BODY CONDITION SCORING METHOD FOR JERSEY CATTLE BASED ON ME-POINTNEXT
/
基于 ME-PointNeXt 的娟姗奶牛体况评分方法

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ABSTRACT
To address the impact of changes in dairy cow posture on intelligent body condition scoring, this study proposes a dairy cow body condition scoring model (ME-PointNeXt). Based on PointNeXt, this model incorporates a dynamic graph convolutional module at the global feature level; furthermore, a selective sequence block is added to the encoder's upper layers, improving the SA-FP architecture and enhancing the model's overall understanding of the structure. Using this model to segment the hindquarters of dairy cows, principal component analysis is performed via eigenvalue decomposition of the local neighbourhood covariance matrix. This enables the determination of edge point normal vectors and the calculation of surface curvature, thereby enabling the scoring of the cows' body condition. Experimental results show that the ME-PointNeXt model achieved an overall accuracy, mean precision, mean recall, and mean F1 score of 91.43%, 84.33%, 87.92%, and 90.74%, respectively, on the test set. Compared with PointNeXt, the ME-PointNeXt model achieved improvements of 2.72, 3.65, 4.13, and 4.19 percentage points in overall accuracy, average precision, average recall, and average F1 score, respectively. This study has significantly improved the efficiency of dairy cow body condition scoring, ensuring accuracy whilst reducing the workload, and can provide technical support for non-contact dairy cow body condition scoring.

摘要
为解决奶牛姿态变化对体况智能评分的影响，本研究提出了一种奶牛体况评分模型（ME-PointNeXt）。该模型基于 PointNeXt，在全局特征层加入一个动态图卷积模块；并且在编码器高层中加入一个选择性序列块，改进了 SA-FP 结构，增强整体对结构的理解。利用该模型对奶牛尻部进行分割，通过计算局部邻域协方差矩阵的特征值分解实现主成分分析，进而确定边缘点法向量并计算表面曲率，对奶牛体况进行评分。试验结果表明，ME-PointNeXt 模型在测试集上的总体准确率、平均交互比、平均准确率与平均 F1 分数分别达到 91.43%、84.33%、87.92%和 90.74%。相较于 PointNeXt，ME-PointNeXt 的总体准确率、平均交互比、平均准确率与平均F1 分数分别提升了 2.72、3.65、4.13 和 4.19 个百分点。本研究显著的提高了奶牛体况的评分效率，在降低工作量的同时保证了精度，可为非接触式奶牛体况评分提供技术支持。

INTRODUCTION
As the scale of dairy cattle farming in China continues to expand *(Zhang et al., 2024)*, the sector is undergoing a transition towards grain-saving and high-efficiency practices, facing significant challenges. Body condition score is a key indicator for assessing animal welfare and herd management; it is closely linked to the health *(Zhao et al., 2025)* and metabolic status *(Sadiq et al., 2017)* of dairy cattle, and provides a reliable basis for formulating feed rations *(Yu et al., 2026).* Body condition scores enable the identification of cows that are either overweight or underweight; formulating rations based on these scores ensures that cows of different body conditions receive appropriate diets. Consequently, body condition assessment is an indispensable part of the dairy farming industry *(Tian et al., 2025)*.

Currently, body condition scoring in dairy cattle is primarily carried out manually; however, due to the subjectivity of human assessment *(Feng et al., 2025)*, the reliability of the results is poor, and the evaluation process is time-consuming and labour-intensive, relying heavily on the assessor's experience *(Huang et al., 2024)*.

Furthermore, the assessment process can induce stress responses in the cattle *(Li et al., 2025)*, making measurement difficult and leading to significant errors *(Fan et al., 2020)*. With the gradual adoption of machine vision and deep learning technologies in the livestock industry *(Qi et al., 2023)*, it is now possible to utilise visual detection techniques to capture conformation characteristics and establish intelligent assessment models linking these to body condition *(Sun et al., 2025)*. Practical evidence indicates that machine vision has already achieved significant success in detecting dairy cow conformation characteristics and behaviour *(Xie et al., 2022)*, offering a new direction for research into dairy cow body condition scoring. *Zhao et al., 2021,* used EfficientNet to identify the structural features of dairy cows and assess their body condition; EfficientNet achieved a recognition accuracy of 73.12% and an average recognition speed of 3.441 s/f, outperforming models such as MobileNet-V2, XceptionNet, and LeNet-5. *Jiang et al., 2025,* incorporated the GSConv module into the YOLOv8s model to enable automatic localisation and detection of the dorsal region of dairy cows, thereby facilitating body condition scoring and individual identification. The improved model achieved accuracy rates of 93.9% and 92.2% for body condition scoring and individual identification, respectively, representing increases of 1.9 and 4.5 percentage points compared to single-task models. *Shi et al., 2023,* proposed a method for body condition scoring in dairy cows based on attention-guided 3D point cloud feature extraction, which incorporates an attention-guidance mechanism into PointNet. This scoring model achieved accuracy rates of 0.49, 0.80, and 0.96 within point deviation ranges of 0, 0.25, and 0.50, respectively, yielding satisfactory estimation results. *Wei et al., 2025,* utilised 3D reconstruction to recreate the spatial morphology of sheep, followed by training a PointNet++ model, achieving relative errors of 3.63%, 1.14%, and 3.57% for chest width, rump height, and body length, respectively. The aforementioned methods all localise the target's entire torso; however, the target's posture and movement can influence the shooting angle, leading to the loss of some key information.

