Vision-based measuring method for individual cow feed intake using depth images and a Siamese network

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Abstract: Feed intake is an important indicator to reflect the production performance and disease risk of dairy cows, which can also evaluate the utilization rate of pasture feed. To achieve an automatic and non-contact measurement of feed intake, this paper proposes a method for measuring the feed intake of cows based on computer vision technology with a Siamese network and depth images. An automated data acquisition system was first designed to collect depth images of feed piles and constructed a dataset with 24 150 samples. A deep learning model based on the Siamese network was then constructed to implement non-contact measurement of feed intake for dairy cows by training with collected data. The experimental results show that the mean absolute error (MAE) and the root mean square error (RMSE) of this method are 0.100 kg and 0.128 kg in the range of 0-8.2 kg respectively, which outperformed existing works. This work provides a new idea and technology for the intelligent measuring of dairy cow feed intake.

Keywords: computer vision, Siamese network, cow feed intake, depth image, precision livestock farming
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1 Introduction

Feed intake is one of the main factors affecting the individual growth and health of dairy cows[1,2], which can reflect the lactation performance of dairy cows[3-5]. It is also an important basis for evaluating the feeding benefit of cattle farms, which can help farmers to adjust pasture management decisions[6-8]. Therefore, the measuring of cow feed intake is of great significance to improve the economic performance of dairy farms.

Traditionally, cow feed intake can be estimated directly by human visual inspection[9]. But it is inefficient and subjective and prone to errors. To measure feed intake more accurately, several feed intake measurement systems have been developed[10,11]. These systems utilize individual weighing stations with electronic scales and RFID (Radio Frequency Identification) antennas in feeding stalls to measure the feed consumed by each cow, which has high accuracy. But most commercial farms cannot afford large-scale usage of those systems because of their high price[12,13]. It is necessary to research some more economical and efficient methods to measure cow feed intake.

Recently, some studies utilized low-cost wearable devices to estimate the feed intake of the individual cow. By using wearable devices such as intelligent necklaces and nasal pressure sensors to collect eating behavior data of livestock, some feed intake prediction models[14-17] were built to estimate livestock feed intake. Galli et al. proposed a method to estimate the dry matter intake (DMI) of grazing sheep based on biting and chewing sounds through acoustic monitoring of the ingestive behavior of grazing sheep[18]. Shen et al.[19] constructed a model based on deep learning for estimating cow feed intake using body weight, lying duration, lying times, walking steps, foraging duration, and concentrate-roughage ratio. Zhou[20] used a 3D acceleration sensor to identify the feeding behavior of cows and estimate feed intake by a 1D convolutional neural network. These methods realize individual feed intake estimation, but the accuracy is not high and these wearable devices may cause stress reactions in dairy cows.

With the continuous development of optical imaging technology[19], vision-based feed intake measuring methods[20-24] using a consumer camera has been studied for a decade, which have the advantage of being contactless and non-stress. An intuitive way of solving this problem is to compute the weight of the feed before and after feeding, and then calculate the difference between the two weights of feed piles. Shelley et al.[22] firstly used a 3D camera to obtain the volume of a feed pile, and model the relationship between the volume and feed weight through regression analysis. The measuring error was about 0.5 kg within the feed pile weight from 0 to 22.58 kg. This study proved that computer vision is feasible in the calculation of feed intake. To make a step forward, Bloch et al.[24] used multiple high-resolution RGB cameras to take multiple photos of a feed pile from various angles to reconstruct it in 3D and predicted the weights of feed piles. The research results show that under laboratory conditions, the error of the predicted weight is 0.483 kg for feed piles below 7.0 kg, and under cowshed conditions, the error is controlled within 0.5 kg. However, on the one hand, the main limitation of that method is that in the actual

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feeding process of cows, it is difficult to arrange multiple cameras. On the other hand, the weight value of a single feed pile obtained by calculation and simulation has a certain error. If the calculation was performed based on the value with error, the error may increase.

