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Study on Pig Body Condition Scoring Based on Deep Learning Model EfficientNet-B0

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Abstract: *Pig body condition scoring is an important tool for pig farmers to ensure the health and nutritional status of pigs. An efficient and accurate body condition scoring method is very important to ensure the health of pigs. This thesis proposes an automatic and objective pig body condition scoring method based on deep learning and EfficientNet-B0. Traditional methods of visual examination and manual palpation are subjective, time-consuming, and can vary from observer to observer, leading to inconsistent and unreliable results. Deep learning model based on artificial neural network shows great potential in automating pig state scoring. The proposed method was trained and evaluated on a large pig image dataset, and compared with traditional manual methods and object detection deep learning algorithms. The results show that this method can improve the accuracy and efficiency of pig body condition grading, with a higher average accuracy of 85.66% for body condition classification, which has certain practical production significance and provides a foundation for further related research.*

Keywords: *Body Condition Scoring, EfficientNet-B0, Deep Learning, Image classification*

1. Introduction

Pig body condition scoring is a critical process in pig farming as it ensures the health and nutritional status of the pigs. Accurate body condition scoring allows farmers to optimize feed and nutrition management, thus improving pig welfare and profitability. Inaccurate scoring can lead to overfeeding or underfeeding, resulting in health problems such as obesity, reduced reproductive capacity, and even death. Therefore, an efficient and accurate body condition scoring method is crucial to ensure pig health[1].

Traditional pig body condition scoring is done through visual inspection and manual palpation, which requires high expertise and specialized training. This method is highly subjective and can vary among observers, leading to inconsistent and unreliable results. It is also time-consuming, particularly for large-scale pig farming, limiting its practicality and efficiency. Machine learning and computer vision technologies have shown great potential in automating the pig body condition scoring process, particularly with the emergence of deep learning as a powerful tool for image classification and recognition[2]. Deep learning models based on artificial neural networks can learn from large labeled data sets and identify complex patterns in images. These models have achieved state-of-the-art performance in many computer vision tasks, such as object detection, image segmentation, and face recognition.

Currently, many scholars are researching automated body condition scoring techniques for livestock. Cao summarized three methods for cow body condition scoring, including manual scoring, ultrasound imaging to measure rump thickness, and visual technology combined with artificial intelligence, and applied them in a cow farming setting[3]. Liu validated the professionalism and consistency of their Lira-BSC fully automated body condition scoring system against manual scoring[4]. Li studied the use of deep learning for cow body condition scoring using target detection algorithms like Faster RCNN, SSD, and YOLO, verifying its accuracy[5]. Kong and Chen proposed a multi-task learning regression network based on the Mask R-CNN target detection network technology to predict pig weight and body condition scoring, dynamically adjusting the weights of different learning tasks to improve prediction accuracy[6]. Zhao Kaixuan et al. constructed a 3D structure feature map based on convex hull distance of point clouds and used it as the input of a two-level model based on EfficientNet network, which realized the

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improvement of recognition accuracy within the error of 0.25 in the automatic scoring of cow body condition[7]. Juan Rodríguez Alvarez et al. proposed a system based on Convolutional Neural Networks to improve overall automatic BCS estimation, whose use might be extended beyond dairy production. The developed system has achieved good estimation results in comparison with other systems in the area[8].To learn a more effective representation of concavity information automatically and focus on vision saliency information precisely of local area of dairy cows' back end, Shi Wei et al. proposed an automatic method to estimate BCS of dairy cows based on attention-guided 3D point cloud feature extraction[9].

The EfficientNet-B0 model used in this study is a deep learning model designed specifically for achieving high accuracy and efficiency in image classification tasks. EfficientNet-B0 is a relatively lightweight model, with only 5.3 million parameters compared to other state-of-the-art models with billions of parameters. Despite its small size, EfficientNet-B0 has achieved the best performance on several image classification benchmarks such as ImageNet and CIFAR-10. The superior performance of the EfficientNet model, which reached the highest image recognition accuracy of 84.3% on Imagenet top-1 in 2019, has made it a popular choice for various computer vision applications, such as plant disease recognition, satellite image classification, and facial expression recognition[3].

