Classification of Carcass Fatness Degree in Finishing Cattle Using Machine Learning

Higor Henrique Picoli Nucci[1(✉)], Renato Porfirio Ishii[1], Rodrigo da Costa Gomes[2], Celso Soares Costa[3,4], and Gelson Luís Dias Feijó[2]

[1] Federal University of Mato Grosso do Sul, Campo Grande, Mato Grosso do Sul, Brazil
higomucci@gmail.com
[2] Embrapa Gado de Corte, Campo Grande, Mato Grosso do Sul, Brazil
[3] Federal Institute of Education, Science and Technology of Mato Grosso do Sul, Campo Grande, Mato Grosso do Sul, Brazil
[4] Universidade Católica Dom Bosco, Campo Grande, Mato Grosso do Sul, Brazil

Abstract. Nowadays, there is an increase in world demand for quality beef. In this way, the Government of the State of Mato Grosso do Sul has created an incentive program (Precoce MS) that stimulates producers to fit into production systems that lead to the slaughter of animals at young ages and superior carcass quality, towards a more sustainable production model. This work aims to build a classification model of carcass fatness degree using machine learning algorithms and to provide the cattle ranchers with indicators that help them to early finishing cattle with better carcass finishing. The dataset from Precoce MS contains twenty-nine different features with categorical and discrete data and size of 1.05 million cattle slaughter records. In the data mining process, the data were cleaned, transformed and reduced in order to extract patterns more efficiently. In the model selection step, the data was divided into five different datasets for performing cross-validation. The training set received 80% of the data and the test set received the other 20%, emphasizing that both had their data stratified respecting the percentage of each target class. The algorithms analyzed and tested in this work were Support Vector Machines, K-Nearest Neighbors, AdaBoost, Multilayer Perceptron, Naive Bayes and Random Forest Classifier. In order to obtain a better classification, the recursive feature elimination and grid search techniques were used in the models with the objective of selecting better characteristics and obtaining better hyperparameters, respectively. The precision, recall and f1 score metrics were applied in the test set to confirm the choice of the model. Finally, analysis of variance ANOVA indicated that there are no significant differences between the models. Therefore, all these classifiers can be used for the construction of a final model without prejudice in the classification performance.

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1 Introduction

Brazil occupies a prominent position in the world scenario of beef production. In the third quarter of 2019 were slaughtered 8.49 million of cattle that were being supervised by a health inspection service, as shown by the statistics report data of Livestock Production, provided by the Brazilian Institute of Geography and Statistics [1]. These data are 2.1% higher than the same period of the previous year. Therefore, in order to remain at the top of the world ranking of exports, the Brazilian government, associations of producers and breeders and slaughterhouses have been committed to create programs that encourage the production of meat with a higher quality than the Brazilian average.

In the state of Mato Grosso do Sul, in the year of 2016, were released a state program, called Precoce MS, that have made improvements to the existing bonus program for early calves, which is managed by the Program for Advances in Livestock of Mato Grosso do Sul (Proape). Among the improvements applied, it can be mentioned as more impacting the inclusion of the productive process of the farm in the calculation for the fiscal incentive.

The Precoce MS program grants to producer with financial returns of up to 67% of the ICMS collected by the carcass of a slaughtered animal and classified as early calf. The calculation of the percentage of the amount of ICMS to be returned to the producer takes into account the carcass fatness degree and the characteristics of the production process from the farm, considering proportionality 70% to 30% respectively.

The classification of an animal as an early calf is performed by the following parameters: gender (F = female; C = castrated male; and M = whole male) and dental maturity (Fig. 1). In order to determine the typification of the carcass, as regards their finishing, the measurement of the subcutaneous fat, as shown in Fig. 2, is adopted as the parameter. Lastly, the pre-slaughter animal weight must be at least 12 *arrobas* for females and 15 *arrobas* for males (whole or castrated) and at least 60% of the lot to be slaughtered must be composed of early calves [2].

The productive processes of a property are evaluated by valuing properties that meet the following criteria: use of tools that allow the individual sanitary management of cattle; apply rules and concepts of good agricultural practices; implement technologies that promote the sustainability of the productive system, particularly those aimed at mitigating carbon emissions through low carbon farming practices; and participate in associations of producers aimed at commercial production systematized and organized according to pre-established standards for the fulfillment of commercial agreements.

Rural establishments are categorized as **Simple** if they meet none or at least one of the criteria. Those that are categorized as **Intermediate** must meet at least two criteria. Lastly, an establishment categorized as **Advanced** must meet at least three criteria.