Recently, Bezen et al.[25] proposed a measuring method of cow feed intake by modeling the relationship between feed intake and the difference in feed pile images before and after feeding. Particularly, difference images were first obtained by subtracting two feed pile images before and after feeding on four channels (RGB and depth). Then a Convolutional Neural Network (CNN) model was constructed and trained based on these different images to estimate feed intake. The results show that the mean absolute error of the model for predicting feed intake is 0.127 kg, and the mean square error is 0.034 kg^2. Compared with the method proposed by Bloch et al, the above method improved the accuracy of feed intake measuring. However, the direct subtraction of images may lose part of the effective information of feed piles, affecting the intake predicting the performance of the CNN model. In addition, the RGB channels used in the above method are easily affected by light, which may introduce some interference in the process of subtraction and further deteriorate the model's performance.

In order to overcome the above problems, this paper proposed a Siamese network-based feed intake measuring method. Rather than using the difference images, two depth images of feed piles before and after feeding are directly used as input of the model, which can avoid the information loss caused by the direct subtraction of two images and the influence of the ambient light. The features of the two images are then extracted separately through two sub-networks with shared weights of the Siamese network, which guarantees the consistency of the extracted features. And the difference between these two features is computed in the feature space, based on which feed intake finally can be measured. The main contributions of this work are summarized as follows:

1) A special automatic data acquisition system was developed, including electronic scales, feed trough, depth camera, RFID sensors, micro-controllers, and a set of special software;

2) A novel vision-based measurement method of individual feed intake of dairy cattle based on depth images of feed piles and Siamese network is built;

3) The proposed method is evaluated on a private dataset where feed intake is within the range of 0-8200 g and achieves an outperformance over existing works.

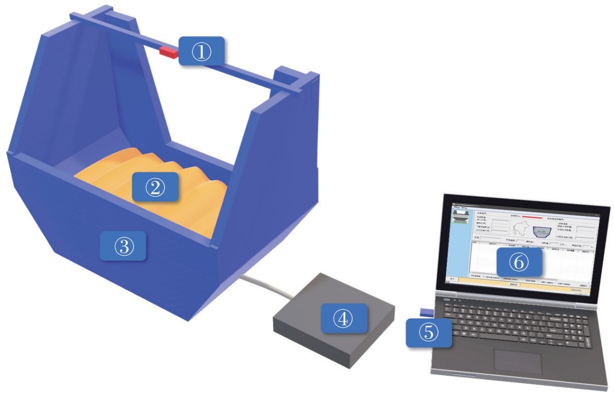
2 Materials and methods

2.1 Data acquisition system

To provide the multitude of data required for the learning of the feed intake measurement model, an automated data collecting system (Figure 1) was developed to collect varied data under different conditions, which can collect the images and weight of feed piles simultaneously.

The RGB and depth images of feed piles are captured by an ORBBEC Astra Mini RGB-D camera (Figure 2) with a working distance of 0.4-2.0 m, a field of view (FOV) of H58.4°, V45.5°, D84°, a working temperature of 10°C-40°C, the precision of 3 mm/m, and depth processing chip MX400. The camera is placed above the feed trough, and the distance from the camera to the ground is 97 cm. The image size is 480×640 (RGB and depth) pixels, as shown in Figure 3.

The workflow of the data acquisition system is as shown in Figure 4: After the RFID sensor detects the ear tag, the system is activated, and the depth camera captures the feed image in the feed trough (before simulating feed intake). At the same time, the RFID sensor starts to collect and record data such as cow ID and feed intake duration. The weight sensor records the weight of the feed pile before eating, which is stored in the local database. The ear tag leaves the feeding area after the simulation is finished. Then, the weighing sensor collects the weight of the feed pile after eating, calculates the feed intake, and stores it in the database. At the same time, the depth camera will take RGB and depth images in the feed tank again (after simulating feeding) and transfer them to the computer for storage.