Given the success of deep learning and EfficientNet-B0 in various computer vision applications, exploring their potential in pig body condition scoring is a natural next step[10]. Based on the automated and objective nature of deep learning methods, accurate and consistent results can be provided, which can help pig farmers make better decisions in terms of feed and nutrition management. Additionally, this method can reduce the manpower and time required for pig body condition scoring, making it more practical and feasible for pig farmers.

In this study, this paper proposes an automatic and objective pig body condition scoring method based on deep learning and EfficientNet-B0. This paper uses a large dataset of pig images collected from 1980 pigs in the same farm to train and evaluate the model. This paper compares the performance of our method with traditional methods and object detection deep learning algorithms, and analyze their data consistency and accuracy. Our method has the potential to improve the accuracy and efficiency of pig body condition scoring and enhance pig welfare in the pork industry.

2. Methodology

2.1 Overall experimental process

This paper proposes an automated and objective method for evaluating the body condition of pigs based on deep learning and EfficientNet-B0. Using a large dataset of pig images collected from 1980 pigs in the same pig farm, this paper trained and evaluated our model. This paper compared our method with traditional methods and deep learning algorithms for object detection, and analyzed the consistency and accuracy of the data. Our method has the potential to improve the accuracy and efficiency of pig body condition scoring and enhance the welfare of pigs in the pork industry.

The overall process of this experiment involved collecting data on pigs, creating a dataset, and using EfficientNet-B0 for image classification. This paper compared our results with those obtained from manual body condition scoring and object detection algorithm scoring for consistency and accuracy, with a focus on the EfficientNet-B0 experimental process and results.

This paper began by recording videos of the backside of all 1980 pigs at the pig farm from the same viewing height. This paper then classified and extracted the images of the pig backs obtained from the videos and ultimately obtained a total of 4343 pig images for dataset creation. Three groups of personnel with years of experience in pig farming were assigned as the manual scoring group. The scores given by the three groups were averaged to divide all data into five categories, which were then annotated and sent into a deep learning machine for training using two different algorithms. This paper completed the experiment by comparing the scores of the two trained deep learning models with those of the manual scoring group for consistency and accuracy.

2.2 Relevant principles EfficientNet-B0

EfficientNet is a convolutional neural network architecture and scaling method that uses composite coefficients to uniformly scale all dimensions of depth, width, and resolution. Previous neural network models have improved accuracy and efficiency by increasing the depth of the grid, changing the

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parameters of feature extraction, or improving the resolution of input images. However, these methods result in a significant increase in computational complexity. EfficientNet scaling method uses a set of fixed scaling coefficients to uniformly scale the network width, depth, and resolution [11]. In addition, in the EfficientNet architecture, although the input image size must be adjusted to 132 × 132 due to hardware limitations, it achieves better results than other CNN models that accept higher resolution input images [12]. EfficientNet-B0 consists of 16 mobile inverted bottleneck convolutional modules, 2 convolutional layers, 1 global average pooling layer, and 1 classification layer, which can be divided into three main parts: backbone, convolutional block, and classification head, as shown in the Figure 1.