To address the aforementioned issues, this study segments the hindquarters of dairy cows based on 3D point cloud imagery, extracting key regions within a small area to obtain accurate body condition scores. This study proposes the ME-PointNeXt model for dairy cow body condition scoring, which primarily builds upon the PointNeXt model by incorporating a dynamic convolutional module to enhance local edge detection capabilities; simultaneously, selective sequence blocks are introduced at the higher layers of PointNeXt to strengthen the model's global consistency. Finally, the curvature is calculated based on the edge points segmented by the ME-PointNeXt model, and a body condition score is derived.

MATERIALS AND METHODS

Dataset construction

Design of a Contactless Data Collection Device for Cattle

This study developed a non-contact point cloud data acquisition device for dairy cows. From the moment a cow enters the acquisition channel until it exits, the device can capture three-dimensional point cloud data from two different rear angles, thereby enabling intelligent body condition scoring. The system comprises a depth camera (Azure Kinect DK), a power supply, a motion controller, and a measurement channel. To capture depth images of the cow's back and hindquarters, the Arzue Kinect DK depth camera is positioned 2.6 m above the ground and at a 45° downward angle 2.4 m above the ground, respectively. This study employs a single-channel data acquisition design to prevent crowding and congestion of cows within the channel, ensuring that cows maintain a normal standing posture, thereby guaranteeing the validity and reliability of the collected data. The structure of the data acquisition system is shown in Figure 1.

Fig. 1 - Data Acquisition Structure

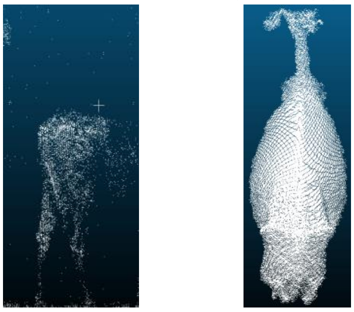
1 – Rear-facing Azure Kinect DK depth camera; 2 – Top Azure Kinect DK depth camera; 3 – Drive shaft; 4 – Steel wire

Test data acquisition

Data collection took place from 25 July to 1 August 2025 at Tibet Nianxiongziji Livestock Co., Ltd. in Zaxi Village, Gadong Town, Bailang County, Shigatse City, Tibet Autonomous Region. The test subjects were Jersey cows with a lactation period of 100 to 300 days. To minimise stress reactions in the cows and their impact on milk yield, data collection commenced after milking. Collection took place between 10:00 and 14:00, and between 15:00 and 19:00. A total of 2,280 point cloud datasets were collected from 104 cows; after removing highly similar datasets, 342 point cloud datasets remained.

Dataset creation

By comparing the point cloud images captured at the tail root and on the back, it was found that the point cloud image at the tail root contained a significant amount of noise and failed to capture key information in full. Consequently, the point cloud image from the back was ultimately selected as the dataset and divided into training, test and validation sets in a ratio of 8:1:1. The point cloud image at the tail root is shown in Figure 2(a), whilst the point cloud image of the back is shown in Figure 2(b).



(a) (b)

Fig. 2 - Point cloud image of the cow's back and hindquarters

The criteria for assessing a dairy cow's body condition are typically based on body fat reserves. These reserves are primarily evident in the area between the hip bones and the ischial tuberosities, with the rump being the most distinctive feature; the degree of contour variation in this region is useful for assessing the cow's fat reserves and health status. The region of interest is shown in Figure 3.