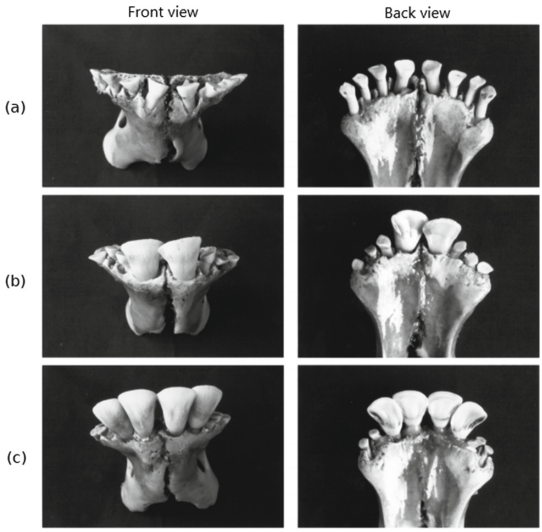

Fig. 1. Dental maturity of early calves: (a) J0 = only milk teeth; (b) J2 = two permanent incisor teeth; and (c) J4 = four permanent incisor teeth. Source: [3].

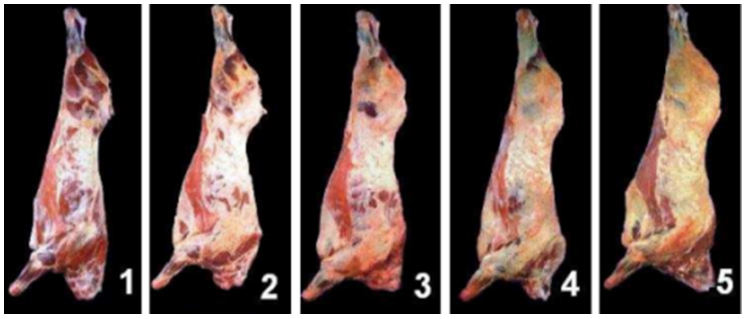

Fig. 2. Carcass fatness degree: 1 = Missing Fat - Fat is absent; 2 = Low Fat - 1 to 3 mm thick; 3 = Median Fat - above 3 and up to 6 mm thick; 4 = Uniform Fat - above 6 and up to 10 mm thick; and 5 = Excessive Fat - 10 mm thick. Source: [4].

In this way, the simplified Table 1 can be used to exemplify the rules of the program. The first three columns show the data of the slaughtered animal and represent up to 70% of the incentive value. The remaining columns refer to the valuation property data and represent up to 30% of the incentive value. Thus, the value of the incentive to be returned by the slaughterhouse to the producer is the percentage he reaches in the table (up to a maximum of 67%) on the value of the ICMS of the cattle while it is still alive.

Apart from Brazil being the world leader in the quantity of exported beef *in natura*, the financial income is relatively low. Since it does not export to the markets that pay the most, because the national meat does not meet the quality

Table 1. Simplified scheme of the classification of subsidized carcasses by the program Precoce MS.

70%			30%		
Product			Productive process		
Gender	Maturity	Fatness degree	Advanced 30%	Intermediate 26%	Simple 21%
M, C, F	J0	3, 4	67	64	61
M, C, F	J2	3, 4	62	59	56
C, F	J4	3, 4	48	45	42
M, C, F	J0	2	62	59	56
M, C, F	J2	2	39	36	33
C, F	J4	2	22	19	16

criteria for some markets that pay more [5]. In this context, there are factors in cattle breeding that can influence the overall quality of the meat produced. A key factor is a high quality and continuous feed for the herd. However, one of the problems in producing of early calves may be the cost with this food of excellence [6].

Thus, the cost-effectiveness of producing the youngest animal for slaughter is high and can put the whole productive system at risk for producers who do not have many financial resources. There are other factors that are also considered important, such as genetic ability and maturity, since young animals with good genetics have a greater efficiency in converting food consumed into fat and weight gain, which will directly reflect the overall yield of carcass [7,8].

From the technological point of view, there is ample room for improvement in the production of beef cattle through precision cattle breeding. For this reason, technologies that result in increased likelihood of economic success are crucial. Given that, the producer will have access to data that will support the most effective decision making, optimize its production and its economic balance and lead to the production of animals with better compliance with the carcass criteria, with lower production costs and greater obtaining of subsidies [9].

The main objective of this paper is to construct a classification model of the carcass fatness using Machine Learning algorithms. This model will support beef cattle producers in decision making, aiming to increase the quality of the meat produced.

2 Materials and Methods

2.1 Approach

In order to implement a carcass fatness degree classifier, the approach used follows the methodology shown in Fig. 3. The first step was to obtain the slaughtering data of cattle and their respective production processes.

