

Non-destructive monitoring of excessive-fat pork belly using VCS-2000 and machine learning algorithms

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Abstract

This study investigates a non-destructive classification framework for identifying excessive-fat pork bellies at the 10th and 11th thoracic vertebrae (TV10 and TV11, respectively) using automated carcass traits extracted from the VCS 2000 system coupled with machine learning. Reference fat percentages of 117 pork carcasses were determined via hyperspectral imaging, with consumer acceptability thresholds established at 45% for TV10 and 40% for TV11 to segregate normal and excessive-fat groups. Six distinct classification models were optimized using a stratified grid search validation approach. Principal component analysis revealed severe spatial overlap and linear indistinguishability between the normal and excessive-fat groups in both anatomical sections. Overall classification performance for the TV10 section remained limited across all evaluated frameworks. In contrast, the optimized Random Forest model demonstrated promising predictive performance at the TV11 position, achieving a test set accuracy of 80.00%, an F1-score of 85.00%, and a recall of 94.44%. Shapley Additive exPlanations analysis identified the engineered carcass fatness index and the first lumbar vertebra backfat thickness as the primary variables of model classification. Given the strong biological correlation observed between these adjacent sections ($r_p = 0.883$), strategically deploying the validated Random Forest model at the TV11 section provides a robust, real-time proxy for monitoring excessive fat trends across the thoracic belly region during commercial slaughter operation without compromising primal carcass value, pending validation across larger, multi-abattoir datasets.

Keywords: Pork belly, VCS 2000, Machine learning, excessive fat, classification

Introduction

Pork belly is a major primal cut and the most economically vital component of the carcass in several East Asian countries [1, 2]. Due to its composition of alternating muscle and fat layers, pork belly exhibits a characteristically juicy and tender texture [2, 3]. It is generally marketed in sliced form, meaning consumer purchasing decisions are largely driven by the visual balance between fat and lean muscle in the individual slices [1, 4, 5]. Although fat content is a critical component of the sensory quality of pork belly, cuts containing excessive fat are increasingly shunned by consumers due to concerns about high fat consumption and the consequent outbreak of various diseases [2]. Consequently, excessive fat in pork belly slices has become a significant industrial problem [2, 5, 6, 7]. To mitigate this, over-fattened portions are typically trimmed before serving, and slices consisting predominantly of fat are discarded entirely, resulting in substantial economic losses. Therefore, providing early and reliable information regarding the fat content of pork bellies is highly critical for producers, retailers, and consumers alike.

The fat content of pork belly varies significantly across different anatomical regions [8]. Generally, the pork belly section corresponding to the 10th to 14th thoracic vertebrae (TV10 to TV14) features a thick fat layer in the dorsal area. Specifically, the highest fat compositions are typically observed at the TV10 and TV11 positions [8, 9, 10]. Furthermore, the fat composition at the TV10 and TV11 positions is highly correlated with the fat composition of other anatomical regions ($r=0.703$ to 0.892) [8]. Therefore, the TV10 and TV11 positions can serve as representative zones for monitoring the total fat composition of the whole pork belly. However, directly measuring the fat content of these slices currently requires destructive sampling techniques, such as slicing and deboning. This results in substantial economic losses due to sample degradation, high labor costs, and time-consuming procedures [2, 8, 11]. Consequently, developing a non-destructive, real-time assessment method would provide significant economic advantages, particularly if integrated directly onto the commercial slaughter line.

The VCS 2000 (E+V Technology GmbH, Oranienburg, Germany) is an automated pork carcass grading system widely utilized on commercial slaughter lines. The multi-camera system of the VCS 2000 gathers optical information on carcass properties such as backfat thickness, intermuscular fat, and specific muscle dimensions to subsequently estimate primal cut yields [12, 13, 14, 21]. Previous studies have reported that carcass properties, including carcass weight, backfat thickness, and overall carcass dimensions, can serve as indicative factors for pork belly fatness [1, 8, 14]. However, these relationships, including that reported by Jo et al. [8], have been characterized primarily through correlation coefficients rather than validated, deployable classification frameworks capable of yielding an actionable sorting decision on the commercial line. Hence, we hypothesized that the fat content of pork bellies could be accurately predicted by training models on the comprehensive data parameters obtained from the VCS 2000 system. Consequently, the objective of this study was to develop a non-destructive screening system for classifying excessive-fat pork bellies at the TV10 and TV11 positions using VCS 2000 data metrics coupled with machine learning classification algorithms.