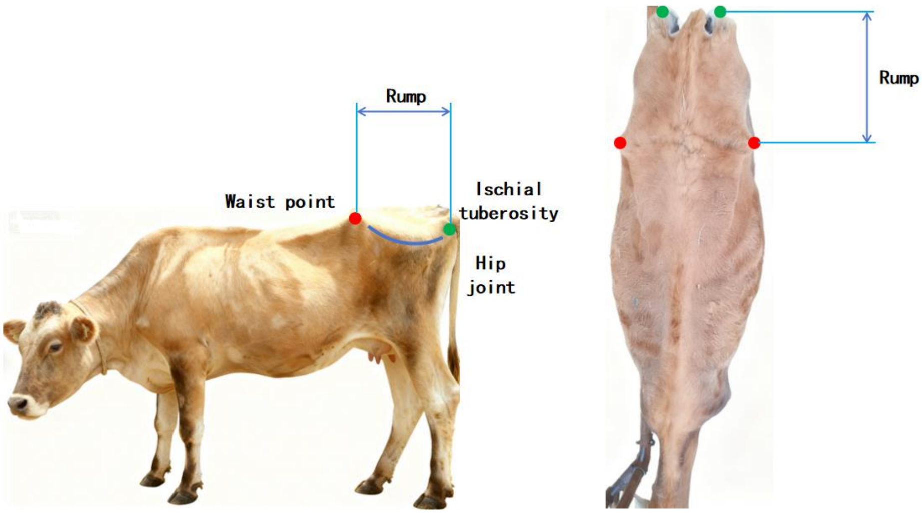
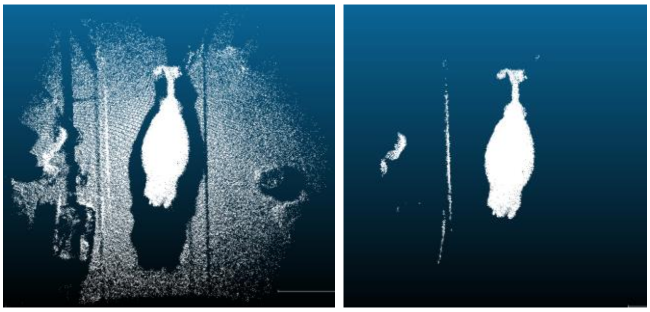


Fig. 3 - Region of interest

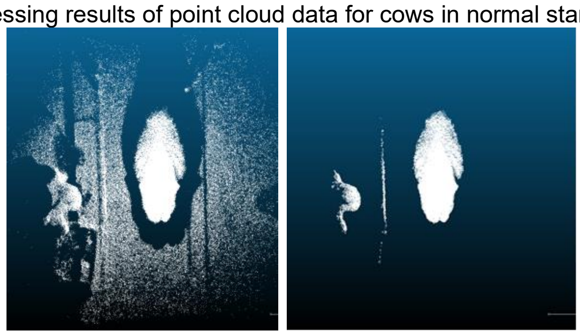
When processing the dataset, CloudCompare was selected to perform radius filtering and statistical filtering as pre-processing steps, followed by manual segmentation and annotation of the filtered dataset. The results of the point cloud data pre-processing are shown in Figure 4.

(1) Statistical filtering. By setting a 30-neighbour radius and a threshold of 1.0 based on the density of the point cloud data, high-frequency noise can be effectively reduced whilst retaining key structural information.

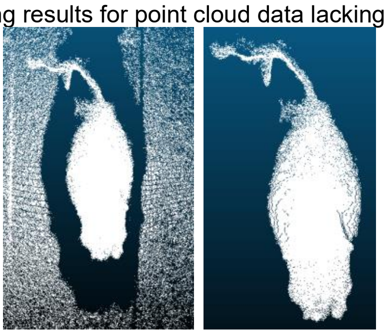
(2) Radius filtering: The radius was set to 15, requiring at least five neighbouring points within the radius. Points where the density within the neighbourhood fell below a specific threshold were treated as outliers and removed. This approach ensures the density of the point cloud after downsampling whilst maximising the retention of the basic features of the cows' hindquarters, and also improves the speed of data processing.



(a) Pre-processing results of point cloud data for cows in normal standing posture



(b) Preprocessing results for point cloud data lacking the cow's head



(c) Pre-processing results of point cloud data from the head of an abnormally standing dairy cow

Fig. 4 - Pre-processing results of point cloud data

Following the removal of duplicates and filtering, manual segmentation and annotation were carried out using CloudCompare. The body part annotated was the rear end of the cow, labelled as “back”; this label is automatically generated once each point cloud image has been annotated. The results of the manual segmentation are shown in Figure 5. To prevent data leakage and overestimation of performance, random noise points were added to the point cloud images during the division of the dataset.

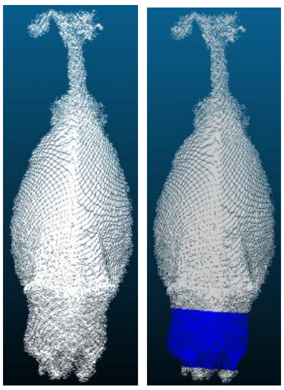


Fig. 5 - Manual segmentation results

Cattle Body Condition Scoring Model

Compared to PointNet, PointNeXt *(Qian et al., 2020)* modifies the training strategy by adopting a hierarchical multi-scale architecture and utilising a feature pyramid, whilst applying local neighbourhood aggregation to the edge features on the cow’s back; this is more conducive to improving the accuracy of the cow’s body condition score. The model applied scaling and rotation enhancements to the data; jittering and randomised data point removal were employed to enhance the model’s generalisation ability.

By introducing slight variations or omissions, the training data was made more diverse, thereby reducing the model’s overfitting to data details.

