

Body contour-based individual cattle identification using Support Vector Machine learning model

K. Boruah^{1*}, S. N. Mandal² and N. Ghosh¹

¹Department of Livestock Production Management, West Bengal University of Animal and Fishery Sciences, Kolkata - 700 037, West Bengal, India; ²Department of Information Technology, Kalyani Govt. Engineering College, Kalyani, Nadia - 741 235, West Bengal, India

Abstract

Individual cattle identification is essential for monitoring, record keeping, registration, preventing disease, and welfare concerns. The traditional methods of identification, viz. branding, tattooing, ear notching, ear tagging, and Radio Frequency Identification (RFID), are invasive, non-permanent, and have more challenges in identifying individual cattle. In this study, for the purpose of individual cattle identification, a Support Vector Machine (SVM)- based learning model was applied on extracted features from segmented whole-body contour images of cattle. Side-view images of 10 adult cows were captured on the farm with a DSLR camera under natural lighting to train the models. The images were segmented using the active snake contour algorithm. The thirteen (13) statistical features, like mean, standard deviation, variance, entropy, skewness, RMS, etc, were extracted from each segmented body contour image, and a feature database was developed. The SVM machine learning model was applied to the extracted features, and F1-scores, precision, and recall were calculated in validation and test data sets. It was observed that the support vector machine achieved an accuracy of 97% validation and 82.5% test accuracy. The proposed model could be used as a tool for individual identification of cattle.

Keywords: Accuracy, Body contour, Features database, Image segmentation, Image statistical features

Highlights

- Body contour-based identification gives an accurate method for recognizing individual cattle.
- This study proposed a novel, non-invasive way to identify individual cattle using a Machine learning algorithm.
- SVM model, achieving 97% validation accuracy and 82.5% test accuracy for cattle identification

INTRODUCTION

Accurate and reliable identification is a vital management practice in scientific dairy farming. Cattle identification plays a crucial role in vaccination and disease outbreak control, production management, insurance, traceability, and ownership verification (Kumar & Singh 2020). Despite the common use of traditional animal identification methods such as tagging, branding, tattooing, and body marking, these methods have several constraints, including being non-permanent, tamperable, and painful to the animals, and are often prone to errors, damage, loss, theft, duplication, and animal welfare concerns (Hossain et al., 2022). These challenges encouraged the search for a non-intrusive, authentic, reliable, cost-effective, and dependable option, leading to the use of computer vision and machine learning techniques for identifying cattle. In this work, we proposed a method for extracting suitable features from side-view images of individual cattle using an SVM learning model for the identification of individual cattle.

In this modern age, there is a rapid increase in the utilisation of pattern-based identification of cattle through image processing and other artificial intelligence technologies due to constraints faced in traditional methods of identification (Lv et al., 2018). A pattern recognition system identifies individual animals based on unique characteristics of specific traits, such as visual biometric patterns, muzzle prints, facial features, ear venation patterns, body patterns, and retinal or iris features (Roy et al., 2020; Andrew et al., 2021; Zhang et al., 2023). Iris pattern matching of Black Bengal goats using a deep learning approach has been reported to achieve high accuracy, indicating its strong potential for reliable biometric identification of individual goats (Laishram et al., 2022).

Side view image-based, i.e., body contour identification, uses statistical data gathered from each cattle's distinct body shape to provide a quick and accurate way to identify individual cattle. The distinct shape patterns of many animals can be measured statistically and remain constant over time. An animal's

