
# Automatic Body Condition Score Classification System for Individual Beef Cattle Using Computer Vision

**Md Nafiul Islam[1] · Jonathan Yoder[1] · Hao Gan[1*]**

**Department of Biosystems Engineering and Soil Science, University of Tennessee, Knoxville, TN, USA**

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***Abstract.***

*Body condition scoring (BCS) is a widely used parameter for assessing the utilization of energy reserves in the fat and muscle of cattle. It fulfills the needs of animal welfare and precision livestock farming by enabling effective monitoring of individual animals. It serves as a crucial parameter for optimizing nutrition, reproductive performance, overall health, and economic outcomes in the cattle industry. The precise and consistent assessment of BCS relies on personal experience using visuals that involve observing the shape of the cattle from both its rear and side. However, this approach is labor-intensive it may lead to incorrect categorizations due to the likelihood of being influenced by prior observations of observed cattle. Therefore, the aim of this research was to develop and validate an automatic system for classification BCS using computer vision. A data acquisition system equipped with three RGB cameras was designed to capture both the dorsal and lateral views of cattle. Computer vision techniques, particularly DeepLabCut with its ResNet50 architecture, were employed for pose estimation. This allowed for the customization of the model to different breeds, ages, and conditions of cattle. Data augmentation techniques, such as convolutional autoencoder, further enhanced model performance and generalization. Before utilizing this data to develop a prediction model, regression analyses were conducted to check the relationship of the variables and find the best combination of independent variables. Various prediction models, including Decision Tree, Random Forest, and Support Vector Machine, were evaluated in terms of consistency, precision, and recall across different validation techniques. The results demonstrated the commendable performance of the Decision Tree model, concluding in an impressive 85.0% accuracy when trained on the full dataset. Its F1-score ranges from 0.84 to 0.92, indicating robust performance across different validation methods, with Mean Absolute Error (MAE) ranging from 0.158 to 0.189. By using deep learning and machine learning techniques, potentially automate and enhance the BCS assessment process, reducing the subjectivity and bias associated with traditional visual methods. This also has the capability to provide more accurate and consistent BCS measurements, which are critical for optimizing nutrition, reproductive performance, overall health, and economic outcomes in cattle. These findings have practical implications for the field of animal science, precision livestock farming, and agricultural technology, making the audience feel the relevance of this research to their work.*

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***Keywords.***
*Body condition score, Beef cattle, Computer vision, Precision livestock farming.*

## Introduction

In the field of cattle farming management, a well-established technique involves the utilization of Body Condition Scores (BCS) to indirectly evaluate the utilization of energy reserves stored in the fat and muscle tissues of beef cattle (Roche et al., 2009). The systematic application of BCS is widespread in monitoring feed consumption and health status, serving as a valuable analytical tool for optimizing both meat and milk production management (Vasseur et al., 2013). Accurate and consistent BCS assessment requires expertise in visual and tactile techniques, involving the observation of specific anatomical features, such as the cow's shape at various points along its body and the assessment of bone structures (Zhao et al., 2020). However, this manual approach is time-intensive and subjective, potentially introducing inaccuracies due to observer bias, particularly when making comparisons with previous observations (Roche et al., 2004, 2009). Recent technological advancements have aimed to automate the BCS evaluation process to address these challenges. Automated visual systems, equipped with different types of cameras, have been developed to analyze cow contours. Especially, these automated systems have demonstrated strong correlations with manual observations, offering a promising opportunity to improve the accuracy and efficiency of BCS assessments (Fischer et al., 2015; Shi et al., 2023).

