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Lamb Meat Quality Assessment by Support Vector Machines

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Abstract. The correct assessment of meat quality (i.e., to fulfill the consumer's needs) is crucial element within the meat industry. Although there are several factors that affect the perception of taste, *tenderness* is considered the most important characteristic. In this paper, a *Feature Selection* procedure, based on a *Sensitivity Analysis*, is combined with a *Support Vector Machine*, in order to predict lamb meat tenderness. This real-world problem is defined in terms of two difficult regression tasks, by modeling objective (e.g. *Warner–Bratzler Shear* force) and subjective (e.g. human taste panel) measurements. In both cases, the proposed solution is competitive when compared with other neural (e.g. *Multilayer Perceptron*) and *Multiple Regression* approaches.

Key words. data mining, feature selection, meat quality, multilayer perceptrons, regression, support vector machines

Abbreviations. FS–Feature Selection; MR–Multiple Regression; NN–Neural Network; SVM–Support Vector Machine; STP–Sensory Taste Panel; WBS–Warner–Bratzler Shear

1. Introduction

A top priority factor in the success of meat industry relies on the ability to deliver specialties that satisfy the consumer's taste requirements. In particular, assessing the quality of an item is important for lamb meat firms, specially if they want to move into niche markets by differentiating their products. Therefore, meat and animal scientists have dedicated high efforts in finding reliable quality estimators. Among the several factors that influence meat quality (e.g. *juiciness, appearance*, or *aroma*), *tenderness* is considered the most important attribute [11]. In effect, consumers are willing to pay premium prices for tender meat.

The ideal method for measuring tenderness should be accurate, fast, automated, and noninvasive. In the past, two major approaches have been proposed [1]: *instrumental* and *sensory* analysis. The former is based in an objective test, such as the *Instron* instrument, which measures the *Warner–Bratzler Shear* (WBS) force and it

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is the most commonly used device. On the other hand, sensory methods are based in subjective information, usually given by a human taste panel. Both approaches are invasive, expensive and time demanding, since they require laboratory work. For instance, the WBS values can only be obtained 72 hours after slaughtering, while the preparation and execution of consumer taste panel may take several days.

An alternative is to use cheap and noninvasive carcass measurements that can be collected within the first 24 hours after slaughtering (e.g. pH and color). Under this scenario, the classic animal science approach is based on *Multiple Regression* (MR) models [1], using meat features as independent (or input) variables and the WBS or *sensory* measures as the depended (or output) ones. However, the linear models will fail when nonlinear relationships are present. In such cases, a better option is to use techniques such as *Neural Networks* (NNs) [9] or *Support Vector Machines* (SVMs) [20]. Indeed, these methods are gaining an attention within the *Data Mining* field, due to their performance in terms of predictive knowledge [8, 16]. It should be stressed that SVMs present theoretical advantages over NNs, such as the absence of local minima in the model optimization phase.

In *Data Mining* applications, besides obtaining a high-predictive performance, it is often useful to provide explanatory knowledge. In particular, the measure of input importance is relevant within this domain. Since carcass features are often highly correlated, *Principal Component Analysis* has been proposed to reduce the input dimensionality [1]. Yet, the principal components are compressed variables and they do not represent a direct meaning for the meat user. An alternative, is to use a *Sensitivity Analysis* procedure, which has outperformed other input selection techniques (e.g. *Forward Selection* and *Genetic Algorithms*) [12].

In the last few years, several authors have proposed nonlinear methods to assess meat quality (e.g. beef, pork, poultry, or sausages) [1]. In the majority of these studies, the *Multilayer Perceptron* neural architecture is the most common approach. However, regarding tenderness prediction, the literature seems scarce and it is primarily oriented toward beef. For example, in the work of Li et al. [15], *Multilayer Perceptrons* outperformed a MR when mapping beef texture images with sensory tenderness scores. In another study, Hill et al. [10] have applied *Multilayer Perceptrons* to predict the *Instron* force, obtaining better results than the MR method. More recently, Diez et al. [6] adapted a SVM with a polynomial kernel of degree 2 to model beef tenderness preferences, surpassing linear, and cubic regression methods.