1. Depth camera 2. Feed 3. Feed trough with electronic scale 4. Micro-controller 5. Data receiver 6. Software.

Figure 1 Data acquisition system

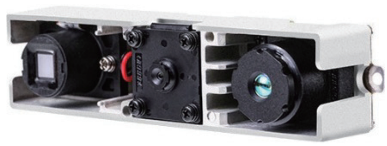
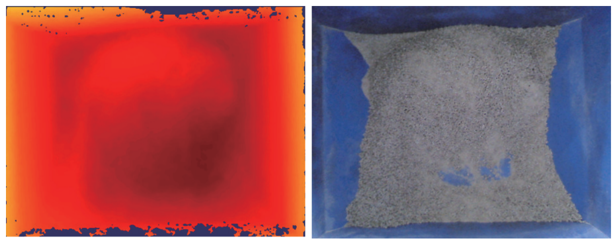


Figure 2 RGB-D camera (Orbbec Astra Mini)



a. Depth image b. RGB image

Figure 3 Image sample of feed pile

2.2 Data Acquisition and Augmentation

The experimental data were obtained by simulation experiments in the Precision Feeding Technology and Equipment Laboratory of Northeast Agricultural University, artificially simulating the feeding scene of dairy cows in a semi-open cowshed environment. Images of feed piles before and after feeding under different light conditions (low light, strong light, indoor light, indoor low light, and no light) were collected. Pellet feed for the calf was used in this experiment. The experiment was conducted from 1st to 7th May 2021.

Taking into account the effect of lighting conditions, images of the feed pile under five different light levels (from strong light to no light) were collected, as shown in Figure 5. During the experiment, a total of 483 groups of depth images and RGB images of the 0-31 kg feed pile were collected. In addition, the model established in this study uses depth images, and RGB images are used in the comparison model.

The training of a feed intake measurement model based on a

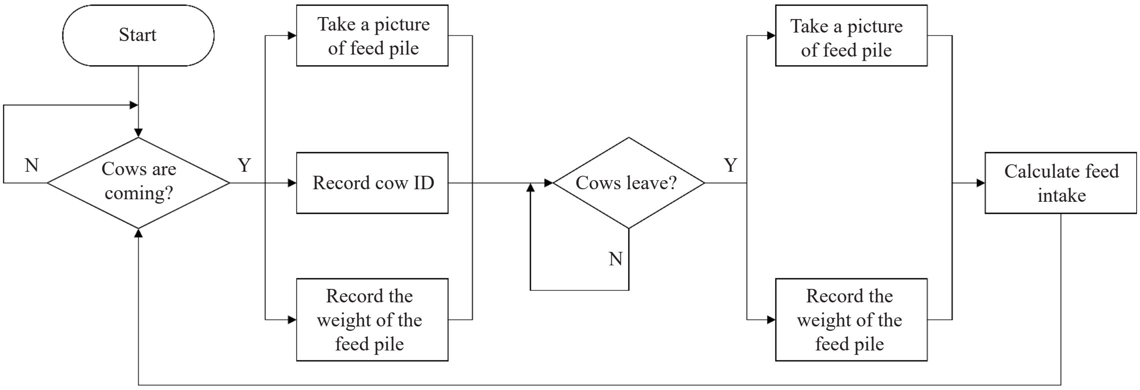
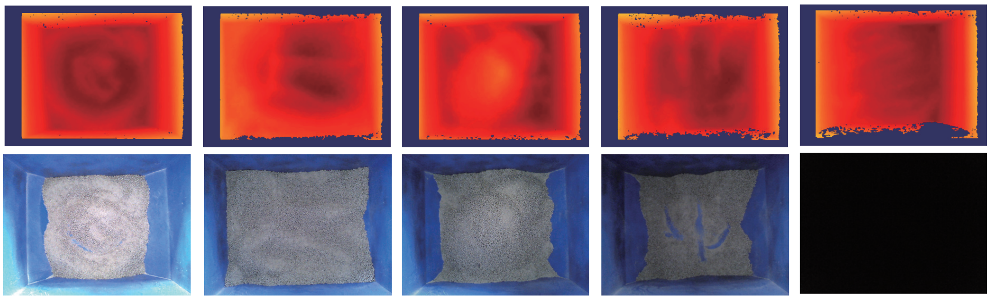