Numerous studies have explored the automation of BCS assessment in cattle farming, utilizing a range of technological innovations. Yukun et al. (2019) developed regression and CNN models using ultrasound and back images, aiming to refine BCS estimation by integrating various physical characteristics like rib visibility and tailhead evaluation. Huang et al. (2019) used network cameras for remote BCS monitoring, demonstrating promising results in accuracy and classification. Liu et al. (2020) introduced a dynamic background model and image processing algorithms. Wu et al. (2021) employed a range of traditional Convolutional Neural Networks (CNNs) alongside transformer models, showcasing high accuracy in BCS estimations through refined feature extraction. Tao et al. (2022) utilized ultrasound and 3D imaging to monitor BCS, offering real-time assessments with high agreement compared to manual scoring. Nagy et al. (2023) investigated the use of computer vision-based supervised deep learning, specifically focusing on neural networks. Shi et al. (2023) proposed a method relying on both 2D and 3D features, employing depth information and region of interest extraction to enhance BCS assessment. Zhao et al. (2023) introduced a shape analysis method focusing on 3D surface evaluation, aiming to develop a universal approach for BCS assessment. These diverse approaches collectively aim to enhance the accuracy, efficiency, and objectivity of BCS assessment in cattle farming management. By integrating cutting-edge technologies such as computer vision, deep learning, and ultrasound imaging, these studies strive to mitigate the limitations of manual scoring, offering an outstanding approach for optimizing livestock health, productivity, and welfare in the agricultural industry.

Although previous research presents promising techniques for automated BCS identification, there are still several factors to consider in enhancing the performance of the applied model. One major concern is the lack of specificity in identifying particular body parts or areas. Authors often attempt to identify the entire body of the animal or use different shape annotators to collect information from specific locations. This study utilizes a computer vision pose estimation technique called DeepLabCut to gather information at precise locations and measure bone-to-bone distances to address this limitation. DeepLabCut models can be trained to detect specific body parts relevant to BCS assessment, making them adaptable to different cattle breeds, ages, and conditions. This flexibility enables customization of the model to meet the specific requirements of farming operations. Therefore, the aim of this research is to develop and validate an automatic system for classifying beef cattle BCS using computer vision.

## Materials and Methods

### Experimental Site

The investigation was conducted at the Middle Tennessee AgResearch and Education Center (MTREC) of the University of Tennessee during the years 2023 and 2024. In the initial phase, occurring on October 19th, November 6th, and November 14th of 2023, a group of twelve Angus and three Charolais cattle, all aged three years, were involved. Afterward, in 2024, on March 4th, March 11th, and March 18th, the study progressed with a focus on a larger group of twenty-four Angus cattle aged 1.5 years each. Throughout the experiments, the dedicated staff at MTREC maintained a cautious watch over the animals' well-being and health, thoroughly observing the farm's standard operating procedures and following veterinary recommendations. For the purpose of capturing video data, a camera system comprising two bullet cameras (PAR-P5BIRA2812NH-AI, Innovative Video Technology, NY, USA) and one dome camera (PAR-P5DRIR28NH-HDMI, Innovative Video Technology, NY, USA), mounted at a height of 2.5 meters, was deployed. These cameras, in combination with a network video recorder (VN2A-8X8, Innovative Video Technology, NY, USA), facilitated the recording and storage of footage from three different angles. The camera system was installed at the chute area where health assessments of the animals were conducted by MTREC personnel. The structural layout of the camera system is illustrated in Fig 1.