In this work, the combination of a feature selection procedure, based on a *Sensitivity Analysis*, with a gaussian kernel SVM is proposed to predict lamb meat tenderness. This real-world problem will be modeled in terms of two regression tasks, using both instrumental and sensory measurements. The devised strategy will be tested on animal data and compared with other NN and MR approaches.

The paper is organized as follows. First, a description is given on the datasets used in Section 2.1. Then, the learning models are presented in Section 2.2. In Section 3, the experiments performed are described and the results analyzed. Finally, closing conclusions are drawn in Section 4.

2. Materials and Methods

2.1. LAMB MEAT DATA

This study considered lamb animals with the *Protected Designation of Origin* certificate, from the *Trás-os-Montes* northeast region of Portugal. The database was collected from November, 2002 until November, 2003, with each instance denoting the readings obtained from a slaughtered animal. With a total of 81 examples, the database is quite small. However, it should be noted that each animal presents considerable costs, around 6 euros per kilogram plus laboratory work. Table 1 presents a synopsis of the data attributes. The HCW is obtained 1 hour after slaughter, exfoliation, and evisceration. The former two attributes (Breed and Sex) are also registered at slaughterhouse, while the others are measured in laboratory. Due to their visual nature, the color attributes (a*, b*, dE, dL, and dB*) have a high impact in consumer's perception. In most of the situations, these are the only attributes that the consumer can judge.

The WBS force is the major index for measuring meat tenderness. It can only be obtained in laboratory, no sooner than 72 hours after slaughter, by using an invasive device called *Instron*. The WBS registers the force (in kg) required to crush a meat sample with a thickness of 1 cm. Low values suggest tender meat while high readings suggest toughness. On the other hand, a more elaborated scheme was devised to obtain the sensory values (STP). A panel of 12 trained individuals, from the *Bragança Polytechnic Institute*, was selected. Then, meat samples from the *longissinus thoracis* muscle were collected and defrost at 4°C in a refrigerator. Next, each sample was randomly encoded with a three digit number, wrapped in an aluminum sheet and heated at 100°C. Then, each panel member was set in an individual compartment, performing a taste proof, under similar conditions, of random

Table 1. The dataset main attributes.

Attribute	Description	Domain
Breed	Breed type	{*Bragançana*, *Mirandesa*}
Sex	Lamb sex	{Male, Female}
HCW	Hot carcass weight (kg)	[4.1, 14.8]
STF2	Sternal fat thickness	[6.0, 27.8]
C	Subcutaneous fat depth	[0.3, 5.1]
pH1	pH 1 hour after slaughtering	[5.5, 6.8]
pH24	pH 24 hours after slaughtering	[5.5, 5.9]
a*	Red color index	[11.5, 22.2]
b*	Yellow color index	[6.5, 12.5]
dE	Total color difference	[46.5, 60.9]
dL	Luminosity differential	[−56, −39]
dB*	Yellow differential	[15.3, 22.5]
WBS	Warner–Bratzler Shear force	[9.5, 57.0]
STP	Sensory taste panel	[0.7, 7.1]

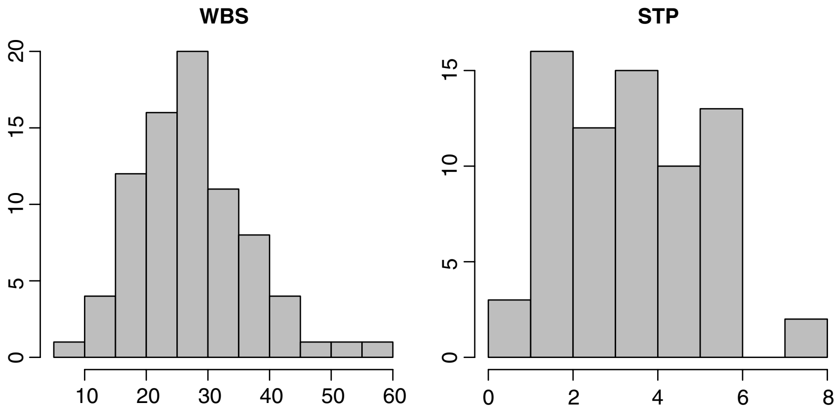

Figure 1. The histograms for the instrumental and sensory output variables.

selected samples. Between different tastes, mouths were cleaned by using water and by eating small golden apple pieces. Each sample was ranked from 0 (the most tender) to 10 (the most tough). Finally, the STP attribute was measured as the average of the grades from the panel.

