Assessment of Body Condition Scores of Holstein Friesian Crossbred Cows Based on Deep Learning

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ABSTRACT

Body Condition Score (BCS) is a measure of body fat or stored energy in the dairy cow. It is an important tool in farm management for achieving better health of cows, reproductive performance and milk yield. Traditionally, BCS is performed visually by veterinary experts, which is time-consuming and involves high cost. Therefore, this study proposed a system based on Convolutional Neural Network (CNN) to automate BCS of cows by image analysis. GNU Image Manipulation Program (GIMP) software was used to remove the background of digitally-captured images of cows, and a MATLAB script was implemented to detect their edges. Finally, the edge-detected images were used as input dataset for the development of deep learning models based on CNN. The image dataset was classified into two groups based on the incremental BCS system of 0.25 (CNN model 1) and 0.5 (CNN model 2). The classification accuracy of the first model for 0.25 and 0.50 error ranges was 63.23% and 85.29%, respectively. In comparison, the second model achieved classification accuracy of 86.02% and 94.85%, for the respective error ranges. Based on the results, the CNN models performed adequately for the middle range of BCS scores wherein the data, most of the cows are present. Therefore, the developed models would perform effectively for commercial dairy farms which do not commonly have cows with poor or high BCS as they would not be very productive.

INTRODUCTION

Assessing the Body Condition Score (BCS) of cows is important to measure the changes in subcutaneous body fat throughout the stages of lactation. This is because the anatomical characteristics of cows such as external shape and tissue cover with frame size can be related to their current nutritional status and productivity. The extremely fat or skinny cows give reduced milk yield, pose risk of metabolic diseases and have low reproductive performance [1]. During early lactation, depletion of their fat reserves takes place, while in late lactation, accumulation of fat takes place. It is therefore important to manage the body condition of cows at various stages of lactation so as to improve their health condition and productive performance. The most common approach for evaluating the BCS is the subjective method that uses a standardized scale based on the amount of tissue coverage at the hindquarters of the cow.

Body condition scoring is visually done by experts by assessing the rear regions of cows such as the loin, tail and pelvis, and providing a score ranging from 1 to 5. This technique is vulnerable to bias in many situations and requires the animal to be confined during evaluation. It is also time-consuming, limiting the number of animals that can be evaluated and the frequency at which it could be done. Hence, it is logical to use an alternative BCS system that has the potential to eliminate bias, reduce animal stress and increase the speed of evaluation. When compared to the visual method, implementation of a camera-based imaging system and analysis could considerably increase the precision and identify changes in the BCS at a much faster rate.

Although the significance of BCS has been evidenced in numerous studies, more than half of the farm producers never record the BCS of cows in their herds regularly [2]. Similarly, the survey conducted by German fresh cow management found that only 36% of farmers measured the BCS of their herd regularly [3]. The lack of adoption of regular BCS measurement is due to practical difficulty in scoring and management of BCS scores by the experts and the farmers [4]. To incorporate high-quality manual scoring into farm management, farmers must employ experienced assessors on a regular basis or obtain training to score their own cows, both methods are time-consuming and costly. Hence, there is a need to develop modern hybrid and machine learning computing tools using the assistance of image processing to determine the BCS in an automated way. Such a system will be a user-friendly technique to estimate the BCS of large herds, analyze the BCS data set, and facilitates in easy identification of the variation in BCS of cows so as to take timely and appropriate management decisions.

Image processing is the important step for training and testing the dataset as it extracts the features that will be utilized for estimation of BCS. Developing a predictive BCS model using conventional feature extraction using manual method is less effective and less precise owing to the small amount of samples and feature points, which result in a poor fit [5]. In general, 3D vision-based systems achieved more accurate results [4, 6, 7]. This is because the concavity information of the cows' body surface, provided by the 3D image characteristics, is more closely related to the fat accumulation beneath the skin.

In recent years, the area of deep learning has made great strides in the field of computer vision and image classification. Feature extraction is a key aspect of machine learning techniques. Deep learning algorithms fix the problem of feature extraction by automatically extracting relevant features from the raw input data rather than requiring pre-selected features. A deep learning model is composed of multiple processing layers that may learn complex input data attributes at various levels of abstraction [8]. The Convolutional Neural Network (CNN) is one of the deep learning techniques that is used for solving complexity of building, training and deploying machine learning models at any scale. It is a biologically-inspired concept of a deep network for feature detection, capable of learning purely complex features, and proves to be more effective in identification of objects [9]. The advantage of CNN's architecture is that it is easier to train, and has fewer parameters than fully-connected networks with the same number of hidden units.

The major attraction of CNN is the concept of weight sharing to reduce the number of parameters that need to be trained to achieve greater generalization and only a few parameters are needed for training to avoid over-fitting [10]. Secondly, the classification stage is combined with the feature extraction stage, both based on the learning process [11]. Thirdly, implementing large networks by use of general models in Artificial Neural Networks (ANN) is more complex than implementation in CNN.

