Identifying dairy cows using body surface keypoints through supervised machine learning

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Abstract

Computer vision systems have been proposed as an automated and non-invasive alternative to identifying animals with distinct coat color patterns, but there are limited applications in solid-colored herds. The aim of this study was to identify dairy cows using infrared image to identify keypoints located at specific anatomical landmarks (e.g., bony prominences). Two-thousand ninety-seven images (top-down view) were collected from 25 dairy cows. Seven keypoints per cow were manually added on the dorsal area. These locations were bony prominences [hip (left and right), pin bone (left and right), tail head, sacral and cervical vertebrae] that can remain constant when cows change body condition score. We used the Euclidean distance between keypoints to generate biometric features for each cow and analyzed the data using a multi-layer feedforward artificial neural network (ANN). The ANN model's hyperparameters were defined using a grid search method, which included 6 activation functions, 76 hidden layers, 5 input dropout ratios, 5 levels of lasso regularization (L1), and 5 levels of ridge regularization (L2). The model was built using a 5-fold cross-validation approach, with 1,690 images selected for training and 407 images used for testing. The final model achieved an accuracy of 80%, precision of 71%, recall of 74%, and an F1 score of 80%. These results suggest that keypoints located on the dorsal body surface can be an effective alternative for identifying individual animals that lack distinct coat color patterns.

Keywords: animal identification, deep learning, euclidean distance, body biometrics

Introduction

Individual animal identification is a crucial step for high-throughput phenotyping in livestock systems. RFID technology is a widely used method for individual identification, but it can be labor-intensive and costly to implement and maintain on a large scale (Awad, 2016; Ferreira et al., 2022). The ongoing expense of replacing tags and the limited distance recognition capabilities of RFID systems can also pose significant challenges (Awad, 2016; Xiao et al., 2022). However, computer vision technology has emerged as a promising alternative for animal identification, with the ability to identify and locate multiple animals simultaneously (Ferreira et al., 2022). In addition, computer vision technology can generate valuable phenotypes for farm management and animal breeding programs. Thus, while RFID technology remains a useful tool for individual animal identification, computer vision technology offers new possibilities for improving efficiency and productivity in the animal agriculture industry.

In this context, several techniques using computer vision were proposed based on biometrics such as coat color (Andrew et al., 2016), muzzle print (Li et al., 2022), and retinal vascular patterns (Allen et al., 2008). For example, Li et al. (2022) found high accuracy (98.7%) when identifying individual beef cattle based on muzzle print. However, the use of biometrics such as muzzle print and retinal vascular patterns may limit scalability due to the impact of head movement on overall image quality (Awad, 2016). On the other hand, identifying animals based on distinct coat color patterns, such as Holstein cows, can be deployed in commercial farms

(Xiao et al., 2022) with an average accuracy greater than 89% (Zin et al., 2018; Bello et al., 2020; Xiao et al., 2022).

Identifying individual animals based on coat color patterns has limited applications for farms with solid-colored herds (e.g., Jersey, Brown Swiss, Angus, and Danish red). Ferreira et al. (2022) used depth images from the dorsal area and convolutional neural networks to identify individual calves and reported great predictive performance. The results found by Ferreira et al. (2022) may be one alternative to identify animals with solid colors. Another alternative to depth images for animal identification would be the use of keypoints, as used by Anciukeyicius et al. (2022) to recognize parts of the human face and body. This method could be applied to specific anatomical landmarks on the body surface of cows (Zhang et al., 2021), and allow the extraction of features representing the animal body biometrics. However, to the best of our knowledge, the use of keypoints for individual animal recognition has not yet been explored. This study aims to develop and evaluate models for animal identification based on body biometrics as extracted from keypoints located at specific anatomical landmarks on the cow's body surface.

Materials and methods

Dataset

A total of 2,097 infrared images (top-down view) were collected from 25 cows (approximately 84 images per cow) using Intel RealSense D435 camera. Seven keypoints per cow were manually added in locations that do not change with changes in body condition score: [hip (left and right), pin bone (left and right), tail head, sacral and cervical vertebrae] (Figure 1). The keypoints were identified individually for each cow image using the VGG Image Annotator (VIA) software, and the Euclidean distance between the keypoints were used as feature (Equation 1).

Three different strategies were used to calculate the body biometric features. In the first strategy, Euclidean distances from the rump area (RA) (F1 to F13; Figure 1) were standardized as a percentage of the sum of all Euclidean distances of RA (Table 1). In the second strategy, sixteen features were used as Euclidean distances between the seven keypoints standardized as a percentage of the sum of all Euclidean distances of not only RA, but the entire dorsal area (DA) (Figure 1; Table 1). The third strategy combined the features from strategy 1 and 2 together. All strategy were presented in Table 1.

$$D(x,y)_{!"} = \text{ß}\overline{(x_{!} - x_{"})^{*} + \ (y_{!} - y_{"})^{*}} \qquad (1)$$

where: D is the Euclidean distance; $(x_{!} - x_{"})$ is the coordinate of the first point; $(y_{!} - y_{"})$; is the coordinate of the second point.