Since the original data contained missing values (2 for the WBS and 10 for the STP), two new datasets were created by discarding these entries. The first contains 79 rows (for the WBS task), while the second has 71 examples (STP). Figure 1 shows the histograms of the target variables.

2.2. LEARNING MODELS

A regression dataset D is made up of $k \in \{1, \ldots, N\}$ examples, each mapping an input vector $(x_1^k, \ldots, x_I^k)$ to a given target yk. The error is given by: $e_k = y_k - \hat{y}k$, where $\hat{y}k$ represents the predicted value for the k input pattern. The overall performance is computed by a global metric, namely the *Mean Absolute Deviation* (MAD) and *Relative Mean Absolute Deviation* (RMAD), which can be computed as follows [6]:

$$
\begin{aligned}
\mathrm{MAD} &= 1/N \times \sum_{i=1}^{N} |y_i - \hat{y}_i|, \\
\mathrm{RMAD} &= 1/N \times \mathrm{MAD} / \sum_{i=1}^{N} |y_i - \bar{y}_i| \times 100(\%).
\end{aligned} \tag{1}
$$

In both metrics, lower values result in better predictive models. The RMAD statistic is scale independent, where 100% denotes an error similar to the naive average predictor ($\bar{y}$).

The MR model is defined by the equation [8]:

$$\hat{y} = w_0 + \sum_{i=1}^{I} w_i x_i, \tag{2}$$

where $(x_1, \ldots, x_I)$ denotes the input vector and $\{w_0, \ldots, w_I\}$ the parameters to be adjusted. This model is easy to interpret and has been widely used in regression applications.

This study will consider the *Multilayer Perceptron* [9], the most popular NN architecture. The base network will use biases, one hidden layer of H hidden nodes and logistic activation functions and one output node with a linear function [8]. Thus, each regression task (WBS and STP) will be modeled by a different NN. The overall model is given by the equation:

$$\hat{y} = w_{o,0} + \sum_{j=I+1}^{o-1} f\left(\sum_{i=1}^{I} x_i w_{j,i} + w_{j,0}\right) w_{o,i}, \tag{3}$$

where $w_{i,j}$ denotes the weight of the connection from node j to i, o the output node and f the logistic function $(\frac{1}{1+\mathrm{e}^{-x}})$.

The NN performance will be sensitive to the topology choice. To solve this issue, a common practice is to use a large number of hidden nodes (H) and train the NN with a *regularization* method. Thus, a *weight decay* procedure will be adopted, where the hyperparameter λ will control the network complexity [8].

All attributes are standardized to a zero mean and one standard deviation. Then, the initial neural weights are randomly set within the range $[-0.7, +0.7]$. Next, the training algorithm is applied and stopped when the error slope approaches zero or after a maximum of E epochs. Since the NN cost function is nonconvex (with multiple minima), R runs will be applied to each neural configuration, being selected the NN with the lowest penalized error.

In SVM regression, the input $x \in \Re^I$ is transformed into a high m-dimensional feature space, by using a nonlinear mapping. Then, the SVM finds the best linear separating hyperplane in the feature space:

$$\hat{y} = w_0 + \sum_{i=1}^{m} w_i \phi_i(x), \tag{4}$$

where $\phi_i(x)$ represents a nonlinear transformation, according to the kernel function $K(x, x') = \sum_{i=1}^{m} \phi_i(x)\phi_i(x')$.

To estimate the best SVM, the ϵ-insensitive loss function (Figure 2) is often used [18]. The *Radial Basis Function* kernel, which presents less hyperparameters and numerical difficulties than other kernels (e.g. polynomial or sigmoid), will also be adopted [4]:

$$K(x, x') = \exp(-\gamma \|x - x'\|^2, \quad \gamma > 0). \tag{5}$$

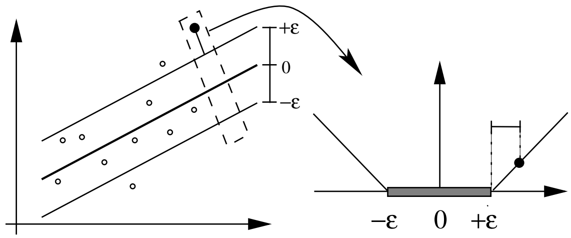

Figure 2. Example of a linear SVM regression and the ϵ-insensitive loss function (adapted from [18]).