A computer-aided CNN model was developed to evaluate the BCS of cows in order to minimize the error and bias that might arise during from interpretation of BCS by experts. The automatic BCS system was developed using various network architecture and general models used in deep-learning techniques, by selecting the body features of cows and extracting them from multiple viewpoints, so that the image-based BCS classification could be accurate and relevant.

MATERIALS AND METHODS

Data collection

To develop and evaluate the CNN model, five dairy farms were visited and 503 images of Holstein Friesian cows with varying body muscle and fat in the hindquarters were acquired. A digital camera (Nikon D5100, Nikon Corporation, Japan) was used to capture the images manually at ISO speed of 100, exposure time of 1/100 s and resolution of 4928 × 3264 pixels by ensuring the same distance and angles during image acquisition such that consistency could be maintained and error could be minimized. The images were acquired after cleaning and milking the animals. The vital areas of the cows were imaged at two suitable viewing angles for evaluation of BCS. The first view was dorsal that provided information on spinal parameters such as hook bones, pin bones and tail head of the cow. The second view was the side image, which gave the edge information of short and long ribs, and the area between the pin and hook bones.

Dataset preparation

A scorecard containing images from the two viewing angles and detailed physiological information of the cows was developed. The images were printed and manually evaluated by three veterinary experts and their BCS were obtained on a 5-point scale. This scale is not breed specific, where score 1 represented thin cows and score 5 represented obese cows as explained [12]. The dataset of scores by experts was divided into 'training', 'testing' and 'validation' sets. Additionally, the image dataset was classified into two groups based on the incremental BCS system of 0.25 and 0.5 and each CNN model architecture was applied. This classification helped in evaluating the model performance for each increment of BCS. For development of CNN model, 70% of images were used, while 30% of them were used for testing and validation.

- Model 1: Increment of 0.25 unit class of BCS
- Model 2: Increment of 0.5 unit class of BCS

System information and software tools

A 2.0 GHz CPU running on 64-bit Windows 10 was used to train the model. The model implementation program for BCS estimation was written in Python (v. 3.7.0, Python Software Foundation, Wilmington, Delaware, United States). The 'Keras' library in Python was used to build the CNN-based image classification. It is a high-level Application Programming Interface (API) that operates on top of Tensorflow, and provides high-level building blocks for designing deep learning models [13]. Computer unified device architecture Deep Neural Network (CuDNN) was used to run the Keras models for high-performance GPU acceleration. CuDNN is a GPU-acceleration package that provides highly-tuned implementation for standard routines such as forward and backward convolution, pooling, normalization and activation layers [14].

Background subtraction and fuzzy logic edge detection of images

The segmentation between background and digitally-captured images was subtracted using the GNU image manipulation program (v. 2.10.22, GIMP Development Team, Charlotte, North Carolina, USA). It is an open-source software for performing image-feature tasks such as modifying, organizing and programming images. The background-segmented images thus obtained were converted to edge images. The edge of a digital image is a collection of pixels with change in gray value as well as the area where the brightness of the local area of the image changes significantly. Edge detection was used as a pre-processing step to obtain low-level boundary features that were passed on to subsequent processing steps like object detection and recognition. The background-segmented images were processed using the image processing toolbox in Matlab (v. R2022a, MathWorks, Natick, Massachusetts, USA). A Matlab code was implemented to locate the sharp changes in intensity and to identify the boundaries or contours of the captured images using fuzzy logic edge detection method. In this method, the cow images were converted to grayscale, and then a gradient image was produced using gradient filters. A fuzzy inference system was then developed for the images to obtain fuzzy-based edge images.

Model implementation

Convolutional neural network: The CNN architecture was designed to evaluate the BCS of the image dataset. There were three types of layers in the CNN architecture namely convolutional, pooling and fully-connected. The convolutional layer computes the convolution operation of the input images using kernel filters to extract various features using spatial filters such as edges, lines and corners. After the convolutional layer, the pooling layer was placed. The pooling layers are effective to minimize the spatial resolution of input volume for the next convolutional layer, making the features robust against noise and distortion [15]. The pooling layers do not affect the dimension of volume. The pooling layer applied non-linear down sampling on the. activation maps. As reduction in size results in loss of information, the process done by this layer is often referred to as sub-sampling

Several convolutional and pooling layers are stacked on top of each other to extract more abstract features in the neural network through fully-connected layers. Fully-connected layers contain a variety of classification techniques depending on the structure and type of network. As their name suggests, the neurons in a fully-connected layer have complete connections to all activation functions in the previous layer [15, 16]. The function of fully-connected layer was to converge the features extracted from convolutional and pooling layers to the number of classes the dataset was intended to be classified.