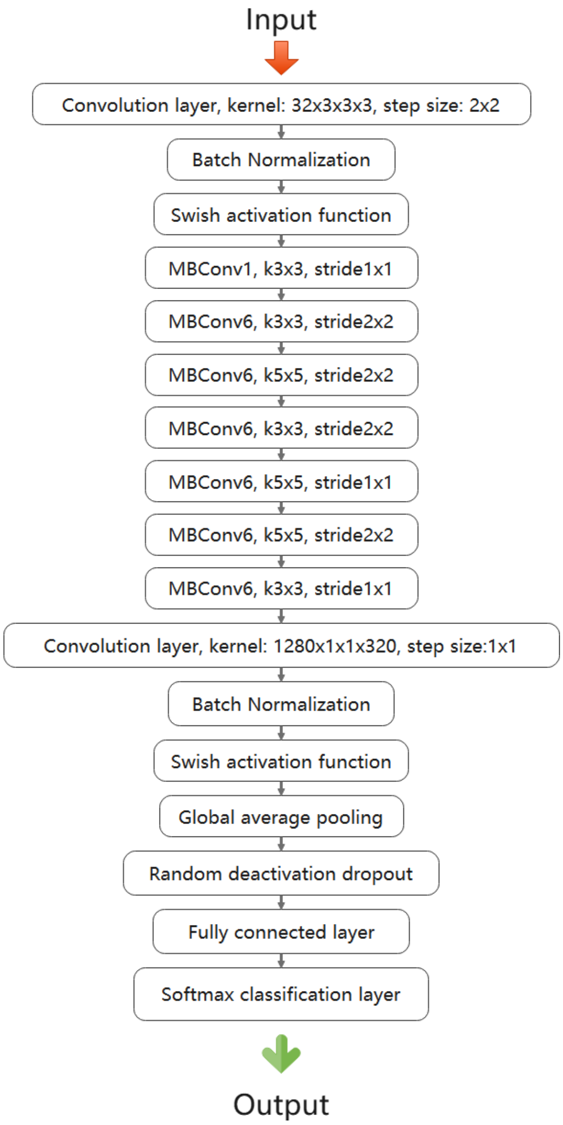

Figure 1. EfficientNet-B0 Network structure chart

The backbone EfficientNet-B0 is a set of initial convolutional layers that are processed before the input images are passed through the convolutional blocks. The stem consists of three layers: the first layer is a 3x3 convolutional layer that applies 32 filters to the input image. The layer has a step length of 2, which reduces the size of the input in half. The second layer is the batch normalization layer, which normalizes the output of the first layer. The third layer is the Swish activation layer. Swish is a nonlinear activation function that has been shown to be superior to other popular activation functions such as ReLU and sigmoid.

There are a total of seven convolutional blocks EfficientNet-B0. Each block consists of a series of convolutional layers, followed by a batch normalization layer and a Swish activation layer. The number of filters in each block increases as you go deeper into the network, allowing the network to learn more and more complex features. The structure of each block is as follows: the first layer is the 1x1 convolution layer, which applies a set of filters to the input; The second layer is a 3x3 depth convolutional layer that applies a set of filters to each channel output from the previous layer; The third

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layer is the batch normalization layer, which normalizes the output of the second layer; The fourth layer is the Swish activation layer; The fifth layer is a 1x1 convolution layer that applies a set of filters to the output of the fourth layer; The sixth layer is the batch normalization layer, and the output of the fifth layer is normalized. Layer 7 is a jump connection that connects Layer 3 outputs to Layer 6 outputs.

The category header EfficientNet-B0 consists of the global average pooling layer, exit layer, and full connection layer. The global averaging pooling layer averages the output of the last convolutional block along each channel, reducing the output to a single vector for each channel. The dropout layer randomly discharges a portion of the output to prevent overfitting. The full connection layer maps the output of the exit layer to the number of classes in the data set.

2.3 Data set collection and manual evaluation

2.3.1 Data set collection

In this study, this paper collected a data set containing images of 1980 pigs of different body sizes from the same pig farm. To verify the effectiveness of the method proposed in this paper, a camera was used to shoot the target pigs as a data set. This paper used a fixed height camera with all white lights turned on in the farm to ensure consistent light sources. The images were captured in a controlled environment by videotapes of pig buttocks at the same height to minimize the effects of light, background, and other irrelevant factors that might affect the algorithm's performance. In this study, the obtained data set videos were intercepted every 1s by the script program, and the captured pictures were selected. After the pictures with unclear targets and unclear pig features were removed, a total of 4343 effective screenshots were obtained, with a resolution of about 1000*720.The target pig image in a data set is shown in Figure 2.

Figure 2. Sample pig data set picture

2.3.2 Manual evaluation

2.3.2.1 Manual evaluation of shortcomings

The traditional posture identification of pigs requires a large number of technical personnel or service personnel, in the identification is also affected by many factors, and each pig farm scale, pig farm environment, pig farm management mode is different, and there is no clear posture standard when the region is divided, so that the workload of the staff unified identification of pigs in the pig farm greatly increases. The traditional artificial identification has the following shortcomings. Therefore, traditional manual identification has problems such as uneven statistical data, untimely data updates and inaccurate data due to frequent turnover of evaluators.