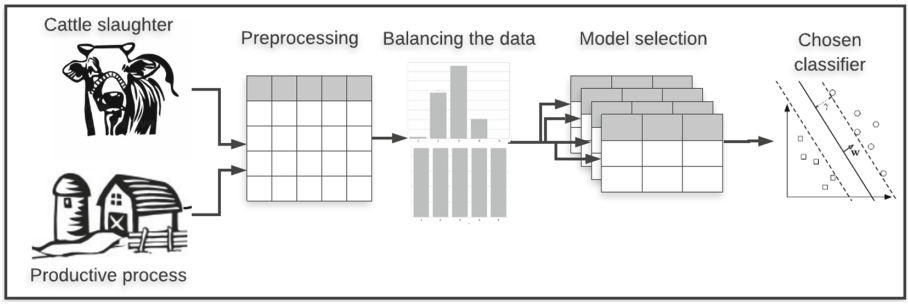

Fig. 3. Complete flowchart of the methodology.

After obtaining the dataset, there was a need for preprocessing the data to remove unnecessary columns, samples with insufficient values and feature selection. The resulted dataset after preprocessing step was very imbalanced. In that case, the next step was balancing the samples of the dataset. With the preprocessed and balanced dataset in hand, a process of comparison of the candidate Machine Learning algorithms called model selection was started.

In addition, it was possible to conclude which are the features that contribute the most to the carcass fatness degree. Thus, the algorithm that presented the best accuracy and f1-score was chosen to be the basis for the creation of a classification model.

2.2 Data Acquisition

The data acquisition process was carried out through a request of the cattle slaughtering data registered in the state program Precoce MS and the production process of each corresponding rural establishment. The request was sent to the Information Management Superintendency (SGI) with the assistance of Embrapa Gado de Corte and the State Secretariat of Environment, Economic Development, Production and Family Agriculture (SEMAGRO), both from Mato Grosso do Sul, Brazil.

The data of the rural establishments participating in the state program were delivered by SGI in two different datasets. The first dataset comprises the basic information of the rural establishments (Table 2) and their respective production processes (Table 3 and Table 4). This dataset consists of 1,595 registered rural establishments and it is filled by technicians, who must have formation as veterinarian, agronomist or zootechnician and are co-responsible for this information.

The questions in the questionnaire are divided into two groups: **"questions that does not qualify"** – that do not increase the percentage of the financial return to the producer (Table 3); and **"questions that qualify"** – which increase the percentage of the financial return to the producer (Table 4). The rural establishments are categorized by the number of question answered as

Table 2. Five random samples of the basic data of a rural establishment.

property_id	city	state	categorization
5159	PEDRO GOMES	MS	21%
1167	CAMAPUA	MS	21%
4960	CAMAPUA	MS	26%
4514	TERENOS	MS	30%
5371	MARACAJU	MS	26%

Table 3. Questions that do not categorize the productive process of a rural establishment, their respective labels in the dataset and their possible values.

Question	Dataset label	Possible answers
"Are there other incentives?"	other_incentives	"Yes", "No"
"Does it manufacture ration?"	makes_ration	"Yes", "No"
"Does it practice pasture recovery?"	pasture_recovery	"Fertigation", "FLI - Farm-Livestock Integration", "CLFI - Crop-Livestock-Forest Integration", "LFI - Livestock-Forest Integration", "None"
"Does it practice field supplementation?"	field_supplementation	"Yes", "No"
"Does it practice semi-confinement?"	semi_confinement	"Yes", "No"
"Does it practice confinement?"	confinement	"Yes", "No"

"Yes": Simple (21%) for none or at least one of the question, Intermediate (26%) for at least two question and Advanced (30%) for three question or more.

The second dataset includes all individual cattle slaughters, from 02-09-2017 to 01-23-2019, with the equivalent carcass finishing (Table 5). This dataset consists of 1,107,689 animals slaughtered.

Each sample, from Table 5, represents the individual slaughter of cattle. When slaughtering an animal, the slaughterhouse registers the **typification** (WHOLE male, male CASTRATED or Female), **maturity** (Milk tooth, Two teeth, Four teeth, Six teeth or Eight teeth), **carcass weight** (in kg), **date of**

Table 4. Questions that categorize the productive process of a rural establishment, their respective labels in the dataset and their possible values.

Question	Dataset label	Possible answers
Does it have a system of individual identification of cattle associated with a zootechnical and sanitary control?	individual_identification	"Yes","No"
Does grazing control that meets the minimum height limits for each forage or cultivar exploited, having as a parameter the meet the rules established by the Brazilian Agricultural Research Corporation (Embrapa)?	grazing_control	"Yes","No"
Does the rural establishment have a certificate of Quality Control Programs (Good Agricultural Practices - BPA/BOVINOS or any other program with requirements similar or superior to BPA)?	quality_programs	"Yes","No"
Is the rural establishment involved with any organization that uses mechanisms similar to the marketing alliance to market its product?	involved_in_organization	"Yes","No"
Does the managed area have a good vegetation cover, with a low presence of weeds and no spotting of uncovered soil in at least 80% of the total pasture area (native or cultivated)?	area_80_vegetation_cover	"Yes","No"
Does the managed area show signs of laminar or furrow erosion equal to or greater than 20% of the total pasture area (native or cultivated)?	area_20_erosion	"Yes","No"
Does it execute SISBOV tracing?	sisbov	"Yes","No"
Is it part of the Trace List?	trace_list	"Yes","No"
Is the area of the rural establishment intended for confinement activity in its entirety?	total_area_confinement	"Yes","No"