Proposed architecture: The designed CNN architecture used the edge-detected images as input with size of 256 × 256 px. The first layer in the CNN applied 32 filters on the input images with size of 3 × 3 px, producing 32 feature maps of 254 × 254 px size. The convolved layer then passed through a max-pooling layer of 2 × 2 px size and produced image size of 127 × 127 px. The second layer applied 32 filters, each of 3 × 3 px size, producing 32 feature maps of 125 × 125 px size and passed through a max-pooling layer of 2 × 2 px size, producing an image size of 62 × 62 px. The third layer applied 64 filters, each of 3 × 3 px size, producing 64 feature maps of 60 × 60 px size. Subsequently, it passed through the max-pooling layer of size 2 × 2 px, producing image size of 30 × 30 px. In this architecture, Rectified Linear Unit (ReLU) function was used as the activation function for both convolutional and fully-connected layers. Dropout was used to prevent overfitting by reducing the correlation between neurons.

Statistical analysis

The classification performance of each CNN model was assessed using a set of metrics, which measured the accuracy of prediction besides comparing the predictive performance of different models. The confusion matrix, commonly used in classification problems is a tool to recognize different classes and show the details of correct and incorrect classification for each class [17, 18]. In a confusion matrix, the rows represent true value and the columns represent predicted value. The diagonal of the confusion matrix represents the number of correctly predicted objects [19]. In fact, for each class, four possible values can be identified. True-Positive (TP) indicated that the true example was positive and the predicted example was positive. True-Negative (TN) indicated that the true example was negative and the predicted example was negative. Meanwhile, a False-Positive (FP) indicated that the true example was negative and the predicted example was positive. False-negative (FN) indicated that the true example was positive and the predicted example was negative [19, 20].

RESULTS AND DISCUSSION

Manual BCS scoring is the traditional method to determine the score of each cow by visual assessment. The images of cows from two viewing angles and their physiological information were compiled. The veterinary experts evaluated the images of these cows and classed them into different BCS, varying from 1 to 5 with increment of 0.25. The digitally-captured images were processed using GIMP software to subtract the background from the images of cows. It was accomplished by using the foreground select tool from the GIMP toolbox. The outline of the cow image was created by choosing each point on the images. Subsequently, the background subtraction methodology was used to obtain processed images without background. The background-subtracted images were used to detect the edges and contours of the cow's body using fuzzy logic edge detection method. A Matlab programme was written to identify the edges and contours of the cow images, and the images with body contours and edges were employed as the training and testing dataset for development of the CNN models.

Table 1 shows the classification accuracy of each model, which was calculated using the values of confusion matrix within various error ranges. The accuracy of the first model for 0, 0.25 and 0.50 error ranges was 46.32%, 63.23% and 85.29%, respectively. Similarly, the second model was achieved classification accuracy of 55.88%, 86.02% and 94.85%, for the respective error ranges. The accuracy of the second model was relatively better as compared to the first model owing to the bigger BCS range of classification (0.5 instead of 0.25) of the dataset. As the BCS increment of the second model was higher, it enabled the model to differentiate the BCS values easily without much misinterpretation. If the increment between the classes of BCS was lower, it would be tough for the model to recognize and classify the dataset for each range. However, the overall accuracy of the model was better (94.85%) as compared to manual assessment (78%) in evaluating the BCS. It was observed that the models of this study achieved the accuracy level similar to earlier works for different error range. A CNN-based BCS system was developed to evaluate the back images of 686 cows, and the model obtained average accuracy of 45%, 77% and 98% within 0, 0.25 and 0.50 error ranges, respectively [21, 22]. The BCS was assessed by manually marking 23 anatomical features from the rear contour of cows, and achieved an accuracy of 92.79% within 0.25 units of error

[23]. A recent study employing image analysis model for CNN achieved an accuracy of 78% within 0.25 error range [7, 24]. From these studies, it could be stated that the method of data collection and feature extraction techniques used in image processing could influence the prediction accuracy of BCS.

Table 1: Classification accuracy of Convolutional Neural Network (CNN) models.

Classification accuracy (%)		
Error range	Model 1	Model 2
0 (exact)	46.32	55.88
0.25	63.23	86.02
0.5	85.29	94.85

CONCLUSION

Body Condition Score (BCS) is an efficient tool to monitor the nutritional status of cows. The quality of manual BCS is decided by the assessor's experience and the standard of scoring technique. As a result, incorporating regular high-quality scoring of BCS of individual cows in a commercial farm as a routine procedure of management is challenging. In this study, two CNN models with two different error ranges were used to estimate the BCS of cows using edge detected images for different increments and error ranges of BCS. The classification accuracy of the models ranged between 85% and 95%, depending on the error range selected. The CNN models performed adequately for the middle range of BCS, wherein the data of most cows lied, but did not predict the extreme BCS classes very well. It is not a major concern as farms do not keep cows with such extreme BCS scores. However, there is further scope to make the system robust for all BCS classes by enlarging the image dataset to train and validate the CNN based system.

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