Under this setup, the performance is affected by three parameters: C, a trade-off between the model complexity and the amount up to which deviations larger than ϵ are tolerated; ϵ, the width of the ϵ-insensitive zone; and γ, the parameter of the kernel. Since the search space for the three parameters is high, the C and ϵ values will be set using the heuristics proposed in [5]:

$$\begin{aligned} &C = 3\sigma_y, \quad \text{if } \bar{y} = 0, \\ &\hat{\sigma} = 1.5/N \times \sum_{i=1}^{N} (y_i - \hat{y}_i)^2, \\ &\epsilon = \hat{\sigma}/\sqrt{N}, \end{aligned} \tag{6}$$

where σ_y denotes the standard deviation of the output (y) and $\hat{y}$ is the value predicted by the 3-nearest-neighbor algorithm. Since all variables were standardized to a zero mean, the $\bar{y} = 0$ condition is met.

The hyperparameters (λ and γ) will be tuned by a two level grid-search. The first level will search the best value (λ_1 or γ_1) within the ranges $\lambda \in \{0.00, 0.01, \ldots, 0.20\}$ or $\gamma \in \{2^{-15}, 2^{-13}, \ldots, 2^3\}$, as advised in [4, 8]. The second level proceeds with a fine tune within the range $\lambda_2 \in \{\lambda_1 - 0.005, \ldots, \lambda_1 - 0.001, \lambda_1 + 0.001, \ldots, \lambda_1 + 0.004\} \wedge \lambda_2 \geq 0$ or $\gamma_2 \in \{2^{s_1 - 1.75}, \ldots, 2^{s_1 - 0.25}, \ldots, 2^{s_1 + 1.25}\} \wedge \gamma_2 \geq 0$. The prediction accuracy (MAD) in the grid-search is estimated by adopting a 10-fold cross-validation [13]. After obtaining the best parameter, the final model is optimized using the whole training data.

2.3. FEATURE SELECTION

Nonlinear models such as NNs and SVMs are sensitive to the *curse of dimensionality* [2, 8], i.e., the number of samples should grow exponentially as number of inputs increases. Hence, when small datasets are available, feature selection is expected to reduce the prediction error. Moreover, measurement requirements are reduced and simpler models, which are easier to interpret by the final user, are produced.

In this work, a *Sensitivity Analysis* procedure will be used to guide the feature selection search. The *Sensitivity Analysis* is performed after model estimation and it is measured by the variance (V_a) produced in the output ($\hat{y}$) when the input attribute (a) is moved through its entire range [12]:

$$V_a = \sum_{i=1}^{L} (\hat{y}_i - \bar{\hat{y}})/(L-1), \tag{7}$$

$$R_a = V_a \Big/ \sum_{j=1}^{I} V_j \times 100(\%),$$

where I denotes the number of input attributes and R_a the relative importance of the a attribute. The $\hat{y}_i$ output is obtained by holding all input variables at their average values. The exception is x_a, which varies through its entire range with L levels.

The proposed feature selection will work as an iterative backward method, using all inputs at the beginning. In each iteration, a 10-fold cross-validation is performed over the training data. The intention is to get a robust estimation of the quality of the inputs. Thus, the input importance values (R_a) are averaged over the 10-fold trainings and the least important attribute ($\bar{R}_{\min}$) is discarded. Due to the computational effort, only one hyperparameter, set to the middle of the first level search range ($\lambda = 0.1$ or $\gamma = 2^{-7}$), is tested during this phase. The algorithm is stopped after T iterations. Then, the second level cross-validation grid search is executed, in order to fine tune the hyperparameter. Finally, the best model is trained using the whole training data.

3. Results

All experiments were conducted with a Pentium IV processor, under the *Linux* operating system. The simulations were programmed in the **R** environment [17], an open source and high-level programming language that provides powerful tools for statistical analysis. The NNs were trained with the BFGS algorithm from the family of quasi-Newton methods, as implemented in the **R** *nnet* library. The **R** kernlab package was adopted for the SVM fitting, which uses the *Sequential Minimal Optimization* algorithm that is implemented by the LIBSVM tool [4].