slaughter and the **carcass fatness degree** (missing fat - fat is absent, low fat - 1 to 3 mm thick, medium fat - above 3 to 6 mm in thickness, uniform fat - up to 6 and up to 10 mm thickness or excessive Fat - 10 mm thick).

Table 5. Five random samples from the bovine slaughtering dataset.

property_id	typification	maturity	carcass_weight	date_slaughter	carcass_fatness_degree
1	INTEGRAL Male	Milk tooth	362.50	2017-10-02	Median Fat - up to 3 to 6 mm thick
1473	CASTRATED Male	Two teeth	252.00	2017-04-26	Low Fat - 1 to 3 mm thick
4312	CASTRATED Male	Four teeth	338.00	2017-05-08	Low Fat - 1 to 3 mm thick
5068	Female	Two Teeth	188.20	2018-01-03	Median Fat - up to 3 to 6 mm thick
4452	CASTRATED Male	Milk tooth	338.00	2018-05-15	Median Fat - up to 3 to 6 mm thick

2.3 Preprocessing

The datasets were combined into a single one using a identifier called *property_id*. The resulting dataset now only has 1,056,586 samples. This was due to the time difference in generating the datasets by SGI. In total, 51,103 slaughter samples did not have identifiers of rural establishments related to the dataset of the productive process.

According to the specialist in zootechnics, data related to micro and mesoregion, which are not in the dataset, may be relevant to discovery how the fauna, flora and cultural factors of a given region can influence the carcass fatness degree. For that, the data of the location of the rural establishment was used to infer two new features for these values.

In this way, the internal division of the State of Mato Grosso do Sul was taken into account. The state is divided in eleven microregions: Alto Taquari, Aquidauana, Baixo Pantanal, Bodoquena, Campo Grande, Cassilândia, Dourados, Iguatemi, Nova Andradina, Paranaíba and Três Lagoas. Another division of the state is the four mesoregions: Centro Norte, Leste, Pantanal and Sudoeste. Both microregions and mesoregions were added to the dataset.

Another relevant specialist opinion was on the possible impact of climate change on the resulting fat level. In this way, the dates of slaughter of a bovine were used to infer a new feature with the season of the year in which the animal was finished. According to the dates of change of stations in Brazil.

In order to create a classifier of carcass fatness degree, we considered a certain animal and the productive process that generated it. Thus, we have five ordinal classes ranging from Missing Fat to Excessive Fat, as shown in Table 6.

Table 6. Classes for the classification of the carcass fatness degree.

Label	carcass_fatness_degree
Missing Fat - Fat is absent	1
Low Fat - 1 to 3 mm thick	2
Median Fat - above 3 and up to 6 mm thick	3
Uniform Fat - above 6 and up to 10 mm thick	4
Excessive Fat - 10 mm thick	5

The process of feature selection used is a wrapper method known as recursive feature elimination (RFE) [12,13]. The RFC classifier was used together with RFE to complete the feature selection task. According to the classifier, the most relevant features for the model are presented in Fig. 4. All the features of this dataset were scored according to its relevance. The most important *carcass_weight* feature received the highest score, 0.3503, and the *area_20_erosion* feature received the lowest value, 0.0003.

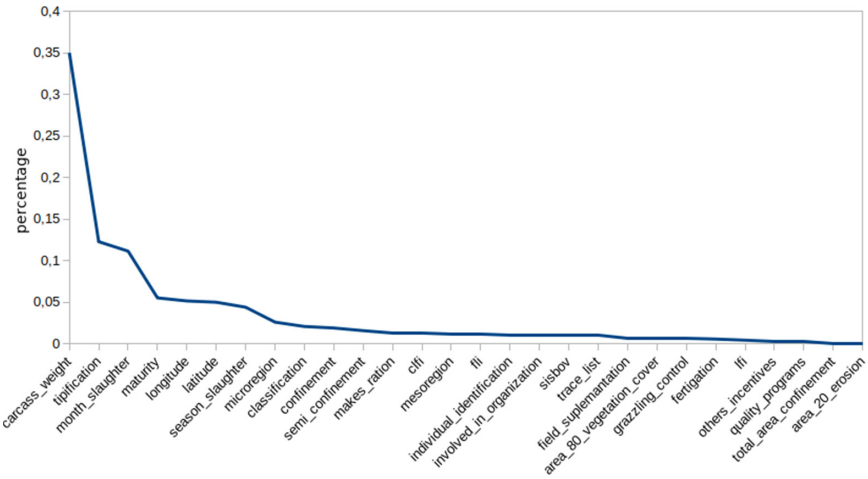

Fig. 4. Most important features according to the RFC algorithm and RFE feature selection technique.