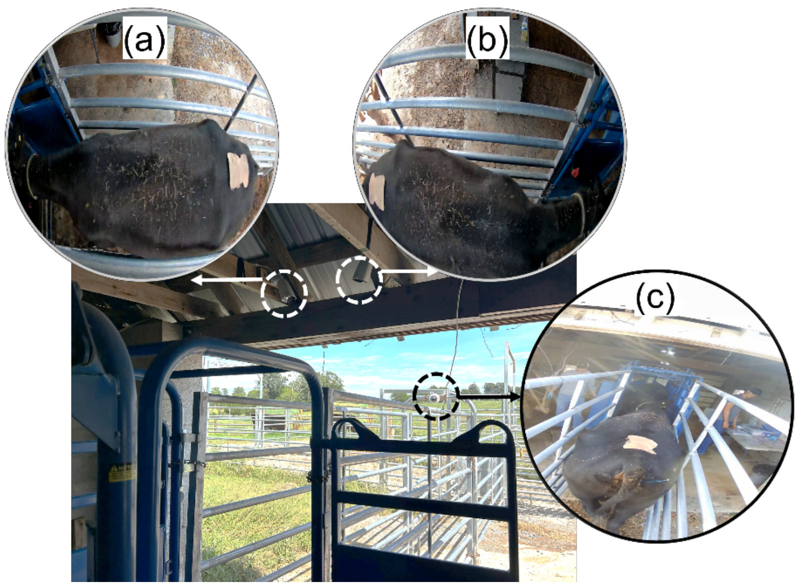


**Fig 1. Structural layout of the camera system: (a) left side view, (b) right side view, and (c) back side view.**

### Data Collection and Annotation

The dataset comprises videos recorded in the mp4 format, capturing the movements and positions of cattle. To analyze the skeletal structure and fat distribution, ten key points were identified for observation, providing valuable insights into their physical composition. Annotations were conducted from various camera perspectives: annotations from the rear camera primarily focused on the pin bone and adjacent fat region near the tail head, while annotations from side cameras (right and left) included additional details such as the pin bone, hip bone, and fat distribution around the tail head. Each animal underwent three recordings during the three-day experiment period, resulting in a comprehensive dataset consisting of 351 videos. Fig 2 describes the annotated key points and corresponding skeletal representations of cattle poses.


**Fig 2. The annotated key points and cattle pose skeleton: (a) back side view, (b) left side view, and (c) right side view.**

### DeepLabCut Pose Recognition

Based on the literature review, DeepLabCut designed specifically for extracting animal poses, is specialized in determining the geometrical configuration of multiple body parts (Mathis et al. 2018; Nath et al. 2019). DeepLabCut offers a choice of two ResNet architectures (50 and 101), which allow for the replacement of deconvolutional layers with dense layers to improve feature extraction. The network can be trained to recognize labeled key body points, increasing the accuracy of recognition and reducing the likelihood of misidentifying other points (Islam et al., 2023). After training, the model can analyze videos and estimate the pose for the entire dataset. In this study, we used the pre-trained ResNet50 architecture for pose estimation as part of a transfer learning approach. Fig 3 provides a diagram outlining the pose estimation workflow.

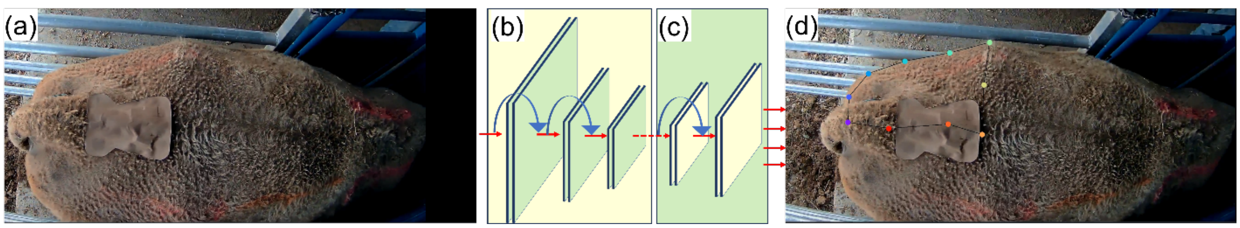


**Fig 3. The diagram outlines the DeepLabCut pose estimation workflow: (a) input, (b) pre-trained model (ResNet50), (c) deconvolutional layers, and (d) output with pose skeleton.**

### Data Pre-Processing and Machine Learning Prediction Models

During the process of identifying BCS manually, a trained cattle specialist observed and recorded each animal's condition, utilizing a scale ranging from 1 to 9, where 1 represents severe emaciation and 9 indicates obesity (Tennant et al., 2002). Although extreme scores were uncommon on the farm, the majority of animals fell within the range of class 5 to class 7, with class 7 being notably less frequent. To rectify this imbalance, a random oversampling technique was employed to ensure a more even distribution of BCS classes within the dataset (Viloria et al., 2020). Recognizing the importance of data augmentation in refining model performance and preventing overfitting, a convolutional autoencoder (C-AE) was utilized before model training. This C-AE was trained on a split dataset, with 80% allocated for training and 20% for testing, across 200 epochs, using the mean absolute error loss function and the Adam optimizer (Islam et al., 2023). The architecture of the C-AE is illustrated in Fig 4.