Figure 4 Workflow of the data acquisition system



a. Strong light b. Low light c. Indoor light d. Indoor low light e. No light

Figure 5 Image of feed intake collected under different light conditions

deep learning framework requires a lot of samples, and the diversity of data also determines the accuracy and generalization ability of the model. Therefore, data previously collected was enhanced by vertically flipping, horizontally flipping, vertically, and horizontally flipping. After data enhancement, 1932 groups of depth and RGB images are obtained.

2.3 Establishment of feed intake images dataset

The proposed method was based on two depth images of feed piles before and after feeding, so the depth images collected in the data acquisition and augmentation stage need to be combined in pairs to generate a feed intake images dataset. In addition, considering that the single feed intake of dairy cows generally does not exceed 8000 g, the weight difference between the two depth images in this work is controlled between 0-8200 g. Based on this premise, a total of 24 150-depth image pairs with their corresponding weight difference were generated to establish a dataset, which was divided into a training set and a test set according to 8:2.

2.4 Feed intake measuring model based on Siamese network

The feed intake measuring model based on a Siamese network[25] proposed in this study is mainly composed of a feature extraction module and a feed intake calculation module as shown in Figure 6. The feature extraction module first maps the depth images of the feed piles before and after feeding to the same feature space. The feed intake calculation module then calculates the difference between the two extracted features and further quantifies it as feed intake. Each branch adopts the same network structure and shares weights, which not only reduces the number of parameters of the model but also ensures the consistency of the mapping.

The specific calculation process is as follows: 1) Input the pair

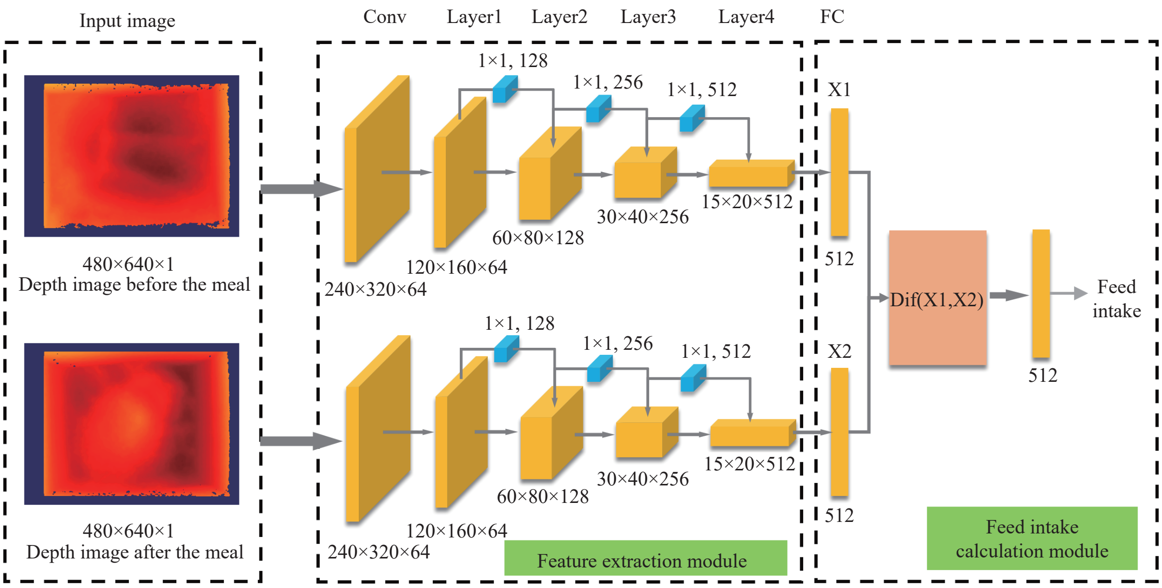


Figure 6 Flowchart of cow feed intake calculation

data into the Siamese network, and map them to the same feature space through the feature extraction network; 2) tile the two obtained multidimensional feature vectors, calculate the difference and generate a new feature vector; 3) measure the feed intake by regression calculation.