After preliminary experiments, the maximum number of NN training epochs was set to $E = 10$. Further values increased the computational effort with no improvement in performance. The number of hidden nodes was fixed to $H = 12$ and the number of runs was set to $R = 3$. Regarding the SVMs, the tolerance of termination criterion was set to the default value (0.001). Finally, the sensitivity parameters were set to $L = 2$ for the binary attributes and $L = 5$ for the continuous inputs, while the termination criterion was set to $T = 6$. This last value was set after monitoring the validation error progress in some of the initial experiments.

In order to compare the learning models, 30 runs of a leave-one-out procedure [13] (computed over all available data) were executed (in a total of $30 \times N$

Table 2. The regression results.

Task	Model	Inputs	Time	MAD	RMAD
WBS	MR	12	53	6.22 ± 0.00	91.42 ± 0.00
	NN	12	69869	6.17 ± 0.09	90.56 ± 1.27
	SVM*	12	28202	5.73 ± 0.04	84.16 ± 0.52
	FSNN	6	72698	6.12 ± 0.06	89.94 ± 0.81
	FSSVM$^{\dagger\diamond}$	6	60554	**5.60** ± 0.02	**82.18** ± 0.33
STP	MR	12	46	1.24 ± 0.00	90.31 ± 0.00
	NN	12	60512	1.35 ± 0.02	98.21 ± 1.19
	SVM*	12	24536	1.22 ± 0.01	88.48 ± 0.83
	FSNN†	6	63345	1.25 ± 0.02	90.91 ± 1.16
	FSSVM$^{\diamond}$	6	52952	**1.21** ± 0.01	**88.28** ± 0.40

* Statistically significant (p-value < 0.05) under pairwise comparisons with the previous MR and NN models.
† Statistically significant under a pairwise comparison with the same model without the FS procedure.
$^{\diamond}$ Statistically significant under a pairwise comparison with FSNN.

experiments). The results are shown in Table 2, in terms of the average of the test errors, with the correspondent t-student 95% confidence intervals [7]. Column Time denotes the required computation for each method (in seconds).

First, the analysis will be given for the models what use all 12 inputs. The MR results are the worst for the WBS task. This scenario changes for the sensory panel, where the MR is the second best method, outperforming the NN method. Regarding the nonlinear methods, the SVM is the best method for both datasets, outperforming (with statistical significance) the NN and MR models. In addition, the computational effort also favors the SVM, since the NN demands a computational increase around a factor of 2.5. Overall, the RMAD values suggest that the second task is more difficult than the first one.

While only using half the inputs, the *Feature Selection* (FS)- based approaches (FSNN and FSSVM) give rise to better/slightly better performances. In terms of the average RMAD values and for the WBS output, there is an improvement of 0.6% (not statisticaly significant) for the FSNN and 2.0% (statistically significant) for the FSSVM model. Turning to the second task, the average RMAD decrease is 7.3% (statistically significant) for the FSNN and 0.2% (not statistically significant) for the FSSVM. In terms of the final comparison, FSSVM is the advised method, since it presents a lower mean and confidence interval values, when compared with the other models.

Table 3 shows the average relative importance (Equation 7) of the input variables for the best methods. To simplify the analysis, the less important attributes ($R_a \leq 1\%$) were removed from the table (Sex, C, and b*). It should also be noted that the table contains more than six attributes, since in each simulation different sets of features can be selected. The **Sex** attribute is the least relevant factor

Table 3. The relative importance of the input variables (in %).

		Attribute								
Task	Model	Breed	HCW	STF2	pH1	pH24	a*	dE	dL	dB*
WBS	FSNN	0.4	7.4	5.2	0.3	1.3	58.4	20.2	2.9	3.6
	FSSVM	0.3	–	25.4	0.4	7.1	32.4	–	19.2	14.9
STP	FSNN	35.3	2.7	4.6	12.9	–	25.1	17.5	0.3	0.3
	FSSVM	41.3	7.8	0.7	16.0	–	26.3	–	0.3	6.9

($R_a \leq 0.1\%$), which contrasts with the knowledge that gender affects tenderness. Since female meat often present a higher weight and fatness, the sex information could be indirectly represented in the HCW and STF2 variables. However, additional experiments where these attributes were replaced by the Sex input and the models retrained did not provide evidence for this claim.

