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BODY CONDITION SCORE ESTIMATION USING SALIENT OBJECT AND CONVOLUTIONAL NEURAL NETWORK

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Abstract

Every human life is associated with dairy products, especially milk. A cow is the root source of milk producers. Body Condition Score (BCS) is the method used to find the amount of amount of energy reserved by the cow. It is used to predict the cow's health. The objective of this paper is to automate the method of estimating BCS. This paper proposed an efficient method for estimating BCS using the salient object and Convolutional Neural Network. The cow's body is identified from the edge map from which the width is used as a feature. The edge map is given to CNN for another feature. These two features are combined and given to a regression technique for predicting BCS. The proposed method is evaluated on BCS dataset with 206 images. The performance of the proposed method is evaluated using the following metrics such as R^2 ,Accuracy and Root Mean Square Error. The efficiency of the proposed method is justified by comparing the proposed method with the existing methods.

Keywords: Convolutional neural network, salient object, regression

1. Introduction

Dairy Products are the basic foods for every human from birth. Proper maintaining of cows is helpful for products to increase their cow-calf enterprise. This method increases production efficiency and also identifies diseases prior to severe conditions. The manual BCS estimation is time-consuming and repetitive during the lactation period. It is a subjective process. The well-trained scorer also estimates BCS with an error of 0.25. It is necessary to find the individuals suffering from metabolic and nutritional problems. It can be done by eventually monitoring the changes in BCS.

BCS is used to improve the nutrition, health, production and pregnancy rate. Automation, Digitalization of livestock is the recent technologies in farming tasks which further offers with an accessible cost. BCS is 5-points scale system and the interval is 0.25 point. In 5-points scale system, the cows having a score of 1 is referred as emaciated and the cows having a score of 5 are referred as obese. Currently, the manual task carried out by the

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experts is a time-consuming process. The BCS scores calculated by the experts is in a naked-eye inspection manner and it is subjective. This manual estimation is computerized by capturing the images of a cow. An alternative technique to calculate BCS is to automate the process.

This paper proposes to use the shape and edge map of the cow to find the BCS. The main contributions of the proposed method include

- The cow is segmented using a salient object detection algorithm.
- The fatty nature of the cow is identified using CNN.
- The edge map is used to calculate the width of the cow.

The proposed method helps the producers to increase the potential cow-calf enterprise. Weaning calves produced from thin cows and supplementing thin cows are the reason for the increase of BCS in that group.

2. Related Works

Various BCS estimation methods are discussed in this section. Initially, this section discusses BCS estimation based on geometrical point analysis. Bewley et al. used twenty three anatomical points to analyze the cows shape and contour. Another method is proposed [1] to reconstruct the shape of cows. To find the shape function the error between contour of the cow and fitted parabolic curves are used [2]. In [3], six local regions are identified which has a strong correlation to the BCS another work is developed in [4] using the camera-based device called the Time-of-flight is investigated in cow barn conditions. In [5] a proven cattle body condition scoring system is proposed. In order to extract the contour information of the cow, a bounding box of rectangles technique is utilized. The distance vectors are found for describing the cow's shape. It has used six regression methods for BCS regression modeling.
In [6], Gaussian Mixture Model is utilized for separating the cow from the background image. After that global and local features have been used. In the end ensemble method has been adopted for training the unbalanced dataset. A geometric imaging approach is presented in [7]. To estimate body condition ratings, some anatomical points have been extracted from a cow's top view and the angle, length and area are to be examined. This method used polynomial and multiple regression and Markov Chain classification.In [8], a new method has been developed for automatically estimating the BCS of dairy cows using analytic geometry-image features. The automated localization of anatomical reference points has been used [9] to find points around the hook bones and along the spinal ridge. This method describes the body condition score of dairy cattle by a range of parameters describing statistical properties. In [10] Anglart et al. have developed an method to automatically estimate the body weight in dairy cows of the following two breeds; Swedish Holstein breed and the Swedish Red Breed (SRB).

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There are few deep learning algorithms for BCS estimation. Three machine vision-based precision technologies for dairy farming have been built and tested in [11]. Another method has been built for estimating BCS values based on CNN [12]. This method is further improved in [13] by employing transfer learning and ensemble simulation techniques. In [14], a low-cost BCS assessment approach is developed focusing on deep learning and machine vision. The Sing Shot multi-box Detector (SSD) method is utilized to find the tail and measure the BCS. A SSD method has been developed by modifying the network connection the real SSD.