However, due to the model’s lack of sensitivity to edge details and its inability to interact with global information, it proved insensitive to information regarding the cows’ backs and exhibited low feature utilisation, rendering it incapable of intelligently scoring the cows’ body condition. Consequently, a dynamic graph convolutional module *(Wang et al., 2019)* and a sequence block *(Ding et al., 2023)* were incorporated into PointNeXt to enhance edge point perception and global information interaction, ensuring the model could capture structural changes between points and edge features.

ME-PointNeXt

ME-PointNeXt consists of an input head, an encoder, a global feature layer, a decoder and an output head. To address PointNeXt’s limited perception of local edge information, a dynamic graph convolutional module is introduced in the global feature layer. By determining the convolutional receptive field through dynamic neighbourhood configuration and constructing geometric convolutional inputs via differential edge features, this enhances the perception of surface curvature changes and boundary details on the cow’s hindquarters. The neighbourhood is shifted from geometric proximity to semantic proximity, thereby improving the ability to represent local structures. Furthermore, to mitigate the attenuation and fragmentation of high-level semantic information during multi-level propagation, selective sequence blocks are introduced as global feature interaction modules in the 3rd and 4th Set Abstraction stages following downsampling in the encoder. Relevant selective parameters are generated via point-level linear projection, and state recursion is employed to model long-range dependencies in the sequence dimension, thereby enhancing the global consistency of high-level features in the encoder. The structure of the ME-PointNeXt model is shown in Figure 6.