Materials and methods

Sample preparation

A total of 120 crossbred [Yorkshire x Landrace x Duroc (YLD)] pork carcasses, slaughtered via standard commercial procedures, were obtained from a commercial abattoir located in Nonsan, Chungchungnam-do, Korea. The left half-carcasses were scanned using the VCS-2000 automated grading system (E + V Technology GmbH, Germany) to capture high-resolution images for the extraction of objective carcass traits. After slaughtering and grading, the carcasses were transported to the laboratory and chilled at 4 °C in a refrigerated room for 24 h, after which 120 untrimmed whole pork bellies were harvested. To analyze excessive fat deposition, 7 mm-thick target slices were obtained from the cross-sections corresponding to the TV10 and TV11 using a commercial meat slicer.

84

85 **Measurement of pork belly slices fat composition**

86 The fat composition of the pork belly slices was determined according to the method described by
87 Jo et al. [8] utilizing a snapshot-type hyperspectral imaging camera (Ultris X20 plus, Cubert GmbH,
88 Germany). Prior to image acquisition, instrumental calibration was performed. White calibration was
89 conducted using a Teflon tile with 99% reflectance, and black calibration was executed by completely
90 covering the camera lens with its protective cap. The pork belly slices were scanned across the visible
91 and near-infrared spectral regions (350–1002 nm, total 164 bands). Following image acquisition, the fat
92 and muscle tissue regions were segmented via a supervised classification approach using PerClass Mira
93 software (PerClass BV, Delft, Netherlands), in which representative pixels for each tissue class were
94 manually annotated to train the underlying classifier. Upon isolating the total fat and muscle pixels, the
95 volumetric fat composition (%v/v) was calculated using the following equation:

$$96 \quad \text{Fat composition (\%)} = \left(\frac{\text{Total fat pixels}}{\text{Total fat pixels} + \text{Total muscle pixels}} \right) \times 100$$

97 Because the pork belly slices were fabricated at a uniform thickness of 7 mm across all samples, this
98 two-dimensional surface fat pixel ratio directly corresponds to the volumetric fat composition (% v/v)
99 of the cross-section.

100 After the initial data screening, three outliers were removed, leaving a final dataset of 117 carcass
101 samples for subsequent analysis.

102

103 **Determination of the consumer acceptability threshold for excessive fat**

104 The consumer survey data used in this study were obtained from a research project commissioned
105 by the Korea Institute for Animal Products Quality Evaluation (KAPE) (Project title: "Establishments
106 of pork belly quality indicators using mechanical measurement data"). A consumer preference survey

was conducted with 1,500 participants to identify the least- preferred pork belly types and the major reasons for consumer rejection. The survey results revealed distinct differences in consumer preferences according to the visual characteristics of the pork belly slices. Based on the consumer rejection patterns driven by excessive fatness, the threshold for the TV10 section was set at 45%, and the threshold for the TV11 section was set at 40%. Pork belly slices with a fat composition at or above these respective thresholds were classified into the excessive-fat group, whereas slices falling below these criteria were designated as the normal group. Specifically, among the fat-composition groups evaluated in the survey, the 45–50% group, corresponding to the fat range typically observed at the TV10 position, was the most frequently rejected group (n = 1,066 respondents), with 89.9% of respondents citing an excessive amount of fat as the primary reason for rejection, followed by insufficient lean meat (5.1%) and unevenly distributed fat (4.2%). The 40–45% group, corresponding to the TV11 position, was the second most rejected group (n = 62 respondents), with 67.7% similarly citing excessive fat as the dominant reason. Because rejection in both groups was consistently and predominantly driven by excessive-fat perception, the lower bound of each group was adopted as the classification threshold for the corresponding anatomical position.

Determination of features

To construct predictive models for estimating pork belly fat composition, five carcass traits directly extracted by the multi-camera array of the VCS-2000 system were utilized as independent variables. The extracted carcass traits were defined as follows: individual backfat thickness measurements were obtained between the 1st and 2nd thoracic vertebrae (1TV BFT), between the 11th and 12th thoracic vertebrae (12TV BFT), and between the last thoracic vertebra and the 1st lumbar vertebra (1LV BFT). Multifidus intermuscular fat thickness (MIFT) was also measured using the VCS-2000. Also, the hot carcass weight (HCW) was concurrently recorded by the system. In this study, an engineered feature

termed the carcass fatness index (CFI) was incorporated as an additional variable and calculated by multiplying 1LV BFT by the HCW as follows:

$$CFI = 1LV\ BFT\ (mm) \times HCW\ (kg)$$

This variable was developed to better reflect the combined effect of carcass fatness and carcass weight on the occurrence of excessive fat in the belly section. These six variables were employed as independent variables to predict the internal, unobservable pork carcass traits in the commercial VCS-2000 system. The product of 1LV BFT and HCW was adopted as a mass-scaled interaction term, capturing the compounding effect whereby a heavier carcass with a deeper fat layer yields a disproportionately greater absolute fat mass in the belly. The 1LV BFT was selected among the available backfat measurements for its anatomical proximity to the posterior belly and its stability as an indicator of systemic subcutaneous adiposity.

