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Determining the body condition scores of sows using convolutional neural networks

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ABSTRACT. ***The body condition of a sow indicates its degree of obesity and, hence, critically determines the health and productivity of the sow during the next pregnancy. Precisely scoring the body conditions of sows is essential in feeding management. Conventionally, the body conditions of sows are scored from rear views by breeders. Manual observation, however, largely relies on the experience of the breeders and can be subjective. This study aimed to score the body conditions of sows using image processing and deep learning. A convolutional neural network was developed to identify the bodies of sows in images. The aspect and conformation ratios of the sows were then determined. Body conditions were then scored based on these ratios. The study proved that image-based scoring of sow body conditions was achievable and could be applied to the livestock industry.***

Keywords. Fully convolutional neural network, sow body condition scores, semantic segmentation, image processing

Introduction

Sows are common livestock worldwide. In the 2017 annual agricultural statistics report of Taiwan, the production value of sows accounted for 13.85% of the total agricultural production. The body conditions of breeding sows play a significant role in sow management during their pregnancies. The feeding strategies for the sows may need to be adjusted accordingly. Conventionally, the breeders scored body conditions of sows from rear views manually or using ultrasonic measurement (Mersmann *et al.*, 1982). The naked-eye approach relies on the experience of the breeders, and the ultrasonic measurement is costly. Thus, an objective and cost-effective approach is needed.

Segmenting sows from the backgrounds is the first step to automatically score the body conditions of the sows using image processing. Pigpens are usually in complex background with miscellaneous items (Fig. 1a). Also, multiple pig bodies may appear in an image. Thus, advanced segmentation approaches are needed. Fully convolutional networks (FCN; Long *et al.*, 2015) is a deep learning approach used for semantic segmentation problems. Lottes *et al.* (2018) developed a system to separate crop from weeds in images using FCN. Huang *et al.* (2018) identified the areas covered with weeds in

UAV images using FCN. Dyrmann *et al.* (2016) distinguished crops, weeds, and soil pixel-wisely in field images using FCN. Picon *et al.* (2018) identified lesions on crops using mobile devices and FCN.

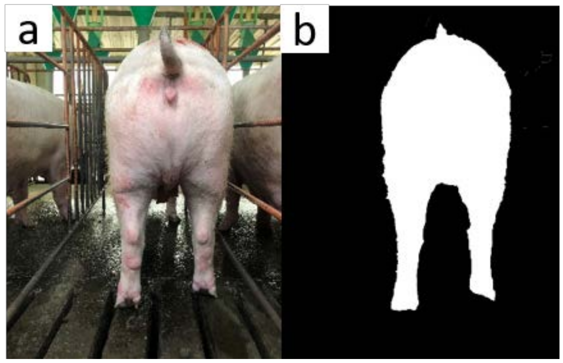

Figure 1. (a) An image of a sow, and (b) the training mask of the sow.

This study aimed to quantify the body conditions of breeding sows using rear-view images. The specific objectives were to 1) segment sows from complex backgrounds using FCN, 2) quantify the widths and heights of the sows using image processing, and 3) quantify body conditions based on the aspect ratios of the sows.

Materials and Methods

Sow image collection

A total of 33 images of sows were acquired using a digital camera and a tabletop tripod. The dimensions of the images were 3024 × 4032 pixels. Among the images, 19 and 14 were used for training and test, respectively. The masks of the sows (e.g., sow bodies; Fig. 1b) in the images were manually labeled using Photoshop. The body condition scores of these sows were determined manually by professionals.

