cattle breeds	SIFT + RANSAC	93.30%
Noviyanto et al. [21]	48 muzzle images	SIFT + PCA	0.0167 (EER)
Kumar et al. [4,23]	300 cattle	PCA + LDA + ICA	85.95%
Gaber et al. [24]	31 cattle	WLD + ABD	99%
Cai and Li [45]	30 cattle	RASL + WLBP	95.30%
Tharwat et al. [46]	31 cattle	Gabor + SVM	99.50%
Kumar et al. [47,54]	Pet animals (dog), 50 dog breeds	PCA + LBP + modified algorithms (Batch-ILDA, CCIPCA, Incremental-SVM)	94.86%
This research study	5000 muzzle point image (500 subject and each subject has 10 images)	Deep learning approaches (Convolution Neural Network (CNN) + Deep Belief Network (DBN) and Stacked Denoisingauto-encoders (SDAE)) + SVM + One-Shot-Similarity (OSS)	95.98% (CNN), 95.99%(DBN) + 96.92%(SDAE),98.99% (DBN)

Where, WLD = Weber's Local Descriptor, ADB = AdaBoost classifier, WLBP = Weber's Local Binary Pattern Descriptor, RANSAC = RANdom Sample Consensus algorithm.

feature extraction and matching approaches cater an explicit encoding mechanism of extracted feature to improve the recognition accuracy of individual cattle.

We have applied the One-Shot Similarity (OSS) similarity using Fisher linear discriminant analysis (FLDA), and incremental support vector machine (SVM) classification models are applied. The 1-class online incremental SVM (1-online ISVM) model is used to classify the extracted texture features of muzzle point images.

The OSS matching is a semi-supervised based matching similarity technique. It selects the unlabeled training data as a set of negative constraints against which two input sample images of muzzle point pattern are matched. Based on the overall experimentations, and achieved recognition accuracy our belief is that handcrafted existing benchmark based texture features extraction and representation have are bound and limited representation capacity as these descriptors are not applicable for better recognition of cattle in the specific problem domain.

The proposed deep learning based framework performs the encoding and learning of the discriminant feature representation of muzzle point image pattern and the machine learning based distance metric techniques capture the semantic representation of features and understanding of the SDAE encoding and decoding scheme.

7.2. Comparative analysis

In this section, we have performed the detailed analysis of experimental analysis of proposed deep learning approach for recognition of cattle based on muzzle point images. We now compare the performance of our proposed deep learning framework based system against current state-of-art approaches for recognition of livestock based on their muzzle print images from the literature.

For, capturing the muzzle image pattern of cattle, the manual acquisition methodologies are not applied. In the classical acquisition methodology of muzzle print images of cattle includes the equipment and materials (such as A5-size white papers, black ink and stamp (impacted), soft cottons, hard ropes, tissue paper and assistant team of the dairy staff members) to capture the images of muzzle print of individual cattle for preparation of database.

The print images of muzzle pattern are captured on A-5 white paper with blue ink. The captured print images are required to mitigate the noises and other artifacts using image processing techniques. However, the captured print images have very low image quality. Therefore, it also requires some enhancement and transformation techniques to convert the print muzzle image into digital muzzle print images (300 dot per inch (DPI), resolution of images).

In the classical muzzle print identification based systems includes well-defined manual procedures for identification of cattle. These systems have provided the paradigm to the interdisciplinary researches, scientists, and veterinary professionals for identification and monitoring of individual cattle. However, muzzle print-image-based identification system consumes more time for processing of images, feature extraction and image analysis works. Therefore, in this research work, we have captured the image of muzzle point pattern of cattle using 30-megapixel digital camera.

To perform the identification of cattle, the muzzle point image database is prepared from the Department of Dairying and Husbandry, Institute of Agriculture Sciences (I.A.S), Banaras Hindu University (B.H.U), Varanasi, India-221005.

The prepared database consists of original images of muzzle point pattern of cattle. The database also includes various covariates of muzzle point images due to poor image quality, low illumination, pose, variation images.