Machine learning classification

The dataset was split into a training set (75%) and a test set (25%) using a stratified approach to maintain consistent class proportions. Feature values were subsequently standardized using a StandardScaler fitted exclusively on the training set, with the resulting transformation applied to the test set. To identify the optimal classification algorithm for each anatomical location of the pork belly slices, six distinct machine learning algorithms were employed: Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost). The range of hyperparameters was explored using a Grid Search approach with 5-fold cross-validation on the training set. In Logistic Regression, the inverse regularization strength (C) was evaluated over the range 0.01 to 100. For KNN, the number of neighbors (k) varied from 3 to 9, testing both distance metrics (Euclidean and Manhattan) and weighting schemes (uniform and distance-based). Multiple kernel functions (linear, radial basis function, and polynomial)

were evaluated for SVM, with C values ranging from 0.1 to 50 and gamma settings configured to “scale” and “auto”. The maximum tree depth was restricted to 3, 4, 5, or 7 for both DT and RF, with RF further exploring estimator counts of 100 and 200. For XGBoost, the learning rate (0.01, 0.05, and 0.1), maximum depth (1, 2, and 3), and subsample ratio (0.5, 0.7, and 1.0) were fine-tuned. Following validation, the optimal hyperparameter configuration for each model was selected based on classification performance.

Software and statistical analysis

To investigate interdependencies among variables before model training, Pearson’s correlation coefficients (r_p) were calculated to assess linear relationships between features. These correlation coefficients were interpreted according to the guidelines of Schober et al. [15]: negligible ($r_p = 0.00$ – 0.10), weak ($r_p = 0.10$ – 0.39), moderate ($r_p = 0.40$ – 0.69), strong ($r_p = 0.70$ – 0.89), and very strong ($r_p = 0.90$ – 1.00). Additionally, principal component analysis (PCA) was performed to investigate the high-dimensional data structure and evaluate the fundamental feasibility of linear group separation between the normal and excessive-fat pork belly groups at the TV10 and TV11 sections. Before PCA implementation, the feature dataset consisting of the carcass traits and engineered parameters was standardized using Z-score normalization to eliminate scale-induced bias.

The classification performance of the machine learning algorithms was comprehensively assessed using accuracy, precision, recall, and the F1-score [16]. For the calculation of these binary metrics, the excessive-fat group was designated as the positive class (1), whereas the normal group was defined as the negative class (0). Accuracy represented the overall proportion of correct predictions. Precision quantified the accuracy of positive predictions, and recall measured the model’s sensitivity in successfully capturing actual over-fattened pork bellies to minimize false negatives on the processing line. The F1-score, computed as the harmonic mean of precision and recall, was established as the

primary determinant for hyperparameter selection and model optimization to account for the class imbalances inherent in the biological target thresholds.

To elucidate the global predictive importance and localized directionality of independent variables within the optimal model, SHapley Additive exPlanations (SHAP) analysis was executed based on cooperative game theory [17].

Data processing, statistical analyses, and machine learning modeling were conducted using Python (version 3.11). Data curation and structural preprocessing were performed using the Pandas and NumPy libraries. The implementation of all machine learning algorithms, grid search validation, and model performance metrics was carried out using the Scikit-learn package, while data visualization was executed via the Seaborn and Matplotlib libraries. SHAP analysis was performed using the shap package (version 0.45.1). Package versions were as follows: scikit-learn (version 1.4.0), pandas (version 2.2.0), numpy (version 1.26.4), and matplotlib (version 3.8.3). The random state used for data partitioning and model training was arbitrarily pre-specified during the initial pipeline development phase, strictly prior to any feature selection, hyperparameter tuning, or model evaluation, ensuring that the partition remained independent of downstream results.

Results and discussion.

Characteristics of carcass traits and fat composition in pork belly

Table 1 presents the descriptive statistics of the measured carcass traits and target belly fat compositions of the evaluated pork carcasses. HCW of the analyzed carcasses averaged 97.54 ± 7.25 kg, ranging from 82.80 to 115.20 kg. The backfat thickness parameters exhibited distinct variations depending on the specific anatomical measurement sites. The 1LV BFT displayed the highest mean thickness of 39.59 ± 4.16 mm. In contrast, the backfat thicknesses at the thoracic regions, specifically 1TV BFT and 12TV BFT, were relatively lower, with mean values of 24.63 ± 4.62 mm and $23.71 \pm$

4.28 mm, respectively. The multifidus intermuscular fat thickness (MIFT) averaged 17.65 ± 4.60 mm. The carcass fatness index (CFI), which reflects the combined structural effect of carcass weight and overall fatness, showed a wide distribution ranging from 1183.00 to 3357.00.