*Corresponding Author, E-mail: kandarpalcvsc@gmail.com

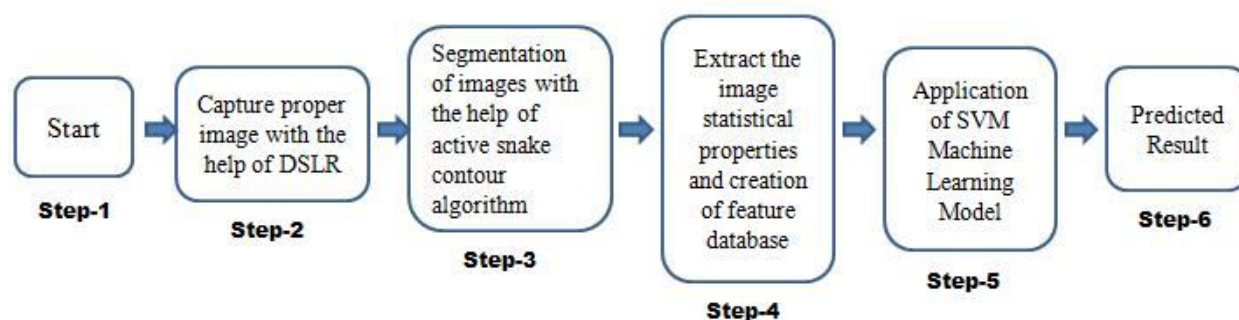


Fig. 1. Phase of cattle identification using body contour

body form has distinct geometric and statistical characteristics that make it a reliable biometric identifier. The contour characteristics can be transformed into powerful numerical representations by statistical parameter techniques, which can then be utilized for machine learning classification for individual animal identification. This research proposed a novel, non-invasive way to identify individual cattle using statistical information gathered from the shape of the animal's body.

MATERIALS AND METHODS

In this study, individual cattle were captured, segmented, and image-based features were extracted. The SVM machine learning model was applied to the extracted features, and performance was calculated. The details of the steps are as follows-

Place of study and animal used: The primary location for capturing and collecting data for this study was at Haringhata cattle farm, Mohanpur, West Bengal, India, and the data processing for this study was at the Department of Information Technology, Kalyani Govt. Engineering College, Kalyani, Nadia, West Bengal.

Ten adult crossbred cattle were used to capture images, and 200 captured images were selected for final processing. The phases of individual cattle identification are furnished in Fig. 1.

Individual cattle identification phases

Image acquisition and Image database- This is the initial step of the image collection procedure, where the images of individual cattle were captured in the farm premises from a distance of 10-12 feet away from the animal under natural light, as shown in Fig. 2. Different views of adult cattle were captured with different angles, different locations of the farm, and in different days. A Japan-made DSLR camera, model no Nikon (D 5300), was used for capturing the image with an image resolution of 2992×2000. The selected images were divided into training and test datasets at a ratio of 80:20.

Image segmentation and features database- The Active Snake Contour (Snake) algorithm (Kass et al., 1988) was employed for image segmentation to extract object boundaries accurately. The images were first preprocessed by resizing, smoothing, and enhancing contrast to reduce noise and improve feature detection. Initial contours were manually or automatically placed near the object of interest. The algorithm then iteratively evolved the contour by minimizing an energy functional that combines internal forces that maintain the contour's smoothness and continuity, and external forces derived from image gradients that attract the contour toward edges.