In the available literature, there is no availability of muzzle point image database in the public domain. Very few researches have been done for the identification of cattle based on the muzzle point image pattern. Based on printed muzzle images, we have compared the experimental results of proposed approach with previously published results for identification of cattle based on muzzle print image database. The experimental results are achieved by applying the computer vision, image processing and pattern recognition techniques. The comparative analyses of the experimental results are shown in Table 6.

Noviyanto et al. [4] proposed a method using speeded up robust features and Eigen-face based approaches for recognition of individual cattle based on muzzle print image database. The major shortcoming of proposed approach is that the authors do not include the image filtering techniques to remove the noise from the captured muzzle print images. It may affect the identification accuracy of proposed system. Furthermore, they performed the experimentations on the small database of muzzle print image of cattle. The proposed approach cannot test on the different rotation and scaling of muzzle print images for identification of cattle.

In [18], authors proposed a cattle recognition based framework for identification of cattle using Eigen-values based approaches. The authors have applied principal component analysis techniques to mitigate the dimensionality of extracted features.

The proposed approach by Minagawa et al. [18] has not reported exactly experimental results the same due to the unexplained filtering techniques. In [19], Barry et al. proposed cattle identification using principal component analysis and Euclidean distance classifier techniques based on muzzle print images.

The proposed approach is selected for training separately on a different number of normalized muzzle images sets of 2, 4, 6, 8, and 10 training images from 29 cattle.

The drawback of the approach is that an experimental result was taken on a separate set of 3 images only per animal. The authors have not performed any cross-validation of the experimental results. The implementation of the approach proposed by Barry et al. [19] is also not exactly the same due to the watershed segmentation technique is not implemented properly. The approach proposed by Barry et al. [19] has been very strict due to the false match has been zero. 468 false non-matches have been reported over 560 genuine matching.

In the similar direction, Awad et al. [20] proposed a method to improve the performance of proposed cattle identification system. They have applied the SIFT keypoint matching based descriptors. The SIFT descriptor technique is utilized to find out the keypoints for matching of muzzle print images. For better identification, Random Sample Consensus (RANSAC) technique is utilized with the SIFT to mitigate the noises such as outlier points. However, the proposed approach has following major limitations-(1) no cross-validation of experimental results, (2) identification accuracy is suffered from the noises such outliers, blurriness, and poor image quality. Noviyanto et al. [21] implemented the proposed a matching refinement technique based on SIFT keypoints matching technique.

In [24], authors proposed a method for identification of cattle using Weber's Local Descriptor (WLD) technique. The proposed approach extract the features from cattle muzzle print images (images from 31 head of livestock). The extracted features are classified by AdaBoost classification model to identify the head of individual cattle from their WLD descriptor features. The limitation of this paper is that experimentations are carried out the small datasets, and no cross-validation technique is applied to validate the experimental results.

Cai and Li [45] proposed a method for automatic recognition of cattle using local binary pattern based facial feature descriptor and extended LBP descriptors techniques. The robust alignment by sparse and low-rank decomposition approaches is applied to align the face images of cattle due to poor illumination, image misalignment and occlusion problem in the test face image of cattle.

The dissimilarity between test and trained images are performed on a separate set of face images using the weighted Chi-square distance technique. The major shortcomings of this paper are that authors have not performed the experimental results on slight datasets, (2) no preprocessing technique is applied for processing of facial images of cattle using image processing technique and (3) any cross-validation is not applied to verify the identification accuracy. In [46], the authors proposed a cattle identification using Gabor filter-based feature extraction technique. The proposed extract Gabor features from muzzle print images. The extracted features are classified by using support vector machine based classification technique at different kernels.

The author, Kumar et al. [48] proposed a real cattle recognition system using Fisher locality preserving projection based recognition algorithm for the recognition of individual cattle in real time. In the proposed systems captures the images of cattle using a surveillance camera and captured image of muzzle point of cattle is transferred them to the server side by using wireless network communication technology [49].