When applying the RFE technique the features *fertigation*, *lfi*, *other_incentives*, *total_area_confinement*, *area_20_erosion* and *quality_programs* have been removed from the dataset. The removal of these characteristics can be attributed to the fact of their high sensitivity.

The categorical column *city* was replaced by its respective *latitude* and *longitude*. The column *maturity* had its values replaced by the number of definitive teeth in integer values. All questions whose possible responses were restricted to "No" or "Yes" had their values replaced by 0 and 1 respectively. In the conversion of categorical features with more than one option per sample, it was used the *one-hot encoding* technique and convert them into new duplicated features, where each one represents one of the feature values. In this technique, the presence of a level is represented by 1 and its absence by 0 [10].

The unit of measure used for a given feature may adversely affect the data analysis. The *min-max* [11] normalization technique consists of expressing the values of a feature in smaller units of measure. In this way, the data is transformed into a more regular distribution, such as $[0.0, 1.0]$.

Finally, at the end of the preprocessing of the data, we have the resulting dataset with 55 training features plus 1 classification feature.

2.4 Balancing the Data

The Fig. 5 shows the distribution of the classes in the dataset. At once, it is perceived that the dataset is unbalanced. In other words, the dataset has 0.48% of its samples for class 1, 40.25% for class 2, 53.31% for class 3, 5.94% for class 4 and 0.02% for class 5.

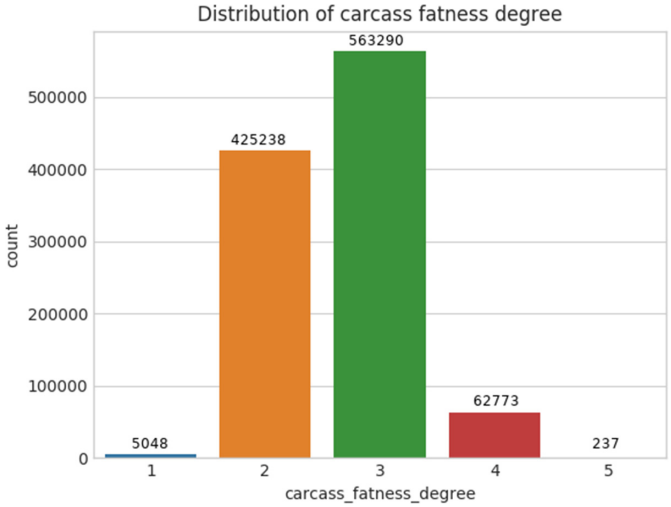

Fig. 5. Distribution of carcass fatness degree.

An unbalanced dataset can negatively affect the learning phase and, consequently, the classification of Machine Learning algorithms. With the intention of balancing the data, there are two methods that stand out: *over-sampling* that replicates minority class samples and *under-sampling* that eliminates samples from the majority class [14]. The result, after balancing, can be seen in Fig. 6

The *under-sampling* technique called Edited Nearest Neighbors (ENN) was used. This technique applies a closer neighbors algorithm and removes samples that do not agree "enough" with their neighborhood. For each sample in the class to be sub-sampled, the nearest neighbors are calculated and, if the selection criterion is not met, the sample is removed [15].

In contrast, the *over-sampling* technique called Synthetic Minority Oversampling Technique (SMOTE) generates new "synthetic" samples by interpolation operating directly under the characteristics rather than the data [16].

However, the use of the SMOTE technique can generate noisy samples by interpolating new points between marginal values and isolated values. This problem can be solved by cleaning up the space resulting from super-sampling with ENN. Therefore, the use of techniques of *over-sampling* SMOTE combined with *under-sampling* ENN, called SMOTEENN, has generated better results [17].