In general, the results are similar for both NN and SVM-based methods. For the WBS task, the red color (a*) is the highest important attribute. Turning to the STP problem, the most relevant features are the Breed and red index (a*). The differences obtained between the two tasks may be explained by psychological factors. For instance, the Breed importance increased from 0.4/0.3% (WBS) to 35.3/41.3% (STP). This is a surprising result, since it contradicts the animal science theory.

As an example, the left of Figure 3 shows the scatter plots (predicted versus the observed values) for the WBS task. In the figure, the diagonal line denotes the perfect forecast. The *Regression Error Characteristic* (REC) curves [3] are also shown (right of the figure) for the FSSVM, MR, and *Average Predictor* methods. The REC curve is used to compare regression models and it plots the error tolerance (x-axis), given in terms of the absolute deviation, versus the percentage of points predicted within the tolerance (y-axis). In the figure, the FSSVM line is above the other curves for the majority of the x values. Overall, it presents an higher area, denoting a better fit.

4. Conclusions

In this work, a FS procedure, based on a *Sensitivity Analysis*, is combined with a SVM, aiming at the prediction of lamb meat tenderness. This real-world problem was addressed by two distinct regression tasks by using instrumental and sensory measurements. The former is based in the WBS force, which is an objective measure obtained from a special device called *Instron*. The latter involves the use of subjective information, requiring the execution of a human *Sensory Taste Panel* (STP). In both cases, the FSSVM combination outperformed other NN and MR configurations.

The final solution is much simpler, requiring only half the number of inputs (6 instead of 12). Moreover, the proposed method is noninvasive, much cheaper than the WBS or STP procedures, and can be computed just 1 (STP) or 24 hours

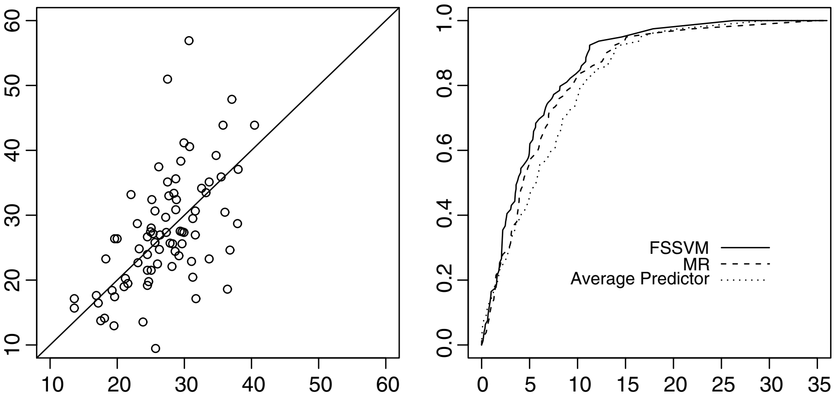

Figure 3. The predicted (x-axis) versus observed (y-axis) values for FSSVM (left) and the REC curves (right) for the **WBS** task.

(WBS) after slaughter. This opens the room for the development of automatic tools for decision support [19].

One drawback may be the obtained accuracy, which is only 18% (WBS) and 12% (STP) better than the simple average predictor. However, it should be stressed that the tested datasets are very small. As argued by Lavrăc et al. [14], there are important *Data Mining* applications where the data is scarce and more research is needed toward methods that can deal with such datasets. This work backs this claim. Furthermore, Díez et al. [6] considered the modeling of sensory preferences a very difficult regression task. To our knowledge, this is the first time lamb meat quality is approached by SVMs and further exploratory research needs to be performed.

Another relevant point regards the input importance. Some results, such as the gender null impact and breed relevance (for the STP task), seem to contradict the animal science theory. Regarding the breed importance, the results were discussed with the experts, which then discovered that the *Mirandesa* lambs were considered less stringy and more odor intense, which may be due to animal stress during slaughter. Nevertheless, further research is needed toward this issue.

In future work, the proposed approach will be tested in a real environment, by attaching computer systems with friendly human interfaces into meat laboratories and/or slaughterhouses. This will allow us to obtain, after some time, a valuable feedback from the meat users, and also to enrich the datasets by gathering more meat samples.

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