The proposed recognition algorithm based on muzzle point features approach yields 96.87% accuracy for identification of cattle. The author Mishra et al. [53] did the dermatoglypics of cattle muzzle pattern using blue ink images to identify bovines. In his study, they have performed the identification of cattle using classification techniques.

Recently, the authors Kumar et al. [51,52] proposed a real time monitoring and tracking systems for the pet animals in smart cities using animal biometrics and computer vision techniques.

The proposed system extracts the facial images based pixel intensity feature for identification of pet animal (dogs). The systems uniquely identify the pet animal based on their primary animal biometric identifiers. The proposed recognition system apply the one-shot similarity matching techniques to calculate the similarity matching score after the matching of query face image of cattle with stored image datasets of animal. Moreover, the distance metric based learning method is used for matching and classifying the extracted features of face images for recognition of pet animals (dog). The efficacy of proposed recognition system yields 96.87% recognition rate.

Based on overall observation, we conclude that our proposed method uses the deep learning based framework for recognition of cattle and achieves significant improvements over all of this existing handcrafted feature descriptor, baselines algorithms which are available in the literature [55–62].

8. Conclusions and future directions

In this paper, we proposed a novel deep learning approach to identifying the individual cattle using muzzle point image pattern. The deep learning approach is applied to learn a discriminatory feature representation of muzzle images with limited training dataset. With the proposed deep learning approaches, such as CNN, SDA and DBN yield 75.98%, 88.46%, and 95.99% identification accuracy, respectively.

The handcrafted texture features based representation algorithms are utilized for evaluations of experimental results. The Local Binary Pattern (LBP) and Circular-LBP (Circular-LBP) feature descriptor based technique provide the rank-1 identification accuracy of 16.80 ± 0.80% to and 26.97 ± 1.2%, respectively with four muzzle point images as gallery image per subject (cattle). In the case of appearance based feature extraction and representation approaches, such as principal components analysis is used to perform dimensionality reduction on the feature space.

The identification of cattle based on their muzzle point images is performed using Linear Discriminant Analysis (LDA) with One-Shot Similarity (OSS) technique. It is used to match a pair of samples and generate the match scores. The identification accuracies are shown in Table 5, respectively. It can be observed that Direct-Kernel-LDA provides the 15.89 ± 1.7% to 29.97 ± 1.13% identification accuracy.

The learnt feature descriptor techniques, such as VLAD + LDA + OSS and VLAD + LDA + SVM techniques yield 45.98 ± 1.5% to 59.64 ± 1.12% and 50.76 ± 1.6 to 67.98 ± 1.17 identification accuracy, respectively. Based on observation, we conclude that deep belief network deep learning approach provides better identification accuracy for recognition of individual cattle. Hence it can be concluded that the DBN based framework is the right choice for recognition purpose.

For further improvisation of deep learning based recognition framework, the proposed framework can be implemented on the android platform that can easily available for smart or android devices for verification and identification and verification of false insurance claims in real time scenario.

We postulate that the traditional animal recognition methodologies and automatic animal recognition algorithms that are tailored specifically for identification of cattle, via unambiguous training. It can be able to perform the recognition of cattle more efficiently. The proposed deep learning based recognition of cattle caters a friendly, non-invasive, robust as well as cost-effective solution using smart devices or low-cost camera for the identification of species or individual animals.

In future, we plan to extend the proposed cattle recognition system for the identification of different animals in the real time. We would like to include the following points as part of our future work:

- We would like to design multi-modal cattle recognition system using muzzle point image and face image of cattle for accurate identification and verification in real-time.
- We would like to increase the performance of the proposed cattle recognition system using multi-modal system and feature fusion techniques. The fusion technique can be fused the discriminatory set

of texture features of the muzzle point images with facial images of individual cattle.

- We postulate that it can be more helpful even depth level analysis of experimental results of proposed multi-model based cattle recognition system.
- Finally, we would like to increase the size of cattle database for validation of experimental results with benchmark existing hand-crafted texture descriptor techniques and deep learning based feature learning and representation techniques in the computer vision.

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