The backbone of the feature extraction network consists of ResNet101[26]. Particularly, In Resnet, the input of a convolutional layer bypasses one or more layers and is added to the outputs of forward layers, denoted as residual mappings. That is, if the input of the neural network is x and the function mapping (the output) to be fitted is $H(x)$ when x and $F(x)$ have the same dimensions, the original function mapping $H(x)$ adopts the following calculation method:

$$H(x) = F(x) + x \tag{1}$$

When the dimensions of x and $F(x)$ are different, the original function mapping is calculated as follows:

$$H(x) = F(x) + W(x) \tag{2}$$

where, $W(\cdot)$ represents the convolution operation, and the role is to adjust the dimension of x.

The introduction of a residual network improves the correlation between input and output, thus ensuring good convergence in the deep network and effectively avoiding gradient vanishing or gradient exploding problems. The internal structure of the network is shown in Figure 7. The structure mainly consists of a single convolution layer and four residual layers. Each residual layer is composed of several residual blocks. Each residual block includes three convolution layers, and the sizes of the convolution kernel are 1×1, 3×3, and 1×1.

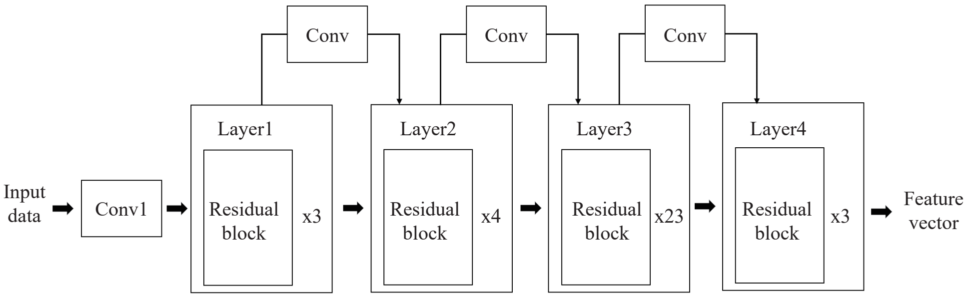


Figure 7 Feature extraction network.

In the feed intake calculation module, the calculation method of difference vector f is shown in Equation (3) :

$$f = \mathrm{DIF}(f_1, f_2) \tag{3}$$

where, f_1 and f_2 are the feature vectors extracted by the feature extraction module from the depth images before and after feeding, $\mathrm{DIF}(\cdot)$ represents the operation to compute the difference between two vectors.

To update model parameters, the MSE-LOSS function is selected as the loss function and the calculation method of the loss value I_{loss} is shown in Equation (4).

$$I_{\text{loss}} = \frac{1}{n}\sum_{i=0}^{n}(\hat{y}_i - y_i)^2 \tag{4}$$

where, $\hat{y}_i$ is the predicted feed intake value; y_i is the actual feed intake value, and n is the number of samples in the training set.

3 Results and discussion

3.1 Implementation details

The experiments were performed on a hardware configuration with an Intel Core i7-7800 3.5 GHz CPU, 16 GB of memory, and an NVIDIA GeForce GTX 1060 GPU with 3 GB memory. In the PyTorch deep learning framework, Python was used as the programming language to implement the Siamese network algorithm in this study, and PyCharm was the development tool. In this study, the stochastic gradient descent method was used, the batch size was set to 32, and the weight decay was 0.1. Whenever the loss value of the model on the verification set decreases, the model was saved, and finally, the model with the lowest loss was selected. The iterative termination condition of the algorithm was that 500 epochs were trained. Since the Siamese network does not easily converge during training, this study first trained the feature extraction network and then fixed its weight and trained the feed intake calculation layer.