SqueezeNet has have utilized the CNN model in [15]. SqueezeNet is a small CNN design. It achieves accuracy of AlexNet on ImageNet that has 50 times lesser parameters than the AlexNet. BCS evaluation is one of the time-consuming procedure, although it gives equivalent accuracy. Subjectivity in evaluator judgment leads to different scores for the same cow under observation, and previously observed cows can affect this [16].

From the study, it is observed that there are more researches based on geometrical properties of the cow rather than deep learning. Hence, this paper also uses geometric feature extraction for BCS estimation.

3. Proposed Methodology

The proposed system architecture is shown in Figure 1. Every input image needs some pre-processing for better processing. Following the pre-processing, the proposed method finds the shape of the cow by identifying the edges. The edges are also used to find the salient object. From the salient object, deep features are extracted using simple CNN. At the same time, the oval shape of the cow is also identified. The width of the top view of the cow is calculated from the oval shape. The CNN features and the deep features are given to regression to predict the BCS.

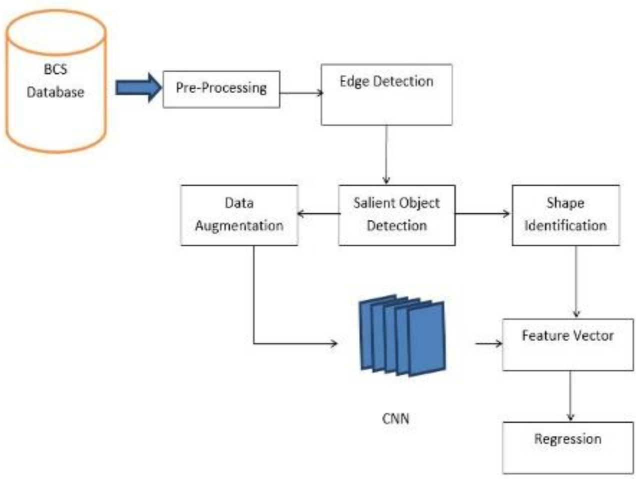

Figure 1: Proposed System Architecture

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A. Pre-Processing

Initially pre-processing is carried out for improving the image quality for a better visualization. Once the image is captured through the camera or through any other devices it is necessary to instigate with the noise present in image, background, blurring, brightness etc. The above mentioned problems regarding the image quality are solved through preprocessing step. The normalization in intensity ranges are done by separating the highest intensity value. The anisotropic diffusion filter is utilized for improving the image to the noise percentage.

B. Edge Detection

This paper formulates the edge detection process as one of the statistical implication. Here data driven method is used for edge detection which is not alike the model based methods. In order to find the local edge cues filters are used. The images before segmentation are processed to find the probability distributions of the filter outcome. It is evaluated based on the on or off an edge. Based on the likelihood ration of the filter edge detection is performed. Edge detection is formulated as a discrimination task specified by a likelihood ratio test on the filter respectively. Figure 2 show some input images and the edge maps. The main advantages of using this method are

- The method used here for gives better results quantitatively which is better than the canny edge detector. It provides good results even there is clutter in the background of image.
- It is used to find the efficacy of the edge cues and also provides quantitative method. The main advantage is multilevel processing which is utilized for the chrominance level and the relative efficacy of the detectors.

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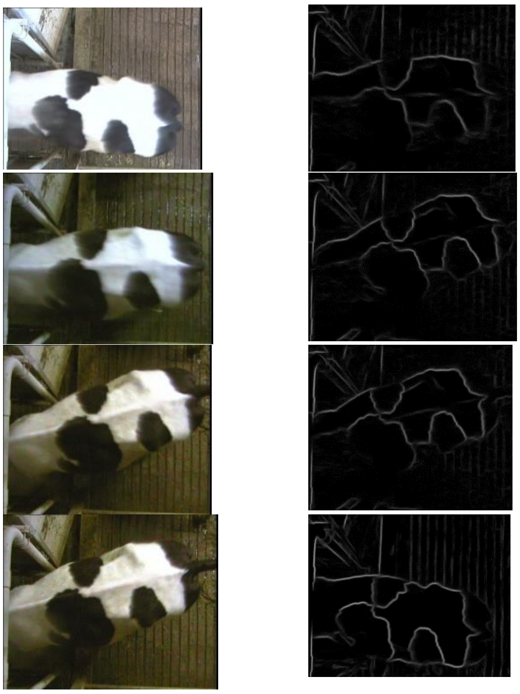