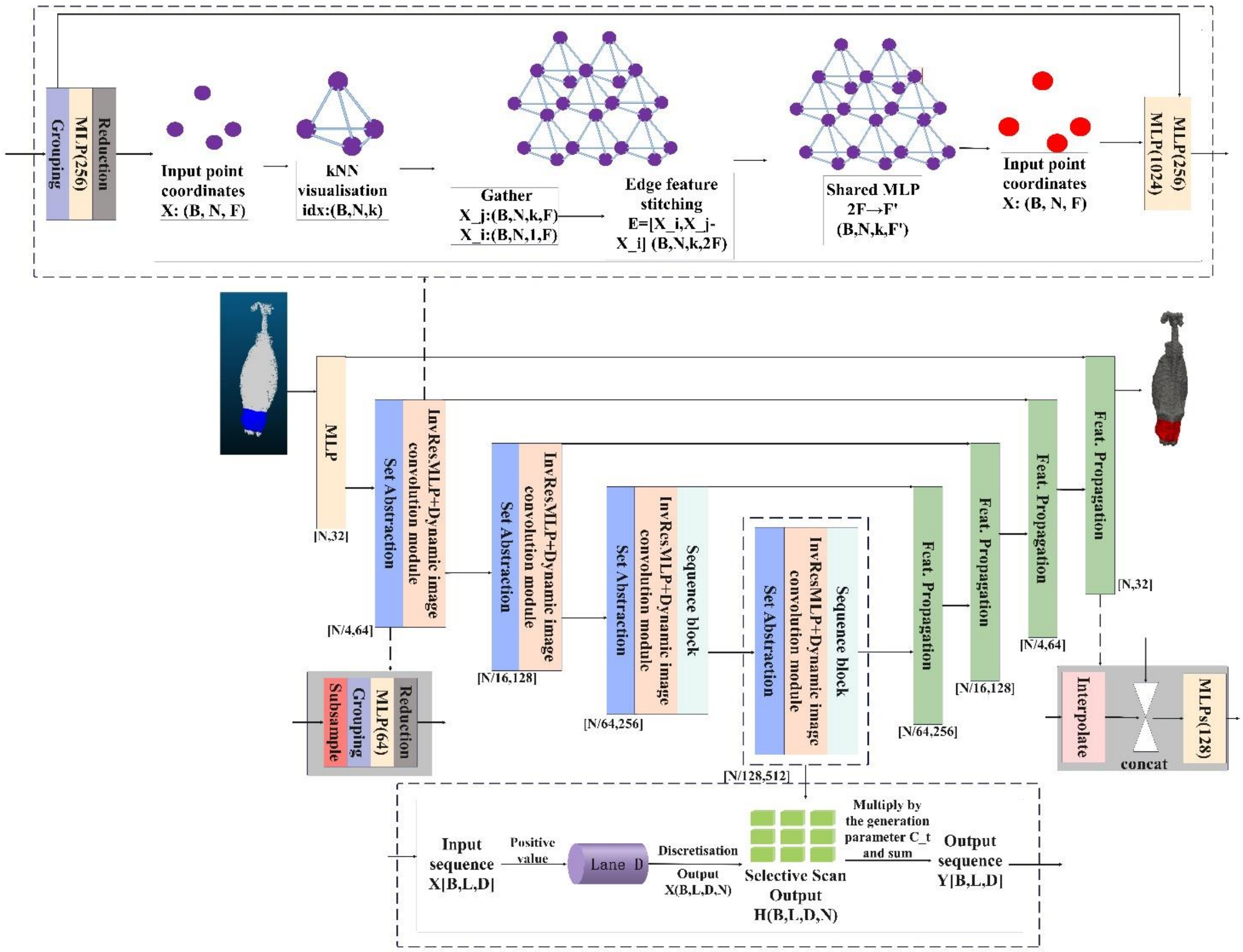


Fig. 6 - ME-PointNeXt Model Architecture

Dynamic image convolution module

To enhance the model's ability to capture global structure and cross-region semantic consistency in the point cloud of a dairy cow's hindquarters, a Dynamic Graph CNN (DGCNN) module has been introduced into the global feature layer of PointNeXt. This module constructs a k-NN dynamic adjacency graph in the feature space to strengthen global semantic representation and robustness. Whilst maintaining the translation invariance of the hindquarters point cloud, the dynamic graph convolutional module effectively mitigates feature instability in the hindquarters region caused by pose variations, sparse sampling or noise interference, thereby improving the consistency of the overall segmentation results and the ability to distinguish boundaries.

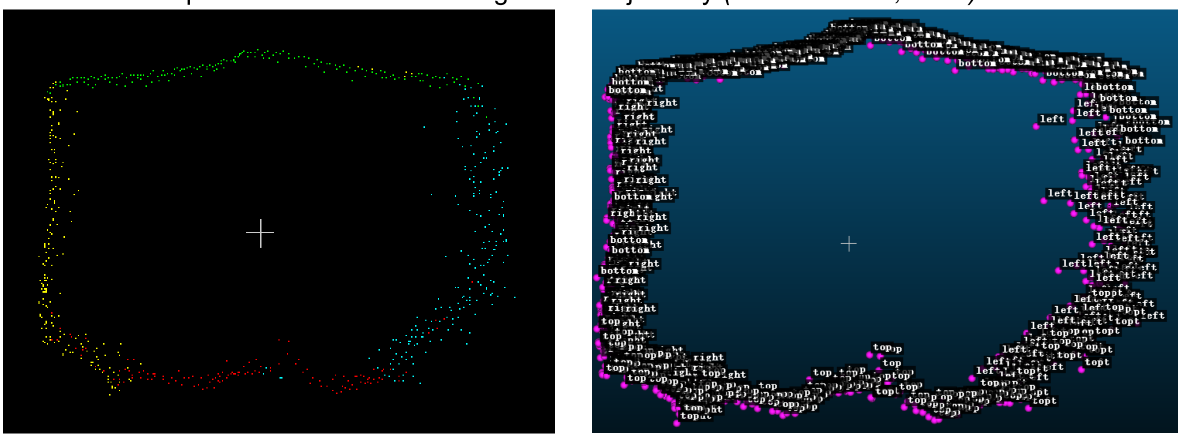
Sequence block

To enhance the model's ability to globally fuse point clouds of dairy cows' hindquarters across multiple scales and its adaptability to complex morphological variations, selective sequence blocks are introduced in the third and fourth Set Abstraction layers of PointNeXt. These sequence blocks establish inter-point relationships through projection and employ grouped vector attention to apply weighted groupings to feature channels, thereby facilitating more accurate capture of morphological contours and boundary transition features in the large receptive field stage. The model can strengthen feature interactions and contextual consistency at a higher semantic level, improving robustness against noise, occlusion, and variations in point density, and consequently enhancing the performance of rump segmentation.

Curvature calculation

In this study, a computational programme was developed to perform principal component analysis on edge feature points on the hindquarters of dairy cows. For each point in the point cloud of a dairy cow's rump, the method calculates the three-dimensional covariance matrix of its k nearest neighbours and performs an eigenvalue decomposition using the formula $k = \frac{\lambda 1}{\sum \lambda}$. Through this eigenvalue decomposition, the eigenvector corresponding to the smallest eigenvalue is defined as the surface normal vector of the rump, and the spatial curvature of the rump's edge is calculated. These quantitative geometric features, which are insensitive to changes in posture, provide robust input data for the subsequent development of an objective and efficient body condition scoring model for dairy cows. The body condition score is calculated using the formula $BCS = -15.0 \times K + 3.55$, where K represents the spatial curvature of the rump edge points. These quantitative geometric features are unaffected by changes in body posture, providing reliable input data for the subsequent development of an objective and efficient body condition scoring model for dairy cows. Figure 7 illustrates the process of extracting edge points and calculating normal vectors.

Manual scoring involves professional and experienced assessors conducting body condition scoring on the same dairy cows. Whilst the Juan Shan cows are being assessed using the scoring equipment, five assessors also carry out manual body condition scoring on the cows at close range. Where the maximum difference in scores between assessors does not exceed 0.50 points, the arithmetic mean of the individual assessors' scores is taken as the cow's manual reference body condition score; where the maximum difference exceeds 0.50 points, the Juan-Shan cow is re-assessed and the final result is determined through consultation amongst the assessors. For this type of classification analysis, where the category intervals are 0.25 points, the mean is rounded to the nearest 0.25 points. When BCS is treated as a continuous variable, the intraclass correlation coefficient (ICC) can be calculated; when treated as an ordered scale, the weighted Kappa coefficient can be reported. BCS involves a degree of subjectivity *(Vasseur et al., 2013)*.