Fig. 2. Cattle whole body image acquisition

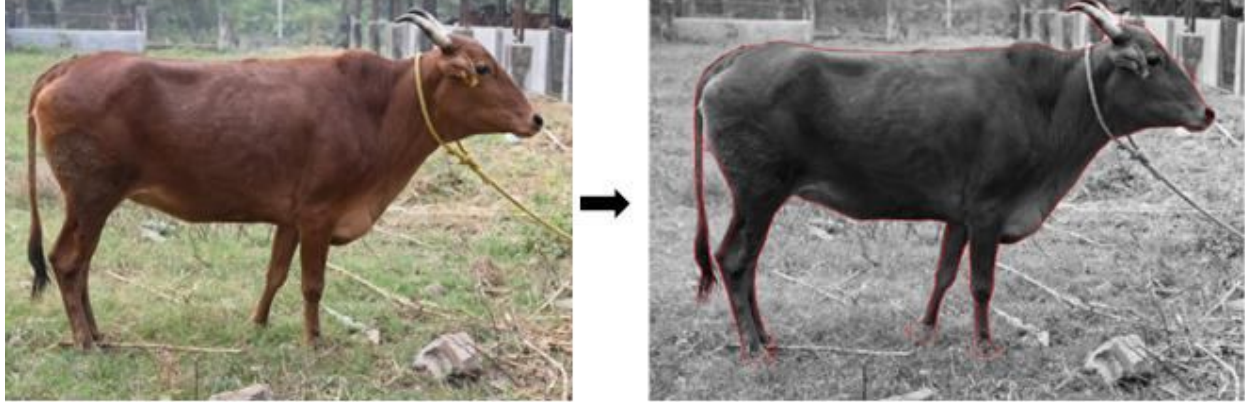


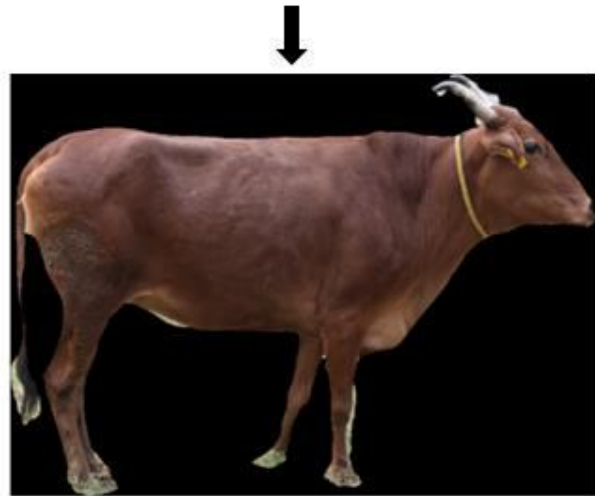
Fig. 3. Captured and segmented image

Mathematically, the energy is expressed as:

$$E_{\text{snake}} = E_{\text{internal}} + E_{\text{external}} \quad (1)$$

Where, E_{internal} controls the elasticity and rigidity of the curve, and E_{external} pulls the contour toward high-gradient regions. The contour evolution continued until convergence or a maximum number of iterations was reached. Finally, the segmented boundaries were visually validated and, where applicable, quantitatively assessed using metrics such as overlap ratio or segmentation accuracy. The segmentation of cattle is shown in Fig. 3.

Support Vector Machine (SVM)- In this work, a SVM classifier was employed for pattern recognition. Initially, the dataset was normalized and partitioned into training and test subsets to ensure reliable assessment. Feature extraction techniques were employed to obtain meaningful representations of the data, such as texture descriptors, intensity values, and shape-based metrics for photographs. The SVM algorithm was then trained to optimize the margin between classes by identifying the optimal separating



hyperplane in a high-dimensional feature space. Mathematically, the decision function of the SVM can be defined as:

$$f(x) = \text{sign}\left(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b\right) \quad (2)$$

Where, x is the input sample, α_i are the learned coefficients, y_i are the proper class labels, K is the kernel function, x_i are the support vectors, and b is the bias term. A range of kernel functions, including linear, polynomial, and radial basis

functions (RBF), was examined in order to capture non-linear correlations in the dataset. The trained SVM model was then assessed to check the performance, using statistical measures such as accuracy, precision, recall, and F1-score on the test set.

Proposed model: This work proposed a model for predicting individual cattle based on their contour images of five modules (Fig. 4). In the first module, side

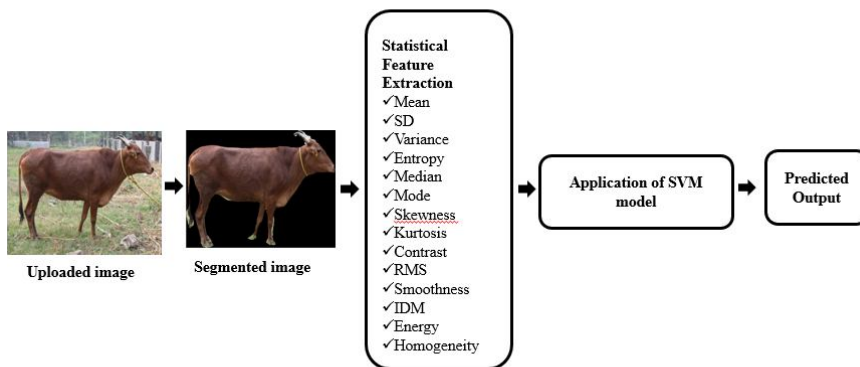


Fig. 4. Proposed model for prediction of contour image based individual cattle identification

profile images of individual cattle were captured. The individual cattle images were segmented to extract their image-based features in the next contour segmentation module. Statistical image-based features were then derived from the segmented images in the feature extraction module. In the next module, an SVM-based machine learning model was applied to extract features after separating the data into training and test datasets. Finally, the model was deployed to predict identities of new images, enabling non-invasive and automated cattle recognition, thereby improving traceability and herd management.