In addition, Table 1 outlines that the reference fat composition at the TV10 section ranged from 28.62% to 58.90%, while values at the TV11 section ranged from 26.72% to 56.34%. Based on the established consumer acceptability thresholds for these variations, the samples were categorized into normal and excessive-fat groups. The TV10 section comprised 65 normal and 52 excessive-fat samples, whereas the TV11 section consisted of 48 normal and 69 excessive-fat samples (Figure 1). To ensure a robust and unbiased model evaluation, Table 2 demonstrates that these classified samples were symmetrically distributed into the training set (75%) and test set (25%) through a stratified partitioning approach. Specifically, the training and test sets maintained parallel mean fat distributions for both the TV10 section ($44.56\% \pm 6.36\%$ and $46.06\% \pm 7.06\%$, respectively) and the TV11 section ($41.62\% \pm 6.04\%$ and $42.25\% \pm 7.28\%$, respectively). This homogeneity between the training set and test sets confirms that the stratified partitioning was successfully executed without data-splitting bias.

Correlation of fat composition among the pork belly slices

The commercial VCS-2000 system utilizes carcass traits measured via its multi-camera system to predict a wide array of non-visible pork carcass traits, such as the overall fat percentage of the primal belly, as outputs. The primal pork belly cut typically spans from between the 4th or 5th thoracic vertebra to the final lumbar vertebra. Jo et al. [8] reported that the reference fat compositions at the TV10 and TV11 sections exhibited strong correlations with the anatomically distant cranial TV6 section ($r_p = 0.703$ and 0.721 , respectively). Furthermore, a moderate yet substantial correlation of approximately 0.67 was consistently observed even with the 4th lumbar vertebra, a region characterized by a lower baseline fat content due to the chronological, cranial-to-caudal lipid reduction gradient in swine. In addition, a strong correlation ($r_p=0.883$, data not shown) was observed between the fat compositions of

TV10 and TV11 in the present study, which closely matches the finding ($r=0.892$) reported by Jo et al. [8]. This result indicates that regional excessive fat accumulation manifested at one thoracic position is systematically accompanied by a similarly excessive fat condition in the adjacent section. Consequently, identifying an excessive-fat status at either TV10 or TV11 effectively reflects the overall fat deposition across the thoracic belly region. Because these adjacent sections share a tight biological relationship, either position can serve as a robust, practical landmark for monitoring regional fatness.

Performance evaluation of machine learning models

The classification performance of six machine learning algorithms, including logistic regression, SVM, Random Forest, XGBoost, KNN, and Decision Tree, was evaluated for TV10 and TV11 sections based on their respective consumer acceptability thresholds. Table 3 shows the training and test set accuracy, recall, precision, and F1-score for each model. To investigate the underlying data structure and evaluate the fundamental feasibility of group separation, PCA was executed prior to model training (Figure 2). Principal Component 1 (PC1) and Principal Component 2 (PC2) accounted for 77.0% and 14.2% of the total variance, respectively. The PCA score plots for both TV10 and TV11 sections exhibited severe spatial overlap between the normal and excessive-fat groups. This multi-dimensional overlap demonstrates that a linear combination of the carcass traits measured by the VCS 2000 system is insufficient to clearly segregate the normal and excessive-fat groups.

For the TV10 section, the overall classification performance across all evaluated algorithms remained limited. Logistic regression, as a linear classification approach, yielded an F1-score of 48.00%, illustrating the inherent limitations of linear decision boundaries when mapping the complex fat composition at TV10 position. The other machine learning algorithms leverage non-linear frameworks. SVM operates as a kernel-based geometric classifier designed to construct an optimal separating hyperplane; however, it exhibited a low classification accuracy of 46.67% in the independent test set. Decision Tree and Random Forest utilize hierarchical partitioning methods to segment the feature space

through recursive splits, achieving test accuracies of 50.00% and 56.67%, respectively. XGBoost, an ensemble gradient boosting framework, and KNN, an instance-based distance method, similarly yielded constrained test outcomes of 53.33% and 50.00%, respectively. Despite their non-linear mapping capabilities, all of these algorithms displayed high classification accuracy on the training set but sharp performance declines on the test set. This phenomenon is primarily attributed to the constrained sample size inherent to biological carcass dataset, which induces model overfitting and subsequently degrades generalization performance on the independent test set. Furthermore, the consistently low predictive accuracy sustained across both linear and non-linear models confirms that the standard carcass traits extracted by the VCS 2000 system do not encompass sufficient descriptive information to resolve the fat composition of the TV10 section.