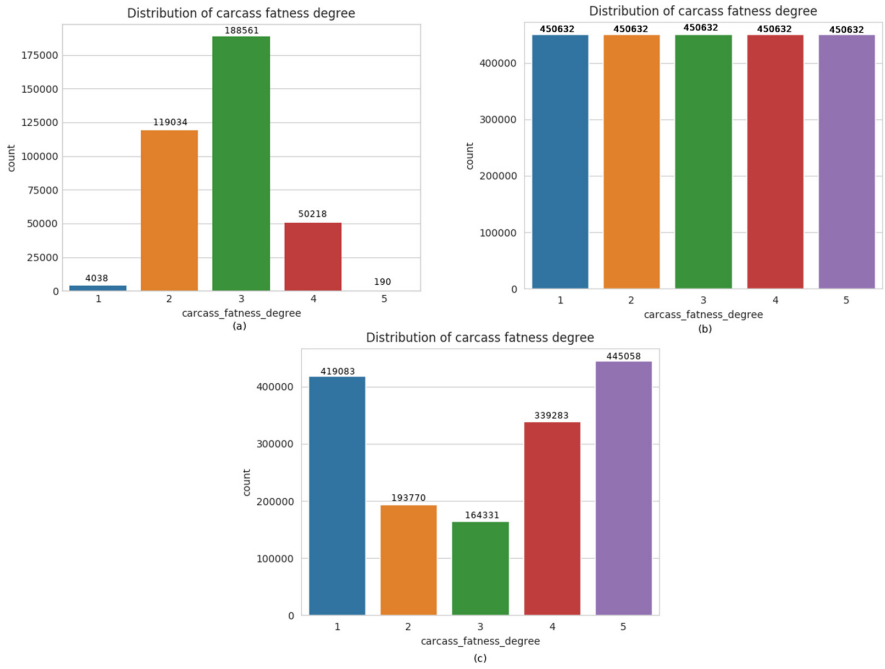

Fig. 6. Comparison of class distribution with dataset balancing using *under-sampling*, *over-sampling* and hybrid techniques. (a) *under-sampling* with ENN; (b) *over-sampling* with SMOTE; and (c) combination of SMOTE + ENN techniques.

2.5 Model Select

The models that were compared in this article are: Multinomial Naive Bayes (MNB), Random Forest Classifier (RFC), AdaBoost (ADA), Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). All of them were applied in the same balanced dataset and the same metrics were used as a result for validation. In the next steps of this paper a Python library called scikit-learn [10] was used to build, test and validate all the different classifiers.

To validate the models, a basic approach is to use the technique called *cross-validation* [21]. The performance measure pointed out by cross-validation is then the mean of *accuracy* values for each loop. Other metrics such as *confusion matrix* [18], *precision*, *recall* and *f1 score* were used to help gain insight during validation of the final model [19].

In all models, the *cross-validation* technique was applied with *5-folds*. The randomization index used to ensure that the training and test datasets are always the same was 42. In the comparison of the models, the mean accuracy of all folds was used as the main metric, by model.

The training set is balanced and the model is trained, as shown in Fig. 7. After training, the test set is used for validation and the results of the classification

are collected. The division was done at random, ensuring that the test data from one fold will not be repeated in the test data in another fold, and taking into account the percentage of distribution for each class.

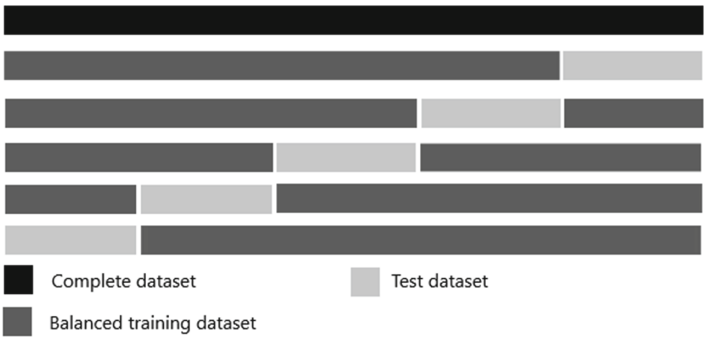

Fig. 7. Visualization of the cross-validation process with the balanced training set.

Another way to improve metrics is to find the best hyperparameters for an algorithm in a given dataset. The process of empirically selecting the best hyperparameters for a model can take a long time and result in an lower *accuracy* [20]. One of the most used techniques for selecting hyperparameters automatically is *grid search* with cross-validation [22], which is an exhaustive search process on a specific dataset.

3 Results and Discussions

The results of the comparison between the classification models collected after the best hyperpameters were chosen while doing grid search with cross-validation and balancing each training set, can be seen in the Table 7.

The results obtained a very low standard deviation, as can be seen in Table 7, for all folds of cross-validation applied in the models. This shows that the results for each fold are not under or overfitted and the data are stratified taking into account the percentage of each class.

When considering the results obtained, it is clear that the models that generalized better were those applied to balanced data using ENN. More specifically the RFC, KNN and SVM algorithms. However, analyzing only *accuracy* can lead to an optimistic estimate if the classifier is biased [23].

This problem can be overcome when the results are analyzed by looking at the normalized *confusion matrix* (Fig. 8). After training the models, classifying using the test dataset and printing their respective confusion matrices the the calculated metrics *precision*, *recall* and *f1-score* were calculated using ENN, as the Table 8 shows.