(a) Edge point extraction (b) Edge Point Normal Vector Calculation

Fig. 7 - Edge Point Extraction and Normal Vector Calculation

Evaluation criteria

To evaluate the algorithm's performance in segmenting different body parts, this study employed mean Intersection over Union (mIoU), mean Accuracy (mAcc), Overall Accuracy (OA) and mean F1 (mF1) as evaluation metrics. Acc stands for Accuracy, which reflects whether the points predicted by the model for each label fall within the cow's hindquarters; IoU stands for Intersection over Union, which reflects the accuracy of semantic segmentation for each label; after calculating the Intersection over Union (IoU) and accuracy for each label, the mean Intersection over Union (mIoU) and mean Accuracy (mAcc) are obtained; Overall Accuracy (OA) refers to the proportion of correctly predicted samples out of the total number of samples; mF1 refers to the average of the F1 scores across all categories.

RESULTS

In a study examining the contour of a dairy cow's hindquarters, the characteristics of point cloud data were utilised to calculate the average curvature of the hindquarter point cloud, thereby assessing the contour of the hindquarters. A five-point scale is widely used for body condition scoring, with increments of 0.25 points. A score of 1.0 is the lowest, indicating that the cow is excessively thin, whilst a score of 5.0 is the highest, indicating that the cow is excessively fat.

Point cloud segmentation results

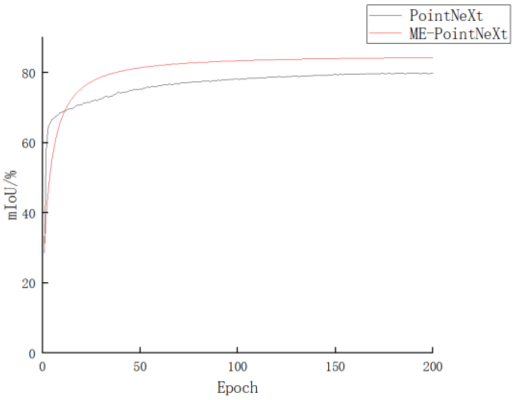
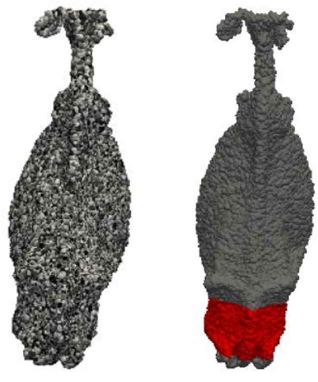


Fig. 8 - Curve depicting the mIoU of the ME-PointNeXt model on the validation set for dorsal segmentation of dairy cows as a function of iteration count

Figure 8 illustrates the trend in the mIoU on the validation set as the number of training iterations increases during the training of the ME-PointNeXt model. In the initial stage, the mIoU increases rapidly with the number of training iterations, indicating that the model is effectively learning the most fundamental and significant patterns from the data. Finally, around 150 iterations, the mIoU levels off and stabilises at approximately 84.33 per cent, suggesting that the model's performance is gradually converging. After 200 iterations, the model converges, and the mIoU on the validation set remains virtually unchanged.

Figure 9 presents a comparison of the model's segmentation results: (a) shows the unlabelled point cloud predicted by the ME-PointNeXt model, and (b) shows the point cloud labelled by the ME-PointNeXt model. The point cloud results demonstrate that incorporating the dynamic convolutional module and selective sequence blocks into PointNeXt enhances the model's ability to extract edge features. The red areas indicate where the rump should be cut. Figure 10 displays the contour map of edge points extracted from the rear of a cow.



(a) (b)

Fig. 9 - Comparison of Model Segmentation Results

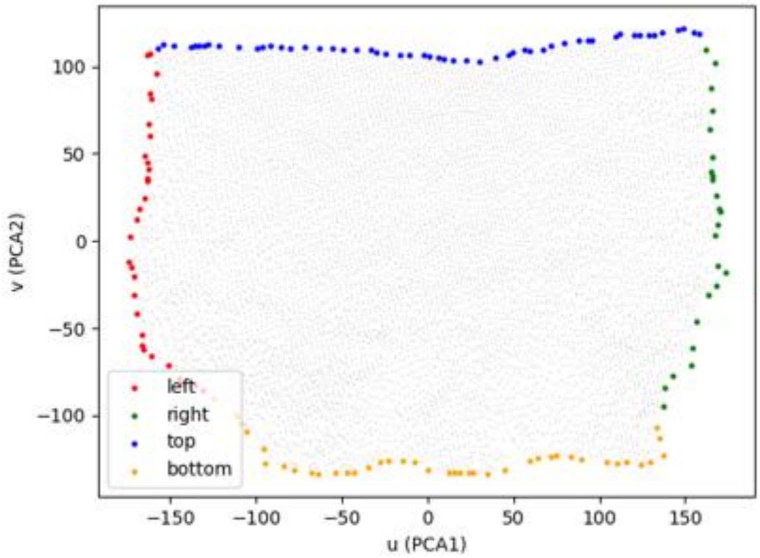


Fig. 10 - Contour diagram extracted from the edge of the cow's hindquarters

A statistical analysis of the segmentation results was conducted using Overall Accuracy (OA), Mean Intersection over Union (mIoU), Mean Accuracy (mAcc), and Mean F1 score as evaluation metrics. The segmentation results for the dorsal region of dairy cows are shown in Table 1.