Semantic segmentation

An FCN (Fig. 2) was trained to automatically segment the sows from the background. The architecture of the FCN was adapted from U-net (Ronneberger *et al.*, 2015). The FCN consisted of a downsampling part and an upsampling part. Each part was composed of four repetitive structures. Each repetitive structure had two convolutional layers with kernels of 3 × 3 pixels and batch normalization (Ioffe *et al.*, 2015), followed by a rectified linear unit (ReLU). In the downsampling part, max pooling operations with kernels of 2 × 2 pixels were applied to downsample feature maps. In the upsampling part, convolutional operations with kernels of 1 × 1 pixel with a bilinear upsampling were applied to upsample feature maps. The results were concatenated with the feature maps from the corresponding layers in the downsampling part. A sigmoid activation function and a convolution operation with a kernel of 1 × 1 pixel was used in the last layer of the FCN. The dimension of the input image was 384 × 512 pixels. Nineteen images were used for training. Dice coefficient (Milletari *et al.*, 2016), a quantity ranging between 0 and 1, was applied to loss function.

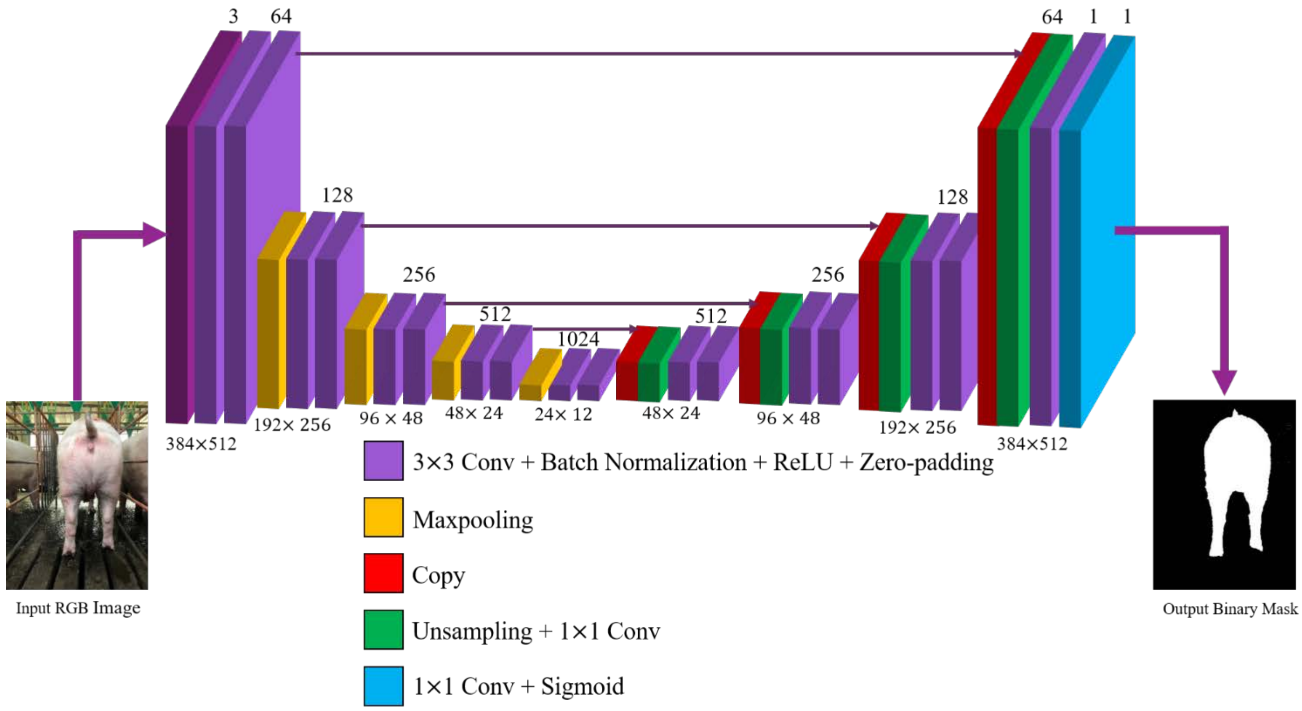

Figure 2. The architecture of the modified FCN model.