Table 1: Description of different strategies for cow identification

Item	Features[1]	Total features
Strategy 1	F1 + F2 + F3 + F4 + F5 + F6 + F7 + F8 + F9 + F10 + F11 + F12 + F13	13
Strategy 2	F_1 + F_2 + F3 + F4 + F5 + F6 + F7 + F8 + F9 + F10 + F11 + F12 + F13 + F14 + F15 + F16	16
Strategy 3	Strategy 1 + Strategy 2	29

[1] The features (F1 to F16) are described in Figure 1 and were calculated in relation to the sum of all Euclidian distances.

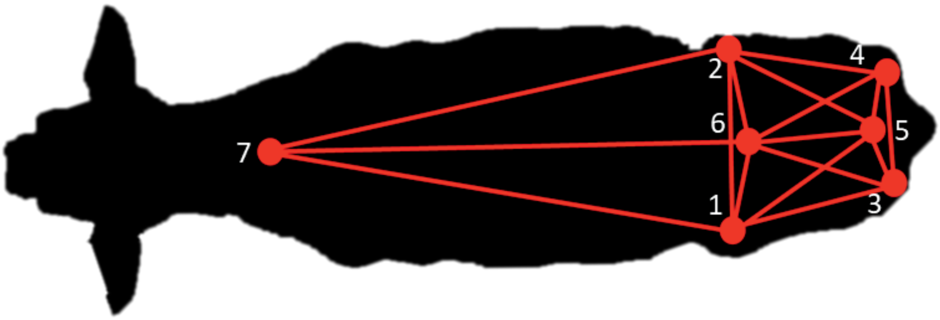

Figure 1: Description of measurement sites for Euclidean distance percentual as a feature. F1, F2, F3, F4, F4, F5, F6, F7, F8, F9, F10, F11, F12, F13, F14, F15, and F16 represents the Euclidean distance between the following points, respectively: 1 à 2; 3 à 4; 5 à 6; 1 à 3; 2 à 4; 3 à 6; 4 à 6; 3 à 5; 4 à 5; 1 à 6; 2 à 6; 1 à 5; 2 à 5; 6 à 7; 1 à 7; 2 à 7 All the computed distances were standardized as percentage of the sum of all distances.

Artificial neural network

Artificial Neural Networks (ANN) were trained using the open-source package in R for big data analysis called H2O (LeDell et al., 2022). Images were collected for each cow over six different days. One day was randomly selected per cow, and all images from that day were used for testing the models (n = 407 images). The images collected on the remaining five days were used to train the models (n = 1,690 images). This strategy was implemented to reduce overfitting, commonly found when similar images are present in the training and testing sets, as they could potentially generate similar keypoint distributions and inflate the predictive performance. To select the best combination of hyperparameters we performed a grid search on the training set and specifying the range of hyperparameters as search criteria. Random combinations of all hyperparameters defined in the grid search [6 activation functions, 76 hidden layers, 5 input dropout ratios, 5 levels of lasso regularization (L1), and 5 levels of ridge regularization (L2), Table 2] were selected to build the models based on 5-fold cross validation. To reduce the time required for training the models, three parameters were used: maximum running time, maximum number of models, and stopping metrics (logloss).

The ADADELTA was used for all models as an adaptive learning rate algorithm (Zeiler, 2012). The data were standardized to a mean of 0 and a variance of 1. The description of the developed ANN can be found in Table 3. The accuracy in the training set was used for selecting the best model.

Table 2: Hyperparameters and search criteria used in the grid search of artificial neural network (ANN)[1]

Hyperparameter					
Activation function	Loss	Hidden layers			
Rectifier	Absolute	20	20,20	20,20,20	20,20,20,20
Tanh	Cross Entropy	30	30,30	30,30,30	30,30,30,30
Maxout	Huber	40	40,40	40,40,40	40,40,40,40
RectifierWith Dropout	Quadratic	50	50,50	50,50,50	50,50,50,50
TanhWith Dropout		60	60,60	60,60,60	60,60,60,60
MaxoutWith Dropout		70	70,70	70,70,70	70,70,70,70
		80	80,80	80,80,80	80,80,80,80
		90	90,90	90,90,90	90,90,90,90
		100	100,100	100,100,100	100,100,100,100
		110	110,110	110,110,110	110,110,110,110
		120	120,120	120,120,120	120,120,120,120
		130	130,130	130,130,130	130,130,130,130
		140	140,140	140,140,140	140,140,140,140
		150	150,150	150,150,150	150,150,150,150
		160	160,160	160,160,160	160,160,160,160
		170	170,170	170,170,170	170,170,170,170
		180	180,180	180,180,180	180,180,180,180
		190	190,190	190,190,190	190,190,190,190
		200	200,200	200,200,200	200,200,200,200
Input dropout ratio	0, 0.1, 0.15, and 0.25				
L1 - L2[2]	0, 0.01, 0.001, 0.0001, and 0.00001				

Search criterion			
Strategy[3]	max runtime[4]	max models[5]	stopping_metric[6]
RandomDiscrete	6000	1000	misclassification

[1] The hyperparameters were combined to find the best ANN structure; [2] L1 = lasso regularization. L2 = ridge regularization; [3] RandomDiscrete = get random search of all the combinations of your hyperparameters; [4]max_runtime_secs = maximum runtime in seconds for the entire grid search;[5]max_models = maximum number of models searched in the grid; [6]stopping_metric = function used for early stopping based on no improvement in the model metric (in this case metric defined as logloss).