3.2 Evaluation metrics

The model evaluation method used the mean absolute error (MAE) and root mean square error (RMSE) to measure the model evaluation performance, and the equation is as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=0}^{n}|Y_{\text{test}}^{i} - \hat{Y}_{\text{test}}^{i}| \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(Y_{\text{test}}^{i} - \hat{Y}_{\text{test}}^{i})^2} \tag{6}$$

where, Y_{test}^{i} is the actual value of feed intake; $\hat{Y}_{\text{test}}^{i}$ is the predicted value.

3.3 Influence of network parameters on model measuring performance

3.3.1 Comparison of different learning rates

Considering different learning rates can affect the performance of the model, taking 0.05, 0.10, and 0.50 as the learning rates, the change in loss value is shown in Figure 8. Among them, the rate of loss value reduction becomes slower with increasing iteration batches. When the learning rate is 0.50, the loss value decreases faster, but it does not easily converge. In contrast, when the learning

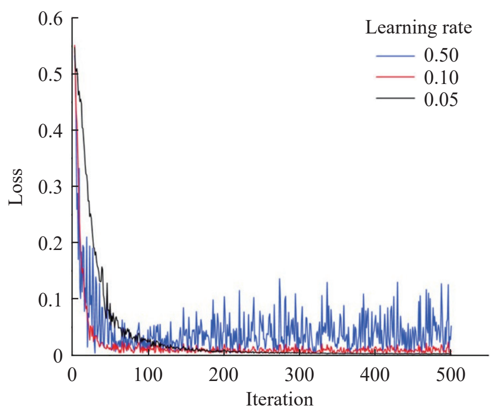


Figure 8 Validation loss value for different learning rates

rate is 0.05, the model converges steadily, so this study sets the learning rate of the algorithm to 0.05.

3.3.2 Comparison of different network depth

Different network depths also affect the performance of the model. To determine the appropriate network depth, this study compared the recognition performance of the Siamese network model under four feature extraction network layers. As listed in Table 1, with an increase in network layers, the prediction error of the model decreases continuously, and the stability increases continuously. When the network depth was increased from 50 layers to 101 layers, the MAE and RMSE only decrease by 0.14% and 0.10%, respectively. Continuing to increase the number of network layers has little effect on the improvement of model performance, so to balance model performance with size, the number of feature extraction network layers was set to 101.

Table 1 Comparison of the prediction performance of models with different network depths

Number of network layers	MAE/kg	RMSE/kg
18	0.106	0.130
34	0.102	0.129
50	0.101	0.128
101	0.100	0.128

Note: The number of network layers here refers to the number of convolution layers + fully connected layers.

3.4 Comparison of different calculation methods of feature vectors

After extracting the feature vector of the feed pile image, how calculating the difference between the feature vectors in the feature space is an important issue. To measure the feature difference by calculating the distance between the two features, such as Euclidean distance or cosine distance, etc., which can be an indicator of the difference between vectors. But in this way, the model is difficult to converge and has a big error. Therefore, another way was used. Particularly, the two feature vectors extracted by the feature extraction module were first computed to generate a new feature vector that contains the different information of the feature vectors of the feed pile before and after feeding. Then based on the new feature vector, the feed intake was calculated through regression.

This study used three methods to calculate new feature vectors. The first method was to directly fuse two 512-dimensional vectors extracted by the feature extraction module into a 1024-dimensional vector, the second method was to subtract the two vectors, and the third method is to divide the two vectors. The comparison results are listed in Table 2. This lists that subtraction works best. When using feature subtraction to compute a new difference vector, MAE is 11% and 21% lower than the other two methods, RMSE decreased by 7% and 19%, respectively.