Table 1

Comparison of partitioning results across test sets for different models

Method	OA/%	mIoU/%	mAcc/%	mF1/%
PointNet	79.65	56.83	69.72	66.49
PointNet++	88.77	80.37	82.83	81.90
PointNeXt	88.71	80.68	83.79	85.55
ME-PointNeXt	91.43	84.33	87.92	89.74

Table 1 presents the quantitative comparison results for PointNet, PointNet++, PointNeXt and ME-PointNeXt on the segmentation task using the test set. As shown in Table 1, because PointNet relies primarily on global feature aggregation, its ability to capture local geometric details and boundaries is limited, resulting in an mIoU of only 56.83%. Following the introduction of hierarchical local neighbourhood modelling, PointNet++ demonstrated a significant improvement in segmentation performance (OA 88.77%, mIoU 80.37%, mF1 81.90%), indicating that local structural features are crucial for this task. Building upon this, PointNeXt further optimises the backbone network and feature extraction methods, achieving further improvements in metrics such as mIoU and mF1 (mIoU 80.68%, mF1 85.55%). In contrast, ME-PointNeXt achieves the best performance across all evaluation metrics, with OA, mIoU, mAcc, and mF1 reaching 91.43%, 84.33%, 87.92%, and 89.74%, respectively. Compared to PointNeXt, ME-PointNeXt's OA, mIoU, mAcc, and mF1 improved by 2.72, 3.65, 4.13, and 4.19 percentage points, respectively, indicating that the proposed improvements effectively enhance the model's ability to recognise key regions and improve prediction consistency, thereby significantly increasing overall segmentation accuracy.

Ablation Test

To verify the impact of different improvement methods on model performance, ablation experiments were designed using PointNeXt as the baseline model. The effectiveness of the improvement methods was assessed using different modules; the experimental results are shown in Table 2.

Table 2

Melting test results

PointNeXt	Dynamic image convolution module	Sequence block	OA/%	mIoU/%	mAcc/%	mF1/%
√			88.71	80.68	83.79	85.55
√	√		89.35	84.72	87.10	89.40
√		√	88.89	82.44	85.83	88.20
√	√	√	91.43	84.33	87.92	89.74

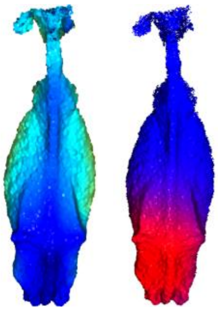
Nota: "√" indicates the adoption of this module; "×" indicates not using this module

As shown in Table 2, adding dynamic graph convolutions to the baseline network effectively improved the model's recognition performance, with the overall accuracy, average precision, average recall, and average F1 score increasing by 0.64, 4.04, 3.31, and 2.85 percentage points, respectively.

This indicates that the use of this convolutional module effectively enhances the model's ability to detect local edge points, helping the network to extract key information from the rear of the cow more effectively. Following the incorporation of the selective sequence block, the overall accuracy, mIoU, average precision and average F1 score increased by 0.18, 1.76, 2.04 and 1.65 percentage points respectively. This indicates that the use of this sequence block helps to enhance global consistency and mitigate the fragmentation of local predictions. Building upon PointNeXt, by incorporating a dynamic graph convolutional module into the global feature layer and adding a selective sequence block to the downsampling layer of the encoder, results in increases of 2.72, 3.65, 4.13, and 4.19 percentage points in overall accuracy, average interaction ratio, average precision, and average F1 score, respectively. This indicates that the simultaneous incorporation of these two modules alongside the sequence block not only enhances sensitivity to curvature changes and boundary regions but also strengthens cross-regional semantic consistency and the ability to model long-range dependencies.

Heatmap visualization

Given the complex nature of the environment in which dairy cows are photographed, heatmaps were selected to visualise the model's recognition performance. A comparison of the heatmaps for the model before and after improvement is shown in Figure 11. As can be seen from Figure 11a, the heatmap of the pre-improvement model shows a relatively dispersed distribution when recognising the rear end of a dairy cow, focusing not only on the key area but also on the middle of the torso and the abdomen. Figure 11b, on the other hand, displays the heatmap visualisation results of the ME-PointNeXt model, which is an improvement based on the PointNeXt model. Following the improvement, the high-response areas are highly concentrated in the hindquarters region, whilst thermal responses in non-target areas are significantly suppressed, markedly reducing activation responses in irrelevant regions.