RESULTS

In this study, Individual cattle were captured, and the whole body was segmented from the captured image. The image-based features were extracted, and a database was created in which the final column represented the class label. The extracted dataset was split into a training and a test dataset in an 80:20 ratio. The training dataset was used to train the machine learning model, and the trained model was subsequently tested using the test dataset. The cattle dataset, consisting of statistical features extracted from each segmented cattle image, was analysed using a machine learning approach. Each row of the dataset represented one individual cattle, with all extracted features included in the columns and the final column denoting the class label. The training set was further divided into training and validation subsets in an 80:20 ratio to build the model. The validation set was used to test the trained model in validation, where the output was known. The trained model, which achieved good accuracy on the validation set, was used for testing on an unknown dataset. In our work, 20% of the whole dataset was kept to test the model after validation. During model training, 128 cattle feature samples were used to train the machine learning model, while 32 feature samples were used for model verification. The performance of the SVM model is presented below.

A Support Vector Classification (SVC) model with a radial basis function kernel was trained using the extracted training data. The performance metrics obtained from the best fold out of five-fold cross-validation on the validation dataset are presented in Table 1. The table shows the metrics of precision, recall, F1-score, and support of each class. For most classes, the precision value of 1.00 indicates that all predicted samples were correctly classified. Moreover, most classes had perfect recall (1.00), meaning all actual samples were correctly classified, except for class 523119 (recall 0.75), where 1 out of 4

samples was misclassified. High F1-scores (close to 1) for most classes indicate excellent model performance. Support shows that the number of test samples per class is small (3–4), which should be noted when interpreting results. Overall, the accuracy was 0.97, indicating that 97% of the 32 test samples were correctly classified. Overall, the model demonstrated excellent performance with only minor misclassification in a single class.

Table1. Classification report on validation set of SVM model

Cattle Id.	Precision	Recall	F1-score	Support
517073	1.00	1.00	1.00	3
517233	1.00	1.00	1.00	3
517244	1.00	1.00	1.00	3
521215	1.00	1.00	1.00	4
521283	0.75	1.00	0.86	3
521306	1.00	1.00	1.00	3
521328	1.00	1.00	1.00	3
521410	1.00	1.00	1.00	3
523119	1.00	0.75	0.86	4
523393	1.00	1.00	1.00	3
Accuracy			0.97	32

DISCUSSION

The present study investigates the performance of an SVM machine learning model for individual cattle identification using body contour image-based features. The evaluation was carried out on identical training, validation, and test datasets to ensure fair comparison. The Support Vector Machine achieved a validation accuracy of 97% and a test accuracy of 82.5%. These results indicate the SVM's superior ability to generalize and discriminate between classes based on the extracted image features. This finding aligns with previous research by Ghosh and Mandal (2022), who reported that the SVM model with an RBF kernel achieved the highest performance in pig breed classification, with a breed prediction accuracy of 98%. A similar result was also observed by Mandal et al. (2019), where whole-body pig images were used for the classification of different pig breeds using a neuro-statistical model. The captured images were segmented using a Hue-based algorithm, and various statistical properties, including entropy, standard deviation, variance, mean, median, and mode, were computed from the contents of the segmented images. All the extracted features were fed into the Neural Network designed for pig breed classification to enable pig breed prediction. The prediction accuracy was 90%. Andrew et al. (2017) reported an average accuracy of 97% during testing over approximately 86,000 image pair comparisons, where The prediction was

generated by the SVM using radial basis function (RBF) kernels for predictions based on the ASIFT descriptor structure. In contrast to the present finding of the Random Forest model, a 90.9% identification accuracy was achieved, which was the best compared to the other applied techniques of machine learning for individual ear-based pig identification, reported by Dan et al. (2023). In conclusion, this experiment revealed that the proposed model may be used as a tool for individual identification of cattle and also shows potential for application to feature-based identification of other livestock species in the future. Furthermore, this study will be extended to include a larger number of individual cattle, and additional machine learning models will be applied in future work, along with their comparative analysis.