Table 2 Comparison of models with different difference calculation methods of feature vectors

Methods	MAE/kg	RMSE/kg
Subtraction	0.100	0.128
Merge	0.113	0.137
Division	0.127	0.157

3.5 Influence of different light conditions on model measurement performance

To determine the influence of light conditions on the model performance, the model was tested under five conditions: low light, strong light, indoor light, indoor low light, and no light. And specific examples are shown in Figure 9. It is worth noting that the method proposed in this study still achieved good accuracy under no-light conditions. The difference between the actual value and the predicted value is 9.1 g before and after feeding under no light conditions, and the difference between the actual value and the predicted value is 8.4 g when it is indoor light before feeding and after feeding under no light conditions. The results are listed in Table 3. The light conditions have little influence on the model, and the prediction performance is almost the same under the five kinds of light. The RMSE is the smallest under no-light conditions, and the MAE is the smallest under strong light conditions.

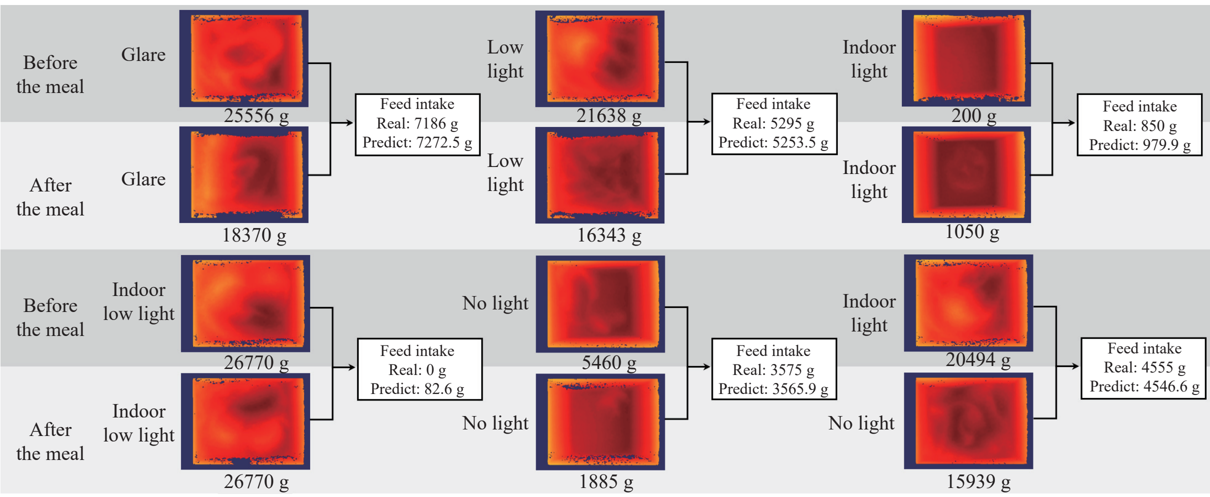


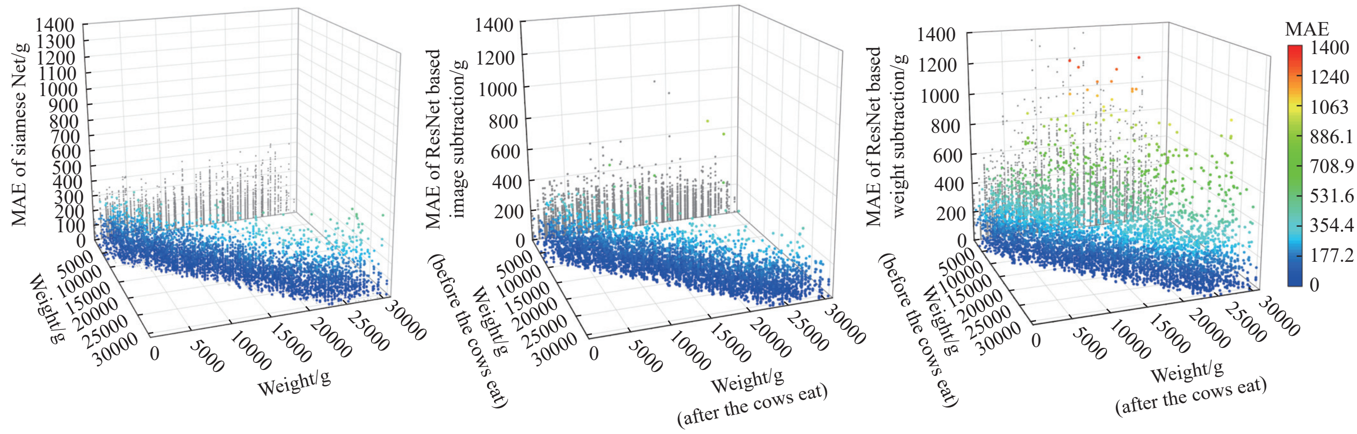
Figure 9 Prediction under different lighting conditions