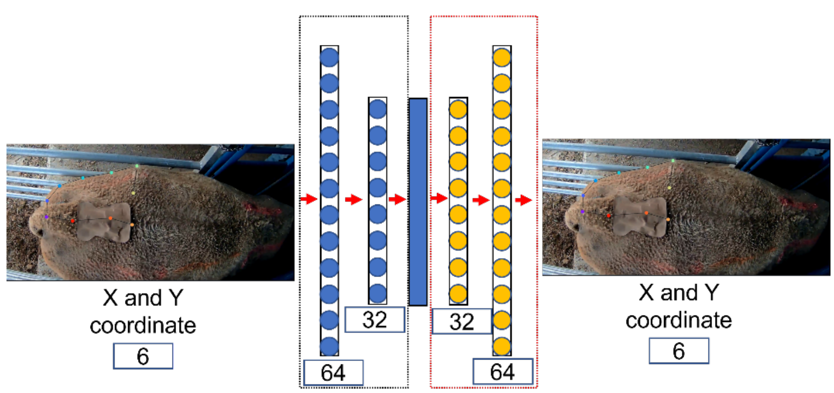


**Fig 4. The architecture of the proposed C-AE.**

Statistical analysis was conducted to explore the correlation between different variables and BCS classes. The dependent variable, BCS, was examined in relation to six independent variables, including body weight, age, area from three sides, and the distance between pin bones and the tail head.

Linear and polynomial regression analyses were performed to select the independent variables set to predict the BCS and different error metrics were evaluated. Error metrics such as coefficient of determination (unadjusted $R^2$), bias, root mean square error (RMSE), mean absolute error percent (MAPE), relative prediction error (RPE), residual prediction deviation (RPD), and the ratio of performance to interquartile distance (RPIQ) were evaluated for this purpose. $R^2$ gives an overall measure of goodness of fit, while RMSE and MAPE provide insights into the magnitude and direction of errors. Bias indicates the presence of systematic errors, and RPD and RPIQ provide information about the precision (Semakula et al., 2020). The analyses were tested against five different sets of independent variables, ranging from specific camera-related features to a combination of variables, including age and weight.

After finding the appropriate variable set, predictive modeling techniques were employed to construct a classification model for identifying BCS values. Decision tree (DT), random forest (RF), and support vector machine (SVM) algorithms were among the methodologies utilized. The performance of these models was evaluated using the entire dataset, as well as various training datasets employing 5-, and 10-fold cross-validation techniques, ensuring the robustness of the findings.

## Results and Discussions

### Evaluating the Pose Estimation and C-AE Model

The evaluation of both pose estimation and the C-AE model involved a thorough analysis of loss metrics and convergence patterns. In Fig 5(a), the loss value of the DeepLabCut-based model was examined, which was employed for identifying key points. The training spanned approximately seven days, concluding in the selection of weights at 1,030,000 iterations, where a notably low loss value of 0.0025 was achieved with a learning rate of 0.001. In Fig 5(b), the loss values of the C-AE model are represented as decreasing with each epoch. It's worth noting that the optimal model exhibited training and testing losses of 0.25 and 0.27, respectively, indicating strong performance. The convergence of the C-AE model became apparent after 100 epochs, with both training and testing loss curves stabilizing. This underscores the effectiveness of the proposed model in achieving satisfactory convergence.