2.3.2.2 Improve the manual evaluation method of this group based on shortcomings

The pigs in this farm are kept in average compartments. The number of pigs in A-Z24 zones is relatively evenly distributed and numbered from 1 in sequence. According to the problems summarized above, the evaluation work will be carried out by three senior pig farmers. Each person will score the 4343 pig photos obtained in two rounds according to the body size of the pig in five grades: 2.0, 2.5, 3, 3.5, and 4. Then, each pig photo will have 6 scores. The average of the six scores is taken and rounded to get the body score of the pig. Finally, the region, number and body data of pigs were input into the table for data storage, and 4343 photos of pigs were classified according to the results.

It is worth noting that only 192 photos of pigs were actually evaluated as Score-2.0, which is significantly less than the number of photos of pigs with scores of other body conditions. This is because

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pigs that are too small in the process of pig breeding are very special. Therefore, it is impossible to guarantee the sufficient quantity of score-2.0 at the data source, and there may be distortion in the training of the Score data set. The other four scores were relatively average.

2.4 Model training

The experiment carried out in this paper is carried out under the Pytorch framework, the operating system is Ubuntu18.04, the hardware is CPU is i7-12700F, the graphics card is NVIDIA GeForce RTX 3090, the memory is 32G, and the training Epoch is set to 2000. 4343 photos of pigs were classified according to the results and input into the deep learning framework for training. The training results are shown in Figure 3.

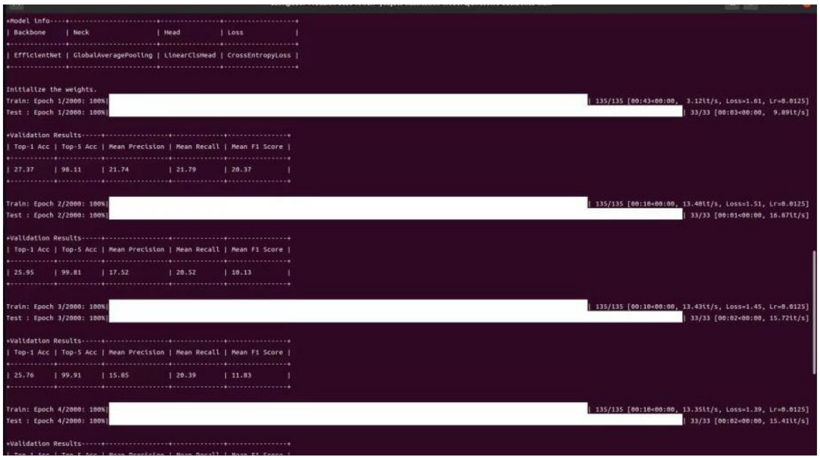

Figure 3. Deep learning machine training process

3. Results and Discussion

3.1 Model result

In this paper, computational Accuracy, Precision, Recall, F1 and average accuracy were selected as the detection performance indicators. According to the preset number of 2000 iterations, a satisfactory model was finally obtained. The curve relationship between Train loss and Val acc of 2000 iterations is shown as the figure below. It can be seen that the Accuracy of the model increased rapidly in the first 90 iterations, while the Train loss also decreased rapidly. However, the Accuracy of subsequent model iterations gradually increased and finally reached more than 85% and still maintained an upward trend. After the 90th iteration, although Train loss also declined slowly, its rate rose faster than Accuracy and finally stabilized at about 0.25 and still maintained a downward trend, indicating good training. This paper finds the iterations based EfficientNet-B0 to be faster and more accurate, and based on the trend shown in the Figure 4 we are reasonable to believe that the accuracy and training loss reach a better level after increasing the number of iterations.The trend are shown in Figure 4.