(a) (b)

Fig. 11 - Heatmap of the model before and after improvement

Discussion

This study employs a method combining 3D data acquisition with deep learning technology to propose a body condition scoring method for dairy cows based on point cloud segmentation. As shown by the comparative results in Figure 12, the improved model is able to accurately capture the rump region of the cow, with a small prediction error. However, the accuracy of the segmentation model has a certain impact on the accuracy of the body condition scoring. Deviations in the segmentation model, particularly segmentation errors in the hindquarters of dairy cows, can lead to prediction errors and inaccuracies in curvature calculations, resulting in significant discrepancies between automatic and manual body condition scores. For example, the incorrect prediction of the critical hindquarter region in Figure 13 led to an erroneous body condition score, thereby reducing the model's reliability. Although the segmentation model proposed in this study has seen a significant improvement in accuracy, it still has shortcomings and considerable room for optimisation. Future work could focus on refining the neural network architecture to improve segmentation accuracy, thereby providing reliable data support for the formulation of dairy cow feed.

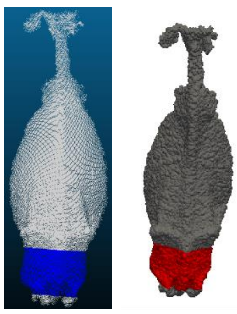


Fig. 12 - Comparison of Manual Point Cloud Annotation and ME-PointNeXt Model Segmentation

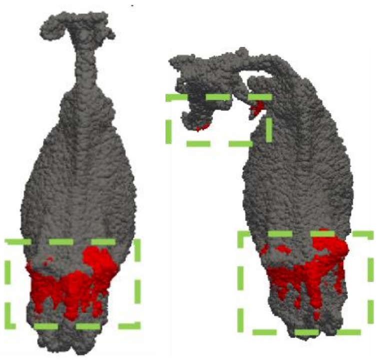


Fig. 13 - Typical Examples of Segmentation Errors

Table 3 presents data on the correlation between the ME-PointNeXt model's automated scores and manual scores. With ten Jersey cows assessed simultaneously, the discrepancy between the automated and manual scores was minimal, with inconsistencies observed in only two cows. This indicates that the method is suitable for assessing the body condition scores of dairy cows and validates the effectiveness of incorporating dynamic convolutional modules and selective sequence blocks into the PointNeXt model.

Table 3

Model scoring versus human scoring error

Cow number	Physical Condition Score	
	Smart Scoring	Manual scoring
20200314	3.25	3.25
20200722	4.00	4.00
20201105	3.25	**3.50**
20210130	3.50	3.50
20210518	4.25	4.25
20210909	3.75	3.75
20211224	4.00	**3.75**
20220214	4.25	4.25
20220607	3.75	3.75
20221031	3.50	3.50

To ensure the accuracy of the model for assessing the body condition score of dairy cows, this study employed the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and correlation coefficient (r) as performance metrics. For the same cattle shed, both manual scoring and model-based scoring were conducted simultaneously, with the results shown in Table 4. The mean absolute error, root mean square error and correlation coefficient were 0.15, 0.22 and 0.80 respectively, all of which indicate that the model-based scores show a high degree of consistency with the manual scores and are capable of accurately reflecting the actual body condition of the dairy cows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{2}$$

$$r = \frac{\sum\left(y_i - \bar{y}\right)\left(\hat{y}_i - \bar{\hat{y}}\right)}{\sqrt{\sum\left(y_i - \bar{y}\right)^2 \sum\left(\hat{y}_i - \bar{\hat{y}}\right)^2}} \tag{3}$$

Here, *n* denotes the total number of samples; is the observed value for the *i-th* sample; is the predicted value for the *i-th* sample; is the arithmetic mean of all observed values; and is the arithmetic mean of all predicted values.

Table 4

Quantitative Error Analysis

Model	MAE	RMSE	r
E-PointNeXt	0.14	0.22	0.79

CONCLUSIONS

(1) By incorporating a dynamic convolutional module into the PointNeXt model, a point cloud segmentation model was proposed. Experimental results demonstrated that this model achieved higher overall accuracy and precision than the PointNeXt model when segmenting local point cloud data from the backs of dairy cows, thereby improving the segmentation accuracy of point cloud data from this region.

(2) By incorporating sequence blocks into the PointNeXt model, experiments have verified that this model demonstrates improved global interaction capabilities when extracting point cloud information from the rear of dairy cows, resulting in more accurate predicted point cloud edges. Compared to the PointNeXt model, this approach has improved the model's prediction accuracy.

(3) Building upon the point cloud segmentation results of the ME-PointNeXt model for the cow's back, an intelligent scoring system was applied to assess the cow's body condition, achieving high accuracy with minimal error. This validated the capability of the segmented point cloud data for body condition scoring.

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