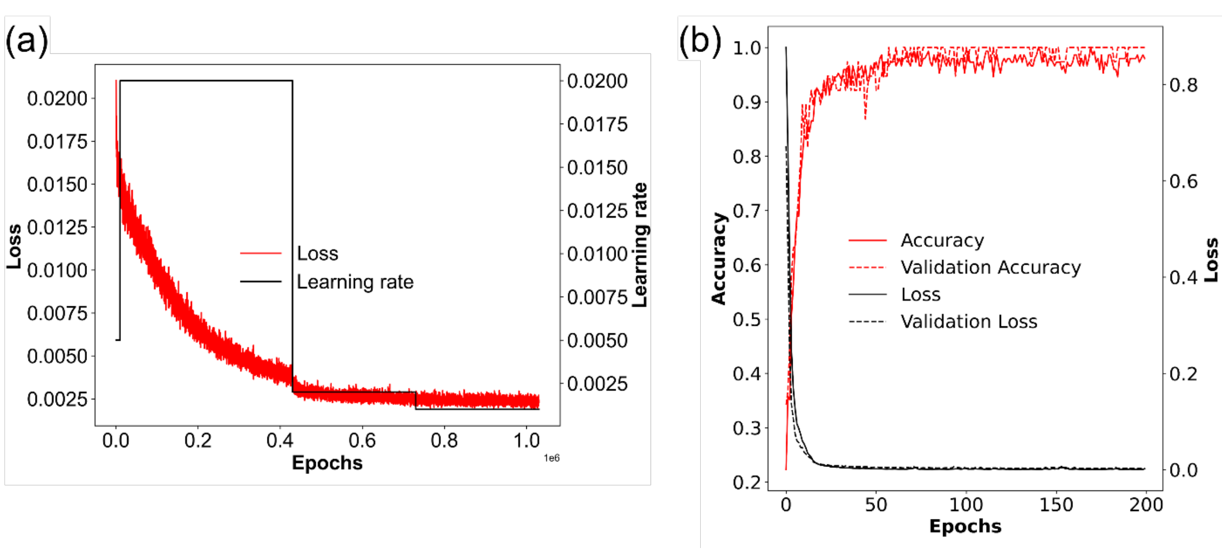


**Fig 5. Evaluation of (a) the DeepLabCut model and (b) the C-AE model.**

## Results of Regression and Prediction Models

Table 1 compares regression error metrics for different models and independent variable sets. Five different sets were used in the analysis: set 1 comprises only variables associated with the back camera (B=back area, D=bone distance); set 2 includes variables linked to the left and right cameras (LS=left side area, RS=right side area); set 3 involves variables from the back camera alongside non-deep learning variables (B=back area, D=bone distance, W=weight, A=age); set 4 contains only non-deep learning variables (W=weight, A=age); and set 5 includes all variables.

In set 1, $R^2$ values range from 0.1042 to 0.1635. For set 2, $R^2$ remains relatively consistent at 0.2733 to 0.2734. However, set 3 yields significantly improved $R^2$ values, ranging from 0.5612 to 0.7100. Furthermore, in set 4, $R^2$ ranges from 0.5044 to 0.7003. The widest range of $R^2$ values, indicating the most comprehensive predictive capability, is observed in set 5, with values spanning from 0.6306 to 0.7655. The trend in $R^2$ values suggests that including additional variables enhances the ability to explain variance in the independent variable.

In set 1, the bias ranges from 0.1033 to 0.1144, indicating relatively consistent performance within this limited scope of variables. As the sets expand to contain additional variables, particularly in sets 3 and 5, the bias spans a wider range, from -0.0251 to 0.0515. This indicates more varied performance, likely due to the increased complexity and diversity of the included variables. Particularly, set 3 shows a negative bias, suggesting that, on average, predicted values may underestimate actual values. Similarly, set 5 demonstrates the widest bias range, suggesting a wider spectrum of predictive accuracy.