(a) (b)

Figure 2: (a) Input Image (b) Edge Map

C. Salient Object Detection

Here spectral salient object detection is utilized [17]. The chosen attributes of normalized cut are utilized, which intern retains the holistic salient objects. It is used to recursively bi-partitions region which offers the lowest cut cost during each iteration. Finally it results in a binary spanning tree structure. The ROI is evaluated using a specific criterion that suits Gestalt laws and statistical prior. The multiple saliency maps are integrated to produce the final outcome. Figure 3 shows the sample input image from the BCS dataset and the segmented salient region based on salient object detection. The cow in the BCS dataset is segmented using the detection window and the corresponding saliency map is also generated. By observing the BCS dataset, it is found that the salient object is present only in the less area. Thus salient object detection algorithm used here provides better results. The ROI of the corresponding input is extracted using the detection window.

Following are the steps to crop salient objects.

1. The saliency maps are generated from the edge map.
2. The salient image is fond using the detection window. In this step, image size may or may not be reduced which depends on the presence of a salient object.

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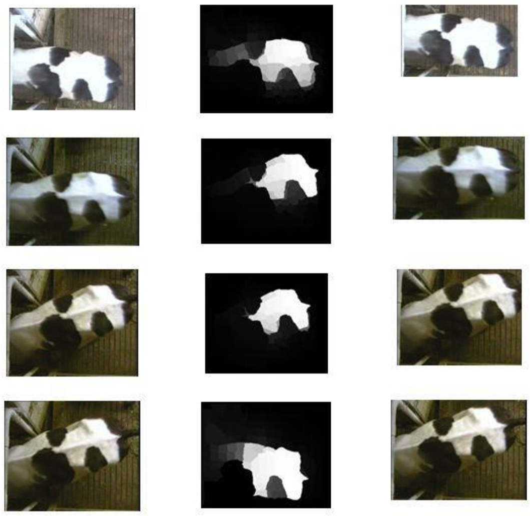

Figure 3: (a) Input Image from BCS dataset (b) Saliency Map of the input (c) Detection of salient object

D. Data Augmentation

In this phase the features are extracted based on all views of the image. In the previous phase, the identified salient objects are of different sizes. As the proposed method includes deep learning for feature extraction, all the images should be of similar sizes. Hence the image is adjusted to the size of the network model, which is 198 x 198. Also, some of the cows are in a diagonal direction. Hence rotation is also used for data augmentation.

E. Shape Identification

The size of the body is very much important for predicting a the health of the cow. The cow's shape is estimated by means of identifying edges of the cow. After edge detection, the shape is identified. The Curvature Scale Space (CSS) descriptor is used in this work. The boundary of cow is treated as a 1D signal. The 1D signal is analyzed in scale-space [18]. CSS relies on multi-scale representation. The planar curves are denoted using CSS curvature. The shape contour's concavities/convexities are identified using zero crossings at different scales. It is useful for shape description and it denotes the shape contour's perceptual features. Using this algorithm, the cow's shape is identified. Figure 4 shows the calculation of width of the cow.

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(a) (b)

Figure 4 (a) Shape of cow (b) Width Estimation

F. Feature Extraction

The very important phase in this system is the feature extraction phase. The salient objects with their augmented set are given to a simple CNN model to extract features. These features can give the thickness of the cow i.e., the fatty nature of the cow. From the edge map, the width is calculated. These two features are united together to form feature vector. These feature vectors are given as input to the regression model.

In this work, a 24-layer deep, 2D CNN is built. It includes convolution layers which are denoted as Conv, maximum pooling layer denoted as Max-pool, Fully Connected layer denoted as FC and Rectified Linear Unit denoted as ReLU. The main architecture of CNN is shown in Table 1. Two Convolution layers are divided with maximum pool stride 2 and ReLU layer. The filter size of all convolution layers is set to 3. After all convolution layers, there are 3 fully connected layers. After each fully connected layer one activation layer and one drop-out layer is present.