Conflict of interest: The Authors have no conflict of interest in this study.

Author's contribution: KB, SNM, NG: Conception and design of experiment; KB, SNM: Acquisition of data; KB, SNM, NG: Performed interpretation of the result and provided technical efforts in drafting the manuscript. The final manuscript was read and approved by all authors.

REFERENCES

- Andrew, W., Gao, J., Mullan, S., Campbell, N., Dowsey, A. W., & Burghardt, T. (2021). Visual identification of individual Holstein-Friesian cattle via deep metric learning. *Computers and Electronics in Agriculture*, 185, 106133. <https://doi.org/10.1016/j.compag.2021.106133>
- Andrew, W., Hannuna, S. L., Campbell, N. W., & Burghardt, T. (2017). Automatic individual Holstein Friesian cattle identification via selective local coat pattern matching in RGB-D imagery. In *2016 IEEE International Conference on Image Processing (ICIP)* (pp. 484–488).
- Dan, S., Das, S., Mandal, S. N., Mustafi, S., & Banik, S. (2023). Ear image-based individual pig identification using statistical parameters. *Applied Biological Research*, 25, 62–70. <https://doi.org/10.5958/0974-4517.2023.00007.1>
- Ghosh, P., & Mandal, S. N. (2022). PigB: Intelligent pig breeds classification using supervised machine learning algorithms. *International Journal of Artificial Intelligence and Soft Computing*, 7(4), 242–266. <https://doi.org/10.1504/IJAISC.2022.126345>
- Hossain, M. E., Kabir, M. A., Zheng, L., Swain, D. L., McGrath, S., & Medway, J. (2022). A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions. *Artificial Intelligence in Agriculture*, 6, 138–155. <https://doi.org/10.1016/j.aiia.2022.09.002>
- Kass, M., Witkin, A., & Terzopoulos, D. (1988). Snakes: Active contour models. *International Journal of Computer Vision*, 1, 321–331. <https://doi.org/10.1007/BF00133570>
- Kumar, S., & Singh, S. K. (2020). Cattle recognition: A new frontier in visual animal biometrics research. *Proceedings of the National Academy of Sciences, India, Section A: Physical Sciences*, 90(6), 689–708. <https://doi.org/10.1007/s40010-019-00610-x>
- Laishram, M., Mandal, S. N., Haldar, A., Das, S., Bera, S., & Samanta, R. (2022). Biometric identification of Black Bengal goat: Unique iris pattern matching system vs. deep learning approach. *Animal Bioscience*, 36(6), 980–989.
- Lv, F., Zhang, C., & Lv, C. (2018). Image recognition of individual cow based on SIFT in L $\alpha\beta$ color space. In *MATEC Web of Conferences*, 176, 01023. <https://doi.org/10.1051/mateconf/201817601023>
- Mandal, S. N., Dan, S., Ghosh, P., Mustafi, S., Roy, K., Mukherjee, K., Hajra, D. K., & Banik, S. (2019). Pig breeds classification using neuro-statistic model. *Science and Technology Journal*, 7(2), 78–88. <https://doi.org/10.22232/stj.2019.07.02.10>
- Roy, S., Dan, S., Mukherjee, K., Mandal, S. N., Hajra, D. K., Banik, S., & Naskar, S. (2020). Black Bengal goat identification using iris images. In *Proceedings of the International Conference on Frontiers in Computing and Systems (COMSYS)* (pp. 213–224). Springer.
- Zhang, R., Ji, J., Zhao, K., Wang, J., Zhang, M., & Wang, M. (2023). A cascaded individual cow identification method based on DeepOtsu and EfficientNet. *Agriculture*, 13(2), 2–19. <https://doi.org/10.3390/agriculture13020279>

Received - 28.11.2025, Accepted - 07.01.2026, Published - 18.02.2026 (Online), 01.06.2026 (Print)

Section Editor: Dr. Arun Kumar Das, Editorial Board Member