In contrast, the overall classification performance significantly improved for the TV11 section. Logistic regression yielded the lowest classification accuracy of 60.00% across both the training and test sets, reflecting the linear indistinguishability previously identified in the PCA trend (Figure 2). Although SVM utilizes non-linear kernel mapping, it also achieved a limited test accuracy of 60.00% (F1-score 75.00%) due to the severe spatial overlap of carcass features, which restricted its ability to establish a clear decision boundary. Conversely, XGBoost and KNN demonstrated general performance improvements, both securing a classification accuracy of 66.67% on the test set. The hierarchical tree-based methods, namely the Decision Tree and Random Forest models, achieved test accuracies of 76.67% and 80.00%, respectively. Crucially, the Random Forest model achieved the highest performance among the evaluated algorithms, securing an F1-score of 85.00% with a recall of 94.44%. This superior performance occurs because the Random Forest architecture mitigates localized data noise through recursive partitioning and ensemble bagging. From an anatomical perspective, this success is heavily supported by the fact that the 12TV BFT is measured directly between the 11th and 12th thoracic vertebrae, thereby providing a highly localized physical proxy for the fat composition of the TV11 section.

To assess model robustness beyond the single train/test split, 5-fold cross-validation performance statistics (mean $\pm$ SD F1-score) were additionally examined within the training pool ($n = 87$) under the fixed stratified partition described in Section 2.6 (Table S1). Cross-validation performance was low and highly variable for the TV10 section (F1-score range: 38.48-57.97%; SD up to $\pm 24.50\%$) but comparatively stable for the TV11 section (F1-score range: 60.57-73.90%; SD $\leq 13.75\%$), with the optimal Random Forest model showing a standard deviation of only $\pm 4.77\%$. This fold-to-fold variability and the training-test performance gap observed in Table 3 likely share a common origin: with only 87 training and 30 test samples, the specific carcasses assigned to each partition can shift performance by several percentage points regardless of whether the partition is a cross-validation fold or a train/test split. The uncertainty of the independent test-set performance ($n = 30$) is further characterized by 95% confidence intervals reported in a note to Table 3. Beyond this sample-size effect, the more pronounced training-test performance gaps shown in Table 3 for several other models (e.g., TV10 Random Forest: 91.95% in training vs. 56.67% in testing; TV10 XGBoost: 90.80% in training vs. 53.33% in testing) may also reflect feature limitations, as the VCS-2000 traits are indirect external proxies for internal fat composition, and class boundary overlap, as shown by the PCA analysis (Figure 2).

Despite the poor classification performance observed at the TV10 position, the strong biological correlation between the TV10 and TV11 sections ($r_p=0.883$) indicates that regional excessive fat accumulation manifested at one thoracic position is systematically accompanied by an identical fat accumulation in the adjacent section. Because the TV11 section yields a highly robust predictive model, it can be strategically established at the definitive representative proxy zone for monitoring regional fatness across the entire thoracic belly region of primal cut.

To quantify the practical risk of relying on the TV11 section as a proxy for TV10, a cross-tabulation analysis of the ground-truth classification labels was conducted across all 117 carcasses. Of the 52 carcasses classified as excessive-fat at the TV10 section, 47 (90.38%) were also classified as excessive-fat at the TV11 section, while only 5 carcasses (9.62%) exhibited excessive fat at the TV10 position

while remaining within the normal range at TV11. Consequently, by deploying the validated Random Forest model tailored to the TV11 section, the pork industry can reliably execute non-destructive, real-time screening of excessive fat distributions across the primal belly regions without requiring destructive slicing or compromising commercial carcass value.

Model interpretability using SHAP analysis

The SHAP summary plot for the TV11 section elucidated the ranking and contextual directionality of the carcass traits within the Random Forest model, which exhibited the highest classification accuracy. The SHAP summary plot is interpreted based on three visual dimensions: feature ranking, impact directionality, and feature intensity [17]. First, the carcass traits are listed along the vertical y-axis in descending order of their global predictive importance. Second, the horizontal x-axis represents the SHAP value, where zero denotes the baseline expected prediction; displacements to the right (positive zone) indicate an increased probability of excessive-fat classification, whereas displacements to the left (negative zone) indicate a shift toward a normal carcass classification. Third, each point represents an individual carcass sample, with the color spectrum shifting from blue to red to indicate low to high biometric values of the corresponding feature.

The analysis identified the engineered feature, the CFI, as the most important parameter, followed sequentially by 1LV BFT, HCW, 1TV BFT, MIFT, and 12TV BFT (Figure 3). The spatial distribution of the SHAP values for CFI demonstrated a clear, proportional trend. High feature values of CFI (represented by red dots) were predominantly distributed within the positive SHAP domain, indicating that an increase in the CFI shifts the algorithmic probability toward the excessive-fat class. Conversely, low feature values of CFI (represented by blue dots) were localized within the negative SHAP domain, representing that lower CFI values contribute to a normal class.