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Table 1: The Main Architecture of CNN

Layer Type	Size of filter	# Filters	FC	Input
Convolution	3x3	32	-	198x198x32
Convolution	3x3	32	-	196x196x32
Rectified linear unit.	-	-	-	196x196x32
Maximum pooling	2x2	-	-	98x98x32
Convolution	3x3	64	-	96x96x64
Convolution	3x3	64	-	94x94x64
Rectified linear unit.	-	-	-	94x94x64
Maximum pooling	2x2	-	-	47x47x64
Convolution	3x3	64	-	45x45x64
Convolution	3x3	64	-	43x43x64
Rectified linear unit.	-	-	-	43x43x64
Maximum pooling	2x2	-	-	21x21x64
Convolution	3 x 3	128	-	19x19x128
Convolution	3 x 3	128	-	17x17x128
Rectified linear unit.	-	-	-	17x17x128
Maximum pooling	2x2	-	-	8x8x128
Convolution	3x3	256	-	6x6x256
Convolution	3x3	256	-	4x4x256
Rectified linear unit.	-	-	-	4x4x256
Maximum pooling	2x2	-	-	2x2x256
Fully Connected	-	-	256	-
Fully Connected	-	-	256	-

G. REGRESSION

BCS estimation is done using various regression models in [19]. From [19], it is observed that Elastic Net (EN) predicts the score with less error. Hence EN is used in this research. EN[20] is one of the linear regularized techniques that is used to linearly combining $L1$ and $L2$. L1 and L2 are the penalties of the Lasso and the ridge regression methods. The EN method estimates are defined as

$$\hat{w} = \arg min_w (\|y - X_w\|^2 + \lambda_2 \|w\|^2) + \lambda_1 \|w\|_1 \quad (1)$$

The loss function is strictly convex and there is a unique minimum in the quadratic penalty function. This kind of estimation incurs adouble shrinkage amount occurs due to this type of estimation. It also leads to an increased bias and very poor predictions.

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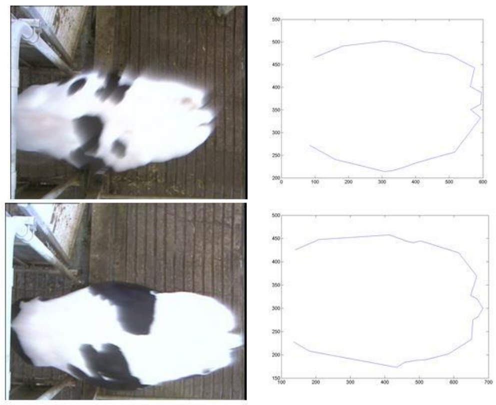
4. Experimental Results

The efficiency of the proposed method is analyzed in this section with experimental results and an ablation study. It starts with a discussion of the dataset used in this work.

A. Details of the dataset

The BCS estimation methods mostly build a dataset for its analysis. Different cameras are used for capturing cow images. Apart from these private datasets, there is only one publicly available dataset, which is the BCS dataset [21]. The BCS data set contains 29 cow's body shape for the corresponding 286 color images of cow. The resolution of the image in the dataset is 704 x 480 pixels. Some sample input images with anatomical points are given in Figure 5.



(a) (b)

Figure 5(a) Sample Images and its (b) anatomical points from BCS Dataset

B. Performance Measures

The efficiency of proposed method is calculated by means of the percentage of error, model accuracy (Acc) and coefficient of determination (R2) are used. Root Mean Square Error (RMSE) is used to calculate the percentage of error which is given as,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \quad (2)$$

Where $x_i$the actual observation is$\widehat{x}_i$ is the estimated observation and, N is total number of observations. The correlation measure is found using the Pearson correlation coefficient.

The global accuracy is estimated using the correct classifications and the varying human Error Ranges (ER): ER=0, ER=0.25 and ER=0.5. The accuracy is the classifier's efficiency. It is also called as the percentage of samples that are correctly classified. It is given as

$$Acc = \frac{No.of\ correct\ predictions}{.of\ Predictions} \quad (3)$$

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To measure reliability During the information gathering within cows the reliability is measured. For each and every individual cow the determination coefficient is calculated for all character. It is also restricted to each individual cow (R^2 cow). The statistics used here denotes how closely the values are acquired from the fitting model and how it matches with the dependent variable that the model is planned to predict. R2 is defined by the statisticians by means of a residual variance from the fitted model:

$$R^2 = 1 - SS_{resid}/SS_{total} (4)$$

SS_{resid} Is the sum of the squared residuals from the regression. SS_{total} is the sum of the squared differences from the mean of the dependent variable (total sum of squares). Both are positive scalars.