Table 3 Comparison of the prediction performance of models under different lighting conditions

Lighting conditions	MAE/kg	RMSE/kg
Glare	0.100	0.128
Low light	0.102	0.128
Indoor light	0.098	0.128
Indoor low light	0.110	0.128
No light	0.100	0.127
All conditions	0.100	0.128

3.6 Comparison of the measurement performance of different models

To compare the measurement performance between the Siamese network-based feed intake measuring method proposed in this study and existing works such as Shelley et al.[20] and Bezen et al.[23], these two works were re-implemented and evaluated on our own dataset. The first method calculated the weights of a single feed pile image before and after feeding and then subtracts them to obtain the current feed intake (hereinafter referred to as WSNet). For the second method, the images of feed piles before and after feeding were subtracted in the RGB-D channels to obtain a new tensor, which was used as the input variable. In addition, feed intake was used as the output variable. Then, a residual network model was trained to calculate the feed intake (hereinafter referred to as ISNet). The average absolute error distribution of the three methods on 4830 sets of test data is shown in Figure 10. It can be seen from the figure that the MAE values of Siamese Net are relatively smaller and more concentrated. And the comparative analysis of the prediction performance of the three models is listed in Table 4.



a. MAE distribution of siamese Net b. MAE distribution of ISNet c. MAE distribution of WSNet

Figure 10 MAE distribution of different methods

Table 4 Comparative analysis of prediction results of various models

	WSNet	ISNet	Siamese Net
MAE/kg	0.198	0.109	0.100
RMSE/kg	0.267	0.133	0.128
Error>0.5 kg	314	8	1.000
Error>0.4 kg	564	23	22.000
Error>0.3 kg	1021	136	149.000
Error>0.2 kg	1871	603	568.000

Through the comparative analysis of MAE and RMSE, it was found that WSNet has the largest error and the worst stability, while the proposed method had the best performance. In 4860 sets of test data, the MAE of the Siamese network decreases by 49.4% and 7.5%, and the RMSE decreased by 51.9% and 4.2%, respectively, compared with WSNet and ISNet. Therefore, compared with the other two methods, the method proposed in this study has superior precision and stability, which can better measure the feed intake of dairy cows. This is because, in the Siamese network model, some errors and redundant information from the original data can be filtered out after feature extraction of the input images. Effective information can be extracted to calculate the difference, which makes the information used in the calculation of feed intake more accurate and improves the measurement performance of the model.

4 Conclusions

In this study, the measurement of dairy cow feed intake was taken as the research object. In order to improve the accuracy of feed intake measurement based on computer vision and solve the problem of being easily affected by different conditions of light, an automatic and non-contact feed intake measuring method based on a Siamese network and depth images was proposed.

1) A data acquisition system was designed based on which a feed intake depth image dataset of 24 150 samples was constructed;

2) A feed intake measurement model based on a Siamese network was designed and the optimal parameters of the model were determined through experiments. The strategy for calculating differences in the features of feed pile images was determined. Feature subtraction works best;

3) The model is trained using depth images collected under different lighting conditions, and the experimental results show that the model is relatively robust to light conditions;

4) The proposed feed intake measurement method has an MAE of 0.1 kg and an RMSE of 0.128 kg on a test set containing 4830 samples when the feed intake range is 0-8.2 kg, which is superior to the existing work.

In the future, a variety of TMR (total mixed ration) feed pile images on the floor should be collected to adjust the model, which can make it more suitable for commercial cowsheds.

Acknowledgements

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