1LV BFT exhibited a distinct positive relationship with excessive fat accumulation at the TV11 position, where the high feature values (red dots) were mainly distributed in the positive SHAP domain,

while low and intermediate feature values occupied the negative domain. This distribution indicates that 1LV BFT serves as a reliable indicator of the overall degree of fat accumulation in the pork carcass, effectively reflecting a systemic excessive-fat state. This phenomenon can be explained by the developmental growth gradient in pigs, where subcutaneous fat deposition progressively advances from the cranial to the caudal region, making the lumbar area a highly sensitive and reactive indicator of late-stage adiposity [19, 20]. The distribution of 1TV BFT is supported by this anatomical theory, here, the red dots corresponding to high feature values were broadly dispersed within the negative SHAP domain, whereas intermediate and low values extended into the positive zone. Because tissue growth and chronological fat accumulation advance caudally from the cranial pole, a highly developed backfat layer at the extreme cranial region (1TV) indicates that the early stages of lipid deposition are fully saturated, causing the subsequent fat accumulation to shift dynamically toward the posterior lumbar direction.

The SHAP values for HCW were moderate and evenly scattered near the baseline index. Jo et al. [8] reported that HCW showed a weak correlation with the fat content of pork belly slices across different anatomical regions. Similarly, a weak correlation between the overall pork belly fatness and HCW was discovered [18]. These consistent findings reinforce that HCW alone does not function as a standalone determinant of the internal fatness in pork belly. Regarding MIFT, the SHAP values displayed an ambiguous distribution, suggesting that this variable primarily reflects individual physiological variation rather than a definitive linear trend. Finally, 12TV BFT demonstrated a clear positive distribution, where high values aligned with the positive SHAP domain and low values occupied the negative zone. This outcome substantiates the hypothesis established in Section 3.3, verifying that the immediate anatomical proximity of the 12TV BFT measurement site provides a direct, localized physical indicator that effectively captures the internal tissue distribution of the adjacent TV11 section.

Conclusion

This study demonstrates the practical feasibility of utilizing objective carcass traits measured via the automated commercial VCS 2000 multi-camera system to classify excessive-fat pork bellies at the 11th thoracic vertebra (TV11) section based on consumer acceptability thresholds. The Random Forest model successfully resolved the spatial overlap of multivariate carcass data, achieving a promising predictive capacity characterized by a test set accuracy of 80.00% and an F1-score of 85.00%. These findings indicate that the developed classification framework offers a viable approach for real-time, non-destructive sorting within commercial slaughter operations.

Nevertheless, a primary structural limitation of this research stems from the relatively limited sample size obtained from a single, localized commercial population. To enhance the algorithmic robustness, statistical power, and industrial scalability of this predictive system across highly heterogeneous commercial processing environments, future validation studies should incorporate larger and more phenotypically diverse pig population. Specifically, all 117 carcasses originated from a single commercial abattoir and a single crossbred population (Yorkshire x Landrace x Duroc), which limits the generalizability of the developed models to other genetic lines, feeding regimes, or slaughter facilities with different VCS-2000 calibration settings. Accordingly, these findings should be interpreted as an initial proof-of-concept requiring further validation rather than a deployment-ready solution.

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Tables and Figures

Figure legends

Figure 1. The distribution of fat compositions of TV10 and TV11 pork belly slices

(A): The distribution of fat compositions of TV10, and (B): The distribution of fat compositions of TV11 TV10 section: n = 117 (65 normal, 52 excessive-fat); TV11 section: n = 117 (48 normal, 69 excessive-fat).

Figure 2. PCA plots of TV10 and TV11

(A) PCA score projection for the TV10 section based on the 45% consumer acceptability threshold, and (B) PCA score projection for the TV11 section based on the 40% consumer acceptability threshold. (65 normal, 52 excessive-fat for TV10; 48 normal, 69 excessive-fat for TV11).

Figure 3. SHAP summary plot of carcass traits for the Random Forest model predicting the excessive-fat status of the TV11 pork belly section