C. Results

The visual results and the quantitative results are discussed in this section. Figure 6 shows the results obtained in each step using the proposed BCS system.

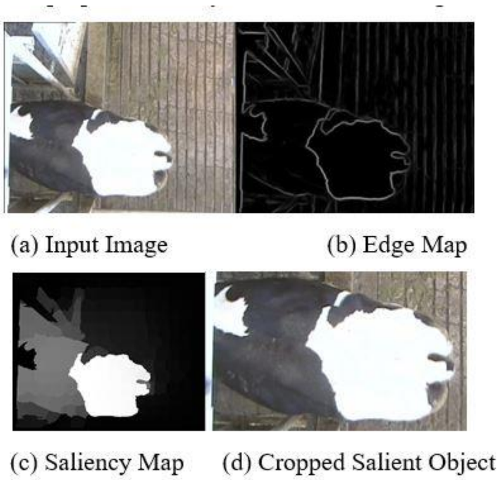

Figure 6: Intermediate Results Obtained using Proposed Method

The evaluation of proposed method is done by using accuracy, RMSE and R^2 and the results are shown in Table 2. The accuracy is calculated for various error ranges (<0, <0.25 and <0.5). The results are analyzed for various regression models such as Lasso and Ridge regression.

Table 2:. Results Obtained by the Proposed Method

Measure		Lasso	Ridge	EN
RMSE		0.27	0.212	0.199
R^2		0.71	0.79	0.79
Accuracy	ER=0	73.6	74.1	74.6
	ER=0.25	85.2	84.7	85.8
	ER=0.5	94	94.6	98.7

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From Table 2, it is clear that the highest accuracy of 98.7% with 0.199 errors with the EN regression model is achieved using this proposed system. The proposed method accuracy is compared with the help of various regression models and it is shown in Figure 7

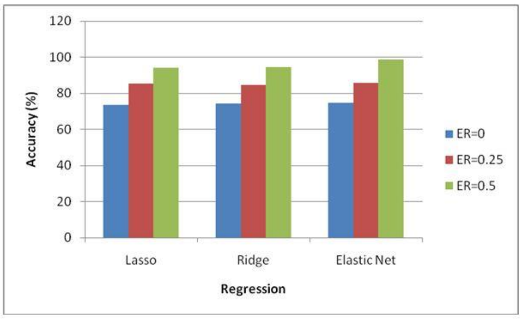

Figure 7 Comparison of Accuracy for various Regression Models

D. Ablation Study

The impact of a salient object is studied by excluding the salient object detection method. Table 2 shows the results of this ablation study of the proposed system on BCS dataset.

From Table 2, it is clear that the inclusion of salient object detection has some contribution to the proposed method. The proposed method accuracy is is 3% higher with the salient object than the proposed method without a salient object.

E. Comparison of Proposed Method with Recent Methods

The proposed method accuracy is compared with the recent existing methods that are discussed in Section 2. All these methods use different datasets. Table 3 shows the comparison result of the proposed system with the existing system.

Table 3 Accuracy Comparison of Proposed Method with Recent Methods

Method	Accuracy (%)	
	ER=0.25	ER=0.5
Shelley (2016) [11]	71.35	93.91
Spoliansky et al. (2016) [3]	74	91
Rodríguez Alvarez et al. (2018) [12]	78	94
Rodríguez Alvarez et al. (2019) [13]	81.31	96.82
Huang et al. (2019) [14]	Average Accuracy = 98.46	
Liu et al. (2020) [6]	76	94.2
Proposed Method	95.8	98.7

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From Table 3, it is studied that all the methods achieve accuracy above 90%. The proposed method provides higher accuracy than the other existing methods.

5. Conclusion

The health of the cow can be estimated using the Body Condition Score. BCS estimation is helpful for dairy producers. This paper estimates the BCS of a cow using salient objects and CNN. The thickness of the cow is studied by the deep features and shape of the cow. The score is calculated by various regression models such as lasso, ridge and elastic net regression. From the results, it is studied that the elastic net regression achieves higher accuracy than other regression models.

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