Aspect ratio and conformation

The body lengths and widths of the sows were quantified using image processing (Fig. 3). In the procedure, connect-component labeling (Fig. 3c) was applied to the output mask of a sow from the FCN (Fig. 3b). The largest component in the mask was considered as the sow. The rest objects were then removed. Next, the tail of the sow was removed. In the procedure, each row in the mask image was examined using thresholding. A row was considered to belong to the tail of the sow if the width of the row did not exceed the threshold. The rows which belong to the tail were then removed (Fig. 3d). In this study, the threshold was set to 40 pixels. Subsequently, the widest width of the sow from the rear view was then identified (red line in Fig. 3d). The body length was identified as the length of the vertical line (green line in Fig. 3d) crossing the center of the widest width of the sow. Two lines perpendicularly crossing the body length line at one-third and two-third of the line were quantified as two approximate widths (blue lines in Fig. 3d). The width of the sow was then quantified as the average of the widest width and the two approximate widths. The aspect ratio of the sow was calculated as the ratio of the width to the length.

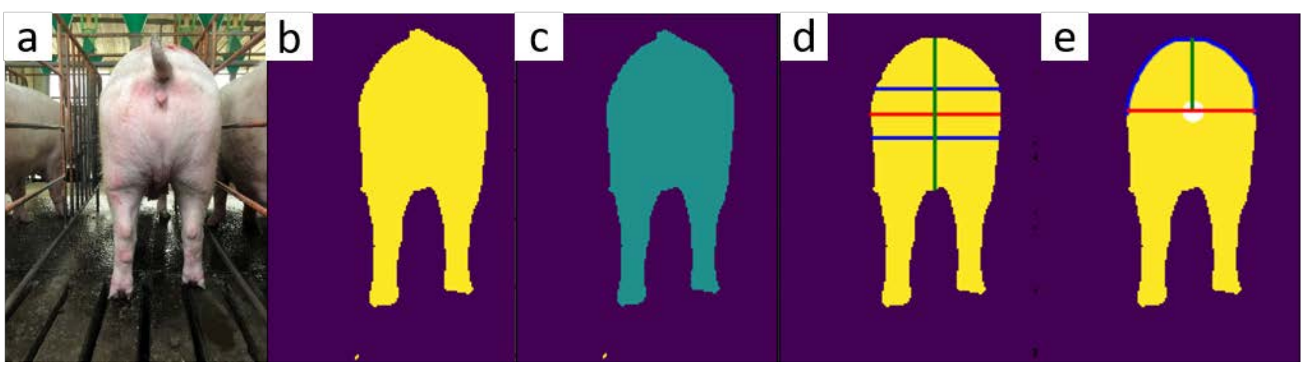

Figure 3. Images of (a) original images of sows, (b) output binary masks of FCN, (c) connect-component labeling, (d) the aspect ratio, (e) the conformation ratio.

The conformations of the sows were also quantified. A conformation was defined as the top half of the rear view of the sow. The conformation of a sow was determined as the ellipse that best fits the contour (Fig. 4) in least-squares sense (Fitzgibbon *et al.*, 1999). Subsequently, the conformation ratio was calculated as the ratio of the minor axis(one-second of red line in Fig. 3e) to the long axis(green line in Fig. 3e) of the conformation.

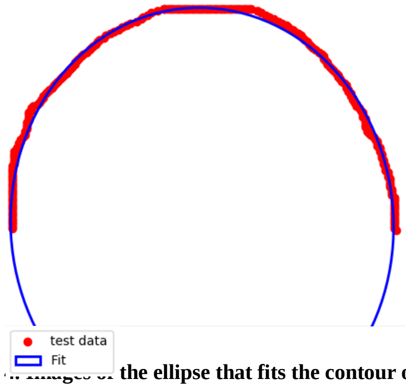

Figure 4. Images of the ellipse that fits the contour of a sow

Body score estimation

The body scores of sows were predicted using the quantified aspect ratios, conformation ratios, and linear regression. The 14 test images were used in the regression, in which 10 and 4 images were used for training and testing, respectively, the regression model.

Results

Training loss of FCN model

The training loss of the FCN was shown in Fig. 5. The loss converged to about 0.015 after 500 epochs. The trained FCN was evaluated using the 14 test images. The model achieved an average accuracy of 93.13%.