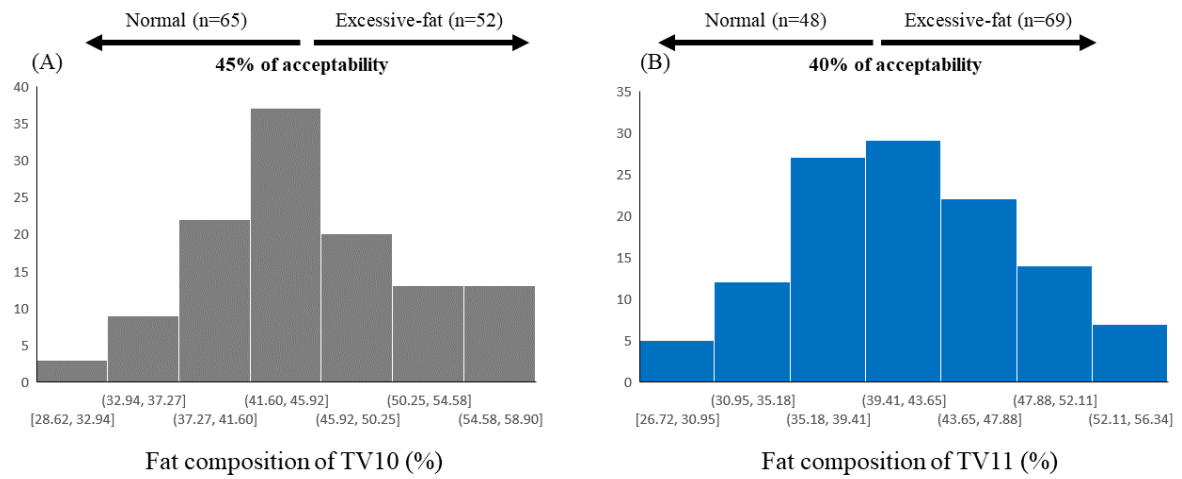


Figure 1.

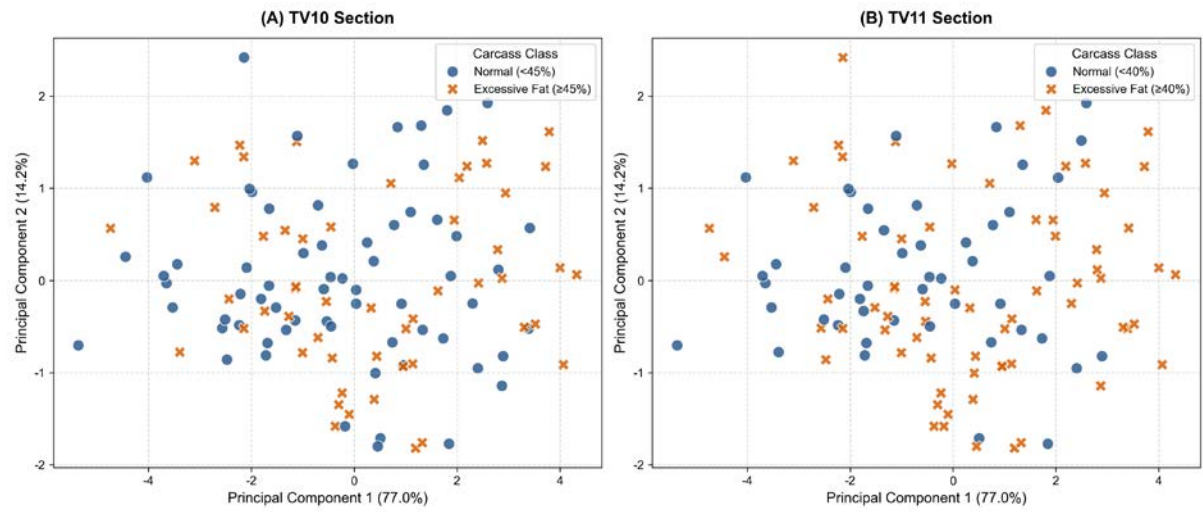


Figure 2.

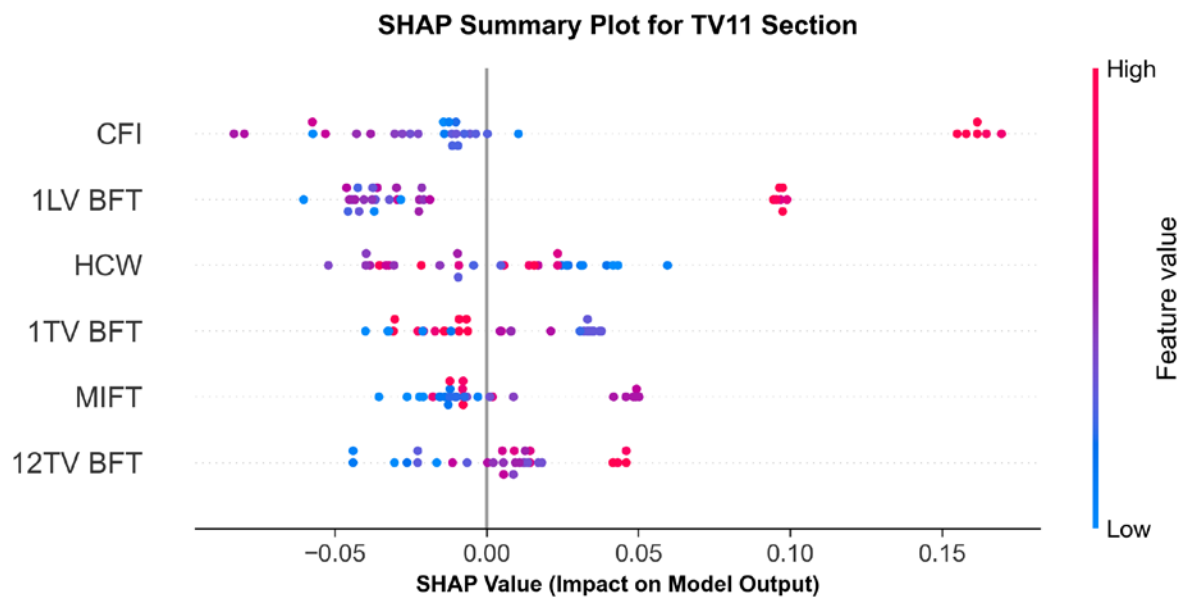


Figure 3.