Table 7. Comparison of the mean of the *accuracy* and the standard deviation among the six chosen models. Acronyms: Multinomial Naive Bayes (MNB), Random Forest Classifier (RFC), AdaBoost (ADA), Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN) and Support Vector Machines (SVM)

Accuracy			
Model	ENN	SMOTE	SMOTEENN
MNB	**58.62%** ±0.102	31.04% ±0.176	22.75% ±0.343
RFC	**70.37%** ±0.075	64.64% ±0.119	65.82% ±0.089
ADA	**60.07%** ±0.153	37.24% ±0.166	12.67% ±0.122
MLP	**66.41%** ±0.022	50.07% ±0.078	45.44% ±0.091
KNN	**69.64%** ±0.048	62.15% ±0.077	64.62% ±0.127
SVM	**69.19%** ±0.116	65.43% ±0.121	67.82% ±0.337

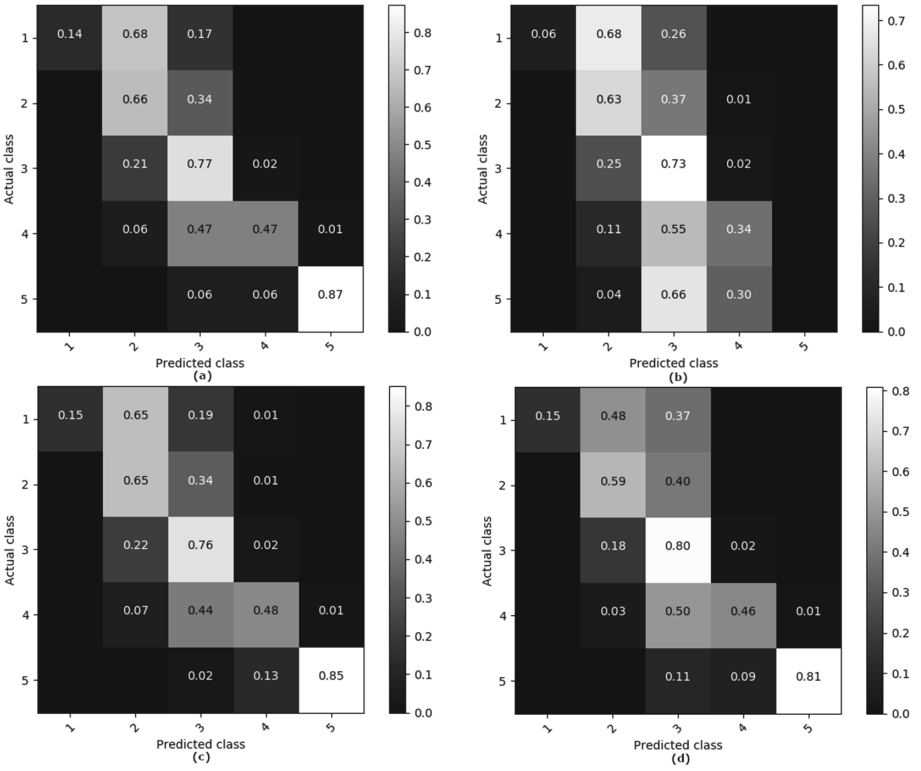

Fig. 8. Normalized results of the prediction models in the test dataset, with representation on a scale of 0 to 1, for error analysis: (a) normalized confusion matrix of the RFC; (c) normalized confusion matrix of the MLP; (d) normalized confusion matrix of the KNN; and (e) normalized confusion matrix of the SVM.

Table 8. Comparison of the metrics *Precision*, *Recall* and *F1-score* for each of the five classes, with their respective averages, between the models. The calculation of the average took into account the weight of each class in the dataset.

Model	Metric	1	2	3	4	5	Average
RFC	Precision	78.26%	68.82%	71.43%	71.43%	17.30%	70.40%
	Recall	14.26%	65.92%	76.87%	46.61%	87.23%	70.37%
	F1-score	24.12%	67.34%	74.05%	56.41%	28.87%	**70.05%**
MLP	Precision	71.43%	64.07%	68.30%	61.39%	–	66.19%
	Recall	05.94%	62.63%	73.40%	34.34%	–	66.41%
	F1-score	10.97%	63.34%	70.76%	44.04%	–	**65.89%**
KNN	Precision	58.71%	68.00%	71.20%	66.52%	10.08%	69.56%
	Recall	15.35%	65.31%	75.81%	47.88%	85.11%	69.64%
	F1-score	24.33%	66.63%	73.43%	55.68%	18.02%	**69.39%**
SVM	Precision	75.90%	70.12%	68.67%	71.56%	10.58%	69.45%
	Recall	14.65%	59.13%	79.88%	45.58%	80.85%	69.18%
	F1-score	24.56%	64.16%	73.85%	55.69%	18.72%	**68.62%**

When looking at the results of class 1 and 2 in the normalized *confusion matrix* of Fig. 8, it can be seen that the SVM algorithm makes a better distinction between these classes. The rural producer receives financial incentives only for carcasses with fat degree 2, 3 and 4. Under these circumstances, it is important that the number of false positives is low at the edges of the matrix, more specifically for classes 1 and 5. Thus, the producer will have a better control when bring the cattle to the slaughterhouse and receive bigger financial incentives.