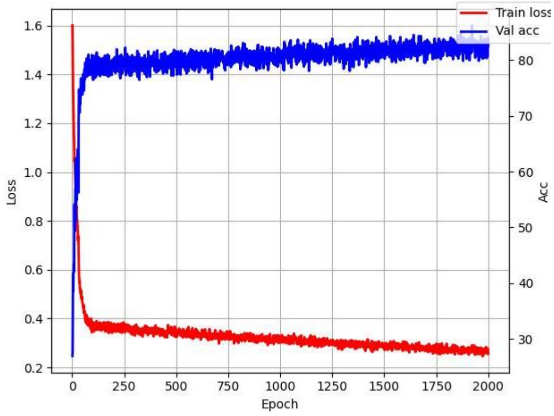

Figure 4. Model iteration times and accuracy effect

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The following two tables summarize the class results and Total results obtained by the training EfficientNet-B0 respectively. It can be seen that the average accuracy of scoring for the five body conditions reached a high level, especially for the pigs with Score-2.0, Score-2.5 and Score-4.0 all reached more than 97%, and the average accuracy of Score-3.0 and Score-3.5 also reached 80%. After analysis, this paper believes that the fundamental reason why score-2.0 gets the highest Score among the four scores is because of the high particularity of this breed of pigs, so there are few data sets, but its characteristics obviously ensure the accuracy of recognition. However, the physical difference between the two types of pigs, Score-3.0 and Score-3.5, was not obvious in actual production, which resulted in the smaller mutual sex of the two types of pigs and thus lower accuracy than the other three types of pigs. However, the practical production significance of the model could still be guaranteed even in this case.The contents of the two tables are shown in Table.1 and Table.2.

Table 1. Classes results

Classes	Precision	Recall	F1 Score	Average Precision
Score-2.0	96.00	100.00	97.96	99.92
Score-2.5	92.39	94.80	93.58	98.77
Score-3.0	75.34	75.86	75.60	83.12
Score-3.5	74.09	68.80	71.35	80.91
Score-4.0	90.45	93.87	92.13	97.50

Table 2. Total results

Top-1 Acc	Top-5 Acc	Mean Precision	Mean Recall	Mean F1 Score
83.41	100.00	85.66	86.66	86.12

3.2 Compare with other methods

To verify the accuracy and consistency of the body condition scoring data, the photo data were also manually identified and the YOLOv5 identified respectively to check the accuracy of the algorithm EfficientNet-B0.

In order to compare accuracy and consistency, in the experiment of artificial recognition, the three self-breeding personnel who helped in photo classification identified the photos again, gave another round of scores, and then directly compared whether the scores given were consistent with the actual scores, calculated the accuracy rate and calculated the average of the three people as AP. Thus, the correct rate of EfficientNet is close to or even better than manual evaluation. The 3.0 and 3.5 levels, which are the most difficult to distinguish, also maintain an accuracy rate of more than 80 percent, indicating that the B0 model meets expectations.

As for the YOLOv5 part, this paper also classified the photo model into 5 categories and made manual delineation frames to provide YOLOv5 with training. Compared with the expected convergence rate when the data is still the same after 2000 iterations, YOLOv5 converges after 500 iterations and the accuracy is only 60% to 70%. The advantages of EfficientNet-B0 were highlighted once. The comparison of the three methods in terms of Average and Mean Precision is shown in Table.3 and Table.4.

Table 3. Total results

Classes	Average Precision (Manual)	Average Precision (YOLOv5)	Average Precision (EfficientNet-B0)
Score-2.0	95.11	63.38	99.92
Score-2.5	87.40	66.62	98.77
Score-3.0	82.33	70.49	83.12
Score-3.5	81.00	62.04	80.91
Score-4.0	92.27	74.83	97.50

Table 4. Total results

Classes	Average Precision (Manual)	Average Precision (YOLOv5)	Average Precision (EfficientNet-B0)
Mean Precision	81.11	63.34	85.66

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4. Conclusion

This work proposes a pig body condition scoring method based on the deep learning model EfficientNet-B0. It takes advantage of the unique features of the algorithm, such as unified scaling grid width, depth and resolution, which are more suitable for image classification, and solves the problems such as strong subjectivity, time-consuming and arduous artificial pig body condition scoring. Meanwhile, the YOLOv5 target detection model has a higher average accuracy for body condition classification, reaching 85.66%. In future work, this paper will considers combining the two models of target detection and image classification to further explore a more efficient and accurate body condition scoring method for pigs.

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