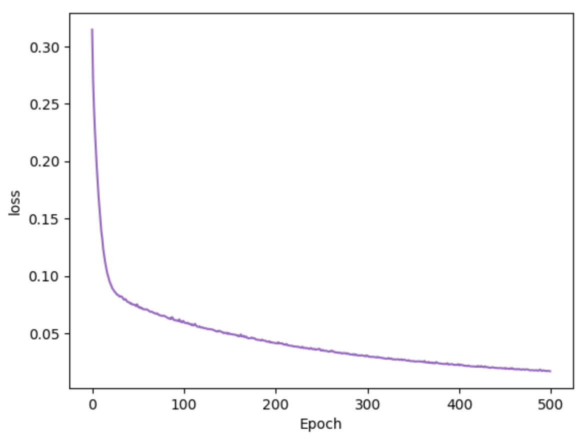

Figure 5. Training loss of the FCN model

The performance of the FCN and ratio quantification

The performance of the trained FCN and proposed image processing procedure was demonstrated using some test images (Fig. 6). The results showed that the FCN could accurately segment the sows from the background. The results also showed that the proposed image-processing procedure could accurately quantify the aspect and conformation ratios.

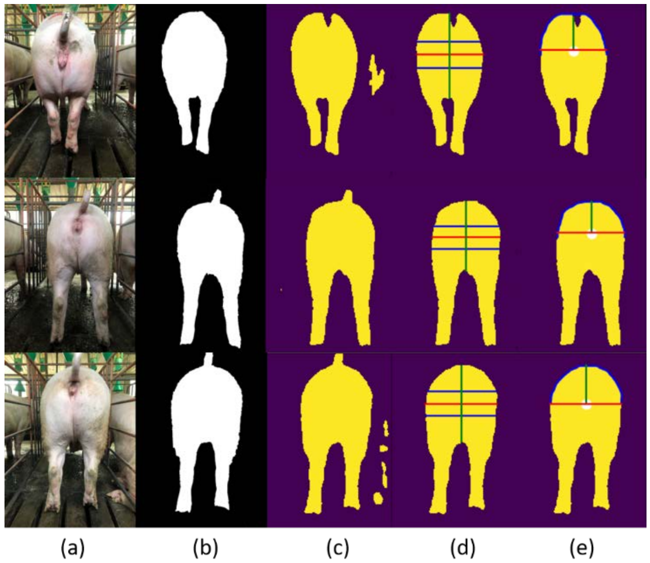

Figure 6. The results of sow segmentation and ratio quantification: (a) original images of sows, (b) the training mask of the sows, (c) output binary masks of FCN, (d) the aspect ratio, (e) the conformation ratio

The performance of body score prediction

The linear regression model was developed following the aforementioned procedure (Table 1). The coefficients of the aspect ratio and the conformation ratio were -2.4475 and 2.1663, respectively, indicating that the aspect ratio was a more important trait for predicting body score. The R^2 was 0.558. The mean squared error was 0.278.

Table 1. Each result of all images used for liners regression

The No. of sows	The aspect ratio	The conformation ratio	The score from rear views manually
7	0.796	1.107	4
8	0.766	1.027	3.5
9	0.899	0.995	3
13	0.769	0.980	3
14	0.883	0.901	3
15	0.970	1.059	3
16	0.860	0.890	3
23	0.908	0.933	3
28	0.908	0.940	3
30	0.790	0.831	3
The No. of sows	The aspect ratio	The conformation ratio	The score from rear views manually / The score from prediction
1	1.226	1.000	3 / 2.282
17	0.971	1.181	3.5 / 3.299
18	0.783	0.961	4 / 3.279
20	0.888	1.020	3 / 3.15

Conclusion

This paper proposed to determine the body condition scores of sows using FCN, image processing, and linear regression. Sows in complex images were first segmented using FCN. The aspect and conformation ratios of the sows were then quantified using image processing. Sow body scores were next determined using linear regression. The FCN model reached an accuracy of 93.13%. The mean squared error of the linear regression model was 0.278. The coefficient of the linear regression model indicated that both conformation and aspect ratios were essential traits for determining the body condition scores.

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