The ROC curves and their respective areas on the curve (AUC) for each of the tested algorithms are shown in Fig. 9. The ROC curves had their AUC calculated for each of the target classes and the micro and macro averages of the classes. In this way, it is possible to check the overall performance of each of the algorithms. The AUC value shows the percentage with which each tested algorithm is able to distinguish between negative and positive results.

In order to verify whether the tested classifiers differ statistically in relation to *f1-score* performance, the one-way ANOVA analysis of variance was used. The p-value of 0.8599 was reached, which is higher than 0.05, suggesting that the classifiers are not significantly different for that level of significance. The result showed that the classifiers are similar and there is no statistically significant difference in performance between them.

This was the first study conducted with supervised machine learning in the Precoce MS database. Despite the low hit rate in classes 1 and 5, their occurrence in real life represents 0.48% and 0.02% respectively and does not, in most cases, threaten the quality of the classifiers when used in day-to-day data of rural producers.

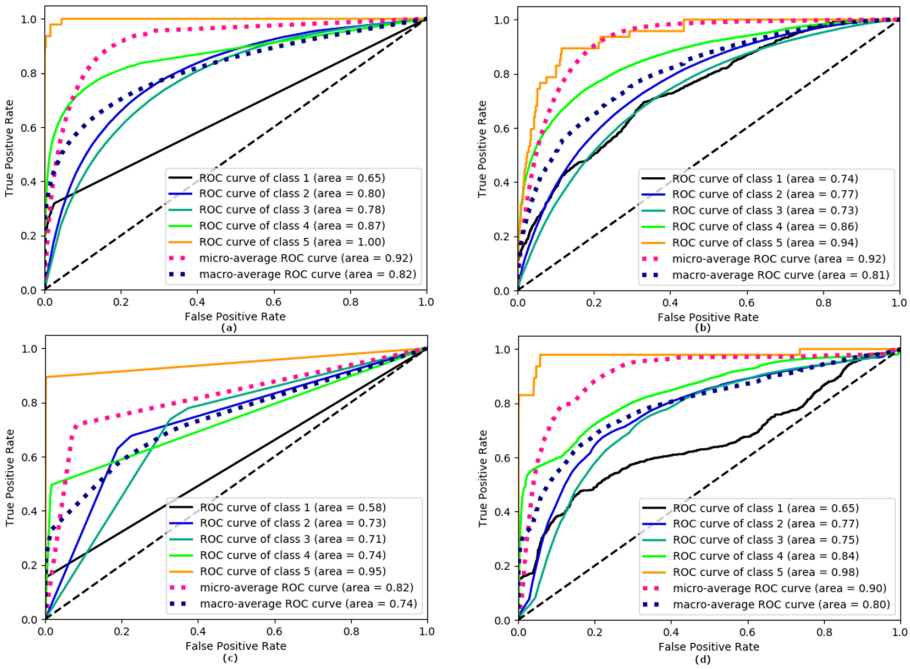

Fig. 9. Results of the ROC curve for the algorithms by class and macro and micro averages: (a) RFC; (b) MLP; (c) KNN; and (d) SVM.

As Fig. 8 indicates, the main objective was achieved by showing that there are no significant differences in the results of the algorithms. Thus, the final model can be generated from any of these models, without risk of damage to the performance of the classification.

4 Conclusions

This paper had the objective of constructing a classifier of carcass fatness degree to assist the rural producers in the decision making to obtain a meat of better quality. For this, we took into account the data of the Precoce MS program that contain 1,056,586 cattle slaughters and their respective productive processes.

The machine learning algorithms tested using the cross-validation result were: Multinomial Naive Bayes (MNB), Random Forest Classifier (RFC), AdaBoost (ADA), Multilayer Perceptron (MLP) K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). Among the six, the most accurate, in a balanced dataset, was the RFC which obtained 70.37% of accuracy and it is considered a satisfactory result.

The rural producer is financially rewarded only for carcasses classified as 2, 3 and 4. An optimization that can be done to assist in obtaining results that favor the rural producer to discover whether or not he will be subsidized and,

after that answer, try to show what type of carcass will be generated is the use of Hierarchical Machine Learning.

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