Regarding the relative prediction interval quality (RPIQ), which assesses the accuracy of prediction intervals, the ranges also show variability across the different sets. In sets 1 and 2, RPIQ ranges from 0.7260 to 0.8357, indicating relatively consistent prediction interval quality within these subsets of variables. However, as the complexity of the variable sets increases, particularly in sets 3, 4, and 5, RPIQ shows a wider range from 0.7749 to 0.9038. This suggests varying levels of prediction interval accuracy across different regression analyses, with set 5 demonstrating the highest RPIQ values. The broader range in Sets 3, 4, and 5 reflects the influence of additional variables on the precision of prediction intervals.

The rest of the metrics follow a similar trend to the variable sets. For set 5, both analyses present their highest $R^2$ values, indicating a good fit to the data. Additionally, set 5 consistently shows lower biases, RMSEs, MAPEs, RPEs, and higher RPIQs compared to the other sets, suggesting that it provides a more accurate representation of the underlying relationships between the BCS and the independent variable. Therefore, all six independent variables were selected to predict the BCS using the different prediction models.

**Table 1. Regression error metrics comparison for different models and independent variable sets.**

| Regression | Error Metrics | Independent variable sets | | | | |
|---|---|---|---|---|---|---|
| | | Set 1 (B, D) | Set 2 (LS, RS) | Set 3 (B, D, W, A) | Set 4 (W, A) | Set 5 (B, D, LS, RS, W, A) |
| Linear | $R^2$ | 0.1042 | 0.2733 | 0.5612 | 0.5044 | 0.6306 |
| | Bias | 0.1033 | 0.1335 | 0.0283 | 0.0448 | 0.0515 |
| | RMSE | 0.7504 | 0.6759 | 0.5252 | 0.5582 | 0.4819 |
| | MAPE | 11.1506 | 10.0357 | 8.3126 | 8.9168 | 7.0196 |
| | RPE | 0.0344 | 0.0353 | 0.0150 | 0.0187 | 0.0160 |
| | RPD | 1.0667 | 1.1967 | 1.5117 | 1.4251 | 1.6548 |
| | RPIQ | 0.7594 | 0.8291 | 0.8685 | 0.9038 | 0.8013 |
| Polynomial (Degree 2) | $R^2$ | 0.1635 | 0.2734 | 0.7100 | 0.7003 | 0.7655 |
| | Bias | 0.1144 | 0.1442 | -0.0251 | -0.0076 | -0.0069 |
| | RMSE | 0.7251 | 0.6759 | 0.4270 | 0.4341 | 0.3840 |
| | MAPE | 10.5042 | 9.9833 | 5.9602 | 6.2931 | 4.9913 |
| | RPE | 0.0354 | 0.0371 | 0.0012 | 0.0046 | 0.0027 |
| | RPD | 1.1073 | 1.2008 | 1.8602 | 1.8268 | 2.0652 |
| | RPIQ | 0.7260 | 0.8357 | 0.8348 | 0.8985 | 0.7749 |

*** B=back area, D=bone distance, LS=left side area, RS=right side area, W= weight, A= age

Table 2 shows the classification results of the prediction models based on different validation data. The evaluation of prediction models is based on the performance of Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) algorithms for this dataset. Among these, the DT exhibits commendable consistency in precision and recall metrics across various validation techniques, concluding in an impressive 85.0% accuracy when trained on the full dataset. Its F1-score ranges from 0.84 to 0.92, indicating robust performance across different validation methods, with Mean Absolute Error (MAE) ranging from 0.158 to 0.189. RF emerges as the top performer in terms of accuracy, achieving an impressive 89.0% accuracy under 10-fold cross-validation, though with slightly higher variability in MAE. The RF model demonstrates generally high precision and recall, with an F1-score ranging from 0.88 to 0.92 and an MAE ranging from 0.108 to 0.216. However, SVM models, while also reaching an 89.0% accuracy in 5-fold cross-validation, exhibit fluctuations in F1-scores from 0.55 to 0.77, indicating potential sensitivity to validation methods. Despite these variations, the DT model's consistent precision-recall balance across validation techniques underscores its reliability in classification tasks, offering a robust choice for predictive modeling from this perspective.