459 **Table 1. Descriptive statistics of carcass traits and belly fat percentages**

Characteristic	Mean	SD	Min	Max
1TV BFT (mm)	24.63	4.62	12.00	35.00
12TV BFT (mm)	23.71	4.28	13.00	33.00
MIFT (mm)	17.65	4.60	8.00	27.00
1LV BFT (mm)	39.59	4.16	28.00	45.00
HCW (kg)	97.54	7.25	82.80	115.20
CFI	2321.46	496.34	1183.00	3357.00
Target variables				
TV10 fat (%)	44.95	6.55	28.62	58.90
TV11 fat (%)	41.78	6.35	26.72	56.34

460 Abbreviation: 1TV BFT, Backfat thickness at first thoracic vertebra; 12TV BFT, Backfat thickness
461 between 11th and 12th thoracic vertebrae; MIFT, Multifidus intermuscular fat thickness; 1LV BFT,
462 Backfat thickness at first lumbar vertebra, CFI= carcass fatness index; VCS fat, the fat percentage (%)
463 of primal pork belly cut predicted by VCS-2000; TV10 fat (%), fat compositions of pork belly at 10th
464 thoracic vertebra; TV11 fat (%), fat compositions of pork belly at 11th thoracic vertebra.

Table 2. Evaluation of reference fat distributions and class frequencies between the training and test datasets

	Training set (n=87)	Test set (n=30)
TV10 section		
Fat composition (%) ¹	44.56±6.36	46.06±7.06
Normal group, n (%)	48 (55.2%)	17 (56.7%)
Excessive fat group, n (%)	39 (44.8%)	13 (43.3%)
TV11 section		
Fat composition (%) ¹	41.62±6.04	42.25±7.28
Normal group, n (%)	36 (41.4%)	12 (40.0%)
Excessive fat group, n (%)	51 (58.6%)	18 (60.0%)

¹Reference value of fat compositions were determined via destructive hyperspectral imaging analysis.

469 **Table 3. Performance comparison of different machine learning algorithms**

Model	Training set accuracy (%)	Test set accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
TV10 (45%)					
Logistic regression	57.47	56.67	46.15	50.00	48.00
SVM	83.91	46.67	46.15	40.00	42.86
Random Forest	91.95	56.67	38.46	50.00	43.48
XGBoost	90.80	53.33	23.08	42.86	30.00
KNN	83.91	50.00	61.54	44.44	51.61
Decision Tree	78.16	50.00	38.46	41.67	40.00
TV11 (40%)					
Logistic regression	58.62	60.00	100.00	60.00	75.00
SVM	58.62	60.00	100.00	60.00	75.00
Random Forest	77.01	80.00	94.44	77.27	85.00
XGBoost	88.51	66.67	83.33	68.18	75.00
KNN	72.41	66.67	83.33	68.18	75.00
Decision Tree	78.16	76.67	77.78	82.35	80.00

470 **Note: 95% Wilson score confidence intervals for the TV11 Random Forest model (best-**
471 **performing model; independent test set, n = 30) were 62.7-90.5% (accuracy), 74.2-99.0% (recall),**
472 **and 56.6-89.9% (precision).**

Table S1. Five-fold cross-validation performance (mean $\pm$ SD F1-score, %) of six classification algorithms for the TV10 and TV11 sections.

Model	5-fold CV F1-score (%), Mean $\pm$ SD
TV10 (45%)	
Logistic regression	51.49 $\pm$ 15.06
SVM	43.17 $\pm$ 19.09
Random Forest	44.80 $\pm$ 24.50
XGBoost	45.08 $\pm$ 21.03
KNN	57.97 $\pm$ 5.41
Decision Tree	38.48 $\pm$ 15.22
TV11 (40%)	
Logistic regression	73.02 $\pm$ 1.30
SVM	73.90 $\pm$ 1.42
Random Forest	64.39 $\pm$ 4.77
XGBoost	61.04 $\pm$ 4.83
KNN	70.22 $\pm$ 3.59
Decision Tree	60.57 $\pm$ 13.75

Abbreviation: KNN, K-nearest neighbors; SVM, Support vector machines; TV10, pork belly slice located in 10th thoracic vertebra; TV11, pork belly slice located in 11th thoracic vertebra.