Table 3: Models developed based on the hyperparameters defined in the grid search for artificial neural network (ANN)

Item[1]	Strategy 1	Strategy 2	Strategy 3
1st neuron layers			
Units	13	16	29
2nd neuron layers			
Type	Tanh	Tanh	Tanh
Units	170	170	200
3rd neuron layers			
Type	Tanh	Tanh	Tanh
Units	170	170	200
4th neuron layers			
Type	Tanh	Tanh	Tanh
Units	170	170	200
5th neuron layers			
Type	Tanh	Tanh	Tanh
Units	170	170	200
6th neuron layers			
Type	Softmax	Softmax	Softmax
Units	25	25	25
Epochs	10	10	10
Loss	CrossEntr.	CrossEntr.	CrossEntr.
L1[2]	0.00010	0.00010	0.00000
L2[3]	0.00100	0.00100	0.00001
Input dropout	0.00000	0.00000	0.00000
Hidden dropout	0.00000	0.00000	0.00000
Momentum	0.00000	0.00000	0.00000
Training set			
Accuracy (%)	83.9	88.0	88.0

[1] CrossEntr. = Cross Entropy; [2]L1 = lasso regularization; [3]L2 = ridge regularization

External model validation and assessment

The best model in each strategy (strategies 1 to 3) was selected to predict the animal identification in the testing set. Accuracy (4), precision (5), recall (6), and F1-score (7) were calculated for each covariate set (strategies):

$$\text{Accuracy} = \frac{cd5ce}{cd5ce5fd5fe} \quad (2)$$

$$\text{Precision} = \frac{cd}{cd5fd} \quad (3)$$

$$\text{Recall} = \frac{cd}{cd5fe} \quad (4)$$

$$F_{\&} = \frac{*cd}{*cd5fd5fe} \quad (5)$$

where: TP = True positives; TN = True negatives; FP = False positives; FN = False negatives. The mean for precision, recall, and F_1 was calculated for each cow using 95% CI.

Results and discussion

The use of ANN approach, utilizing body biometric features extracted form manual keypoints as inputs, achieved an accuracy range of 72% to 80%. The strategy of using Euclidean distances from the rump area (strategy 1) had the lowest accuracy of 72%. Although the RA-based features did not produce the highest accuracy, it does demonstrate the potential for this specific strategy when the animal is partially occluded and only the RA is visible in the image. Furthermore, incorporating these measures as a feature in strategy 2 resulted in a 4 percentage points increase in accuracy (Table 4). Despite not performing as well as previous studies that used muzzle print and coat color identification techniques (Li et al., 2022; Xiao et al., 2022), the proposed method offers the ability to be applied on a large-scale, as it uses top-down view images and can be used in solid-colored herds. Our results are comparable in accuracy to those found by Ferreira et al. (2022) who used depth images from the dorsal body area to identify individual calves.

Table 4: Accuracy, precision, F_1 scores and recall using mode prediction to identify individual cows

Artificial neural network Method	N° Train	N° Test	Test			
			Accuracy	Precision	F1 - Score	Recall
Strategy 1	1,690	407	72.0	66.0	68.0	72.0
Strategy 2	1,690	407	76.0	65.3	68.7	76.0
Strategy 3	1,690	407	80.0	71.3	74.0	80.0

In this study, we used the body biometric features represented as a percentage of the total distance, under the assumption that body would remain proportional as animals progress through growth development. Training models for animal identification based on absolute distances could be misleading due to changes in biometrics because of animal growth. Rashad et al. (2022) evaluated morphometric growth (e.g., body length, diagonal length, wither height, rump height, and chest girth) in forty Holstein heifers from weaning at four months to eight months of age and found that the proportions between these measurements remained consistent throughout the growth period. However, future studies will be necessary to evaluate if our method would present similar performance in growing animals. For application in real-world scenarios, automatic keypoints such as detection in a 3D image (Creusot et al., 2011) or 2D image such as made for detector pose estimation in humans (Zhang et al., 2021) need to be trained to automate the tool and facilitate its use on farms.

Conclusions

Our results indicate that keypoints located at the dorsal body surface can serve as a reliable alternative for identifying individual animals that lack distinct coat color patterns without requiring depth images to capture body shape characteristics. Additional studies are necessary to evaluate this technique in growing animals. To facilitate practical application in real-world scenarios, automatic keypoint detection mechanisms in 3D or 2D images, similar to those used for detector pose estimation in humans, must be developed and trained to automate the system in commercial and research settings.

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