**Table 2. Classification results of the prediction models based on different validation data.**

| Model | Validation | Acc, % | Precision | | | Recall | | | F1-score | | | MAE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | BCS | | | BCS | | | BCS | | | |
| | | | 5 | 6 | 7 | 5 | 6 | 7 | 5 | 6 | 7 | |
| DT | 5-fold | 81.0 | 0.71 | 0.78 | 1.00 | 0.92 | 0.58 | 0.92 | 0.80 | 0.67 | 0.96 | 0.189 |
| | 10-fold | 84.0 | 0.77 | 0.89 | 0.87 | 0.83 | 0.67 | 1.00 | 0.80 | 0.76 | 0.93 | 0.189 |
| | Full | 85.0 | 0.78 | 0.83 | 0.95 | 0.84 | 0.73 | 0.98 | 0.81 | 0.77 | 0.96 | 0.158 |
| RF | 5-fold | 78.0 | 0.67 | 0.75 | 1.00 | 0.92 | 0.50 | 0.92 | 0.77 | 0.60 | 0.96 | 0.216 |
| | 10-fold | 89.0 | 0.79 | 0.90 | 1.00 | 0.92 | 0.75 | 1.00 | 0.85 | 0.82 | 1.00 | 0.108 |
| | Full | 87.0 | 0.77 | 0.84 | 0.99 | 0.88 | 0.74 | 0.98 | 0.82 | 0.79 | 0.98 | 0.137 |
| SVM | 5-fold | 89.0 | 1.00 | 0.75 | 1.00 | 0.77 | 1.00 | 0.92 | 0.87 | 0.86 | 0.96 | 0.108 |
| | 10-fold | 86.0 | 1.00 | 0.71 | 1.00 | 0.58 | 1.00 | 1.00 | 0.74 | 0.83 | 1.00 | 0.135 |
| | Full | 84.0 | 1.00 | 0.68 | 1.00 | 0.55 | 1.00 | 0.98 | 0.71 | 0.81 | 0.99 | 0.158 |

## Conclusion

In conclusion, this study presents an innovative approach to automated BCS identification in cattle using computer vision techniques, specifically DeepLabCut for pose estimation. By focusing on the precise localization of key body points and bone-to-bone distances, this method offers improved specificity compared to previous techniques. Utilizing DeepLabCut's ResNet50 architecture, coupled with data augmentation techniques like convolutional autoencoders, enhances model performance and generalization across different breeds, ages, and conditions of beef cattle.

Regression analysis was conducted to find the best combination of the variable set. The analysis applied five variable sets to predict the dependent variable (BCS). As more variables were included, $R^2$ values increased, indicating improved explanatory power. Bias varied across sets, with wider ranges in more complex sets. Including all variables consistently surpassed other sets, showed higher $R^2$ values, lower biases, and better prediction interval accuracy. Overall, including all six independent variables provided the most accurate representation of the relationship with the dependent variable. Furthermore, the evaluation of prediction models, including Decision Tree, Random Forest, and Support Vector Machine algorithms, highlights the Decision Tree model's commendable performance in terms of consistency, precision, and recall across different validation techniques. Its robust performance underscores its reliability for predictive modeling in BCS classification tasks.

While this study provides valuable insights into automated BCS assessment in cattle farming, further research could explore integrating real-time monitoring capabilities into the developed system. This would enable continuous assessment of cattle health and welfare, facilitating timely intervention when necessary. Moreover, investigating the economic feasibility and scalability of implementing such technology on a larger scale could provide valuable insights into its practical adoption by cattle farmers. Overall, this research contributes to advancing automated BCS assessment in cattle farming, offering a reliable and adaptable solution that can potentially improve management practices and animal welfare. Combining computer vision techniques with machine learning algorithms demonstrates promising prospects for enhancing livestock monitoring and management systems in the precision agricultural sector.

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