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USAGE OF THE NEURAL NETWORK TO PREDICT MEAT TENDERNESS APPROACH

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Abstract. Meat tenderness is one of the main qualitative attributes sought after by consumers when purchasing beef. Among the various properties of meat, tenderness is one of the most appreciated by the public that buys this type of food. The tenderness of the meat is influenced by several factors in the constitution, from genetic, food, and environmental factors is the tenderness evaluated in the post-mortem of the animal is a direct and objective measure to be quantified. This property is obtained through mechanical tests already known in the literature, by obtaining the shear force necessary to break the set of muscle fibers of the tissue examined. In this way, this paper estimates the tenderness of the meat in a non-destructive way through the use of computational techniques using machine learning, such as the use of artificial neural networks, to quantify the dependence of variables that can be obtained without the destruction of the sample, but that obtain a satisfactory approximation in obtaining the shear force of the analyzed beef tenderloin samples. Thus, to evaluate the tenderness parameters, measurements made from tests were used for the values of PH, sample color, hot carcass weight, loin eye area, breed, sex, infrared and ultraviolet images, and shear force of fillet samples. In this way, the objective of the neural network was to find the dependence of the variables on the shear force necessary to break the fibers of the sample. For this, a cross-data model known as Random Forest was used for training neural network was performed based on the present data, and an average error of 20% was obtained compared to the value obtained for the shear force through the mechanical test. It was observed that the shear force prediction values are directly influenced by the number of variables to be introduced in machine learning, as well as the number of observed samples.

Keywords: Machine Learning, Computational Methods, Prediction, Tenderness, Deep Learning

1 Introduction

Brazil has been growing considerably, being a world highlight in the production of beef, holding the largest commercial bovine herd in the world, with 214.7 million cattle, slaughtering and deboning, selling 44 million carcasses annually, according to the panorama of the National Confederation of Agriculture. ([1] and [2]).The state of Mato Grosso contributes as the largest meat producer in Brazil, with a herd of more than 30.9 million heads of cattle, presenting a growth of 15.37% in exports in 2020, reaching 47.95 thousand tonnes equivalent in carcass sold ([3]). To feed 210 million Brazilians, beef is delivered to countless niche markets, representing 80% of what is produced, earning R$97.3 billion in addition to exports to more than 150 countries, earning R$24.1 billion, -market share- totaling 22% of all beef exported in the world ([4], [1], [2]).

That said, it is also in the Brazilian interest to be the largest exporter of beef with recognized quality, with quality being a very broad property, involving intrinsic and extrinsic attributes, but overcoming sanitary aspects, there is a unanimous agreement with the proposal by [5], that the tenderness of the meat is the most important organoleptic property, influencing the acceptability, satisfaction, and repurchase of the product by the consumer. Meat tenderness is mainly affected by the amount and solubility of connective tissue, the composition and contractile state of muscle fibers, and the extent of muscle proteolytic [6], with the most scientifically accepted analysis of tenderness being the Shear Force, proposed by Bratzler (1954) and established the preparation protocol in 1995 by the American Meat Science Association ([7]).

To predict the tenderness of the meat, variations in color, age, sex, species, some biochemical variables can be measured and are important as they determine the visual appeal and sensory acceptability. These traits are also important for economic reasons, as the industry loses money due to undesirable color (citação) and due to weight loss of product. The industry can also achieve higher prices for assured tenderness and eating quality [7].

The biochemical properties, and pH of meat, are influenced by pre- and postmortem which have their action on structural components in muscle cells and their associated connective tissue.

The particular influence of pH fall on protein denaturation, the myofibrillary lattice spacing, and the shrinkage in muscle cells are fundamental in determining the quality of raw and cooked meat.

Meat science represents two leading fields of research, which are aimed at pursuing the production of safe, high-quality meat for a larges number of consumers. Meat quality is appreciated by end consumers based on three main criteria: flavor, juiciness, and, above all, tenderness [8]. To improve meat tenderness, investigations have been successfully performed over the years to delve into identifying the principal variables for yielding tender meat. [9]

Objective measures of beef quality have been a longtime desire of the industry and there have been many research efforts in developing instruments. One popular, and obvious, approach has been to measure the mechanical properties as indicators of tenderness. Several devices have appeared. The most well-known one may be the Warner–Bratzler shear force instrument. The shear strength of cooked meat is correlated with sensory tenderness scores [10].

The development of fast and efficient tools to be implemented in the industry of food attracted great interest in the last decade ([11]). Modern techniques, including electronic noses, computer vision, spectroscopy and spectral imaging, and so on, have been widely used to detect meat attributes. These techniques can acquire a large amount of digital information relating to food properties. Data analysis of these techniques is extremely important due to the fact that a large amount of data contain much redundant and irrelevant information. Many data analysis methods have been developed to deal with a large amount of data, for modeling such as partial least squares (PLS), artificial network (ANN), support vector machine (SVM),random forest, k-nearest neighbor (KNN) and another different computational method. These methods have shown great value in dealing with these data ([12].

Artificial intelligence methods (ANN) were mainly investigated for the evaluation of the properties that are subjectively evaluated or classified such as tenderness ([13]). Studies base application of ANN for meat quality assessment using just several simple physical measurements of meat reporting a supervised learning strategy of ANN was used for addressing the issues of meat quality and composition, denoting an interest of prediction ability.

This paper, an investigation using machine learning and neural network by highlighting the main technics improvements and how applied different algorithms predict the tenderness of meat approach and variable feature importances.

2 Methodology

The conceptual model for meat tenderness was used a database obtained using a approach of the shear force in meat samples. The 206 meat samples were cut into regular pieces of 10x10x30 mm along the fibre direction. The average maximum force (givem as $N.cm^{-2}$ was used in the data analyzis. For each sample was discrebed mensures for loin area, animal's sex, animal weight after slaughter, number of teeth of the animal, medial loin area, pH and flesh color. Using the database generated from data obtained in a laboratory environment, a computational approach was applied using two principal methods: Random Forest Machine Learning and Neural Network to predicted the values of shear force obtained in laboratory.

Random forest is a popular machine learning procedure which can be used to develop prediction models. First introduced by Breiman in 2001 [14] random forests are a collection of classification and regression trees ([14]), which are simple models using binary splits on predictor variables to determine outcome predictions. Random forests is a ensemble classification technique developed by Breiman [14]. A collection of mtree decision trees are created and the final decision for a test point is obtained by aggregating the results for each tree using majority vote. Trees are constructed using different bootstrap samples of the original dataset. At each node of a tree, a set of mtry features are randomly selected from the F available features and the best split is chosen among those mtry features. Random Forests performs very well compared to other classifiers [15] with the main advantage of being robust against overfitting.

Artificial Neural Networks (ANN) are a group of computational techniques to obtain answers that present a mathematical model that corresponds to the neural structure of living organisms, managing to learn and obtain better results with training and applications (Araujo et al. [16]). Neural networks have numerous highly interconnected processing elements (nodes) that demonstrate the ability to learn and generalize from training patterns or data. They, like humans, can perform pattern-matching tasks, while traditional computer architecture, however, is inefficient at these tasks. On the contrary, the latter is faster at algorithmic computational tasks.

Using a database with 206 samples and 7 variables defined in the laboratory, the Machine Learning has been constructed using a Random Forest Regressor methodology using 60% to train and 40% for validation, where an accuracy value of 85% was obtained as an answer, 69%, the importance of each variable in the training of the network was also extracted from it. Subsequently, Machine Learning was applied to the 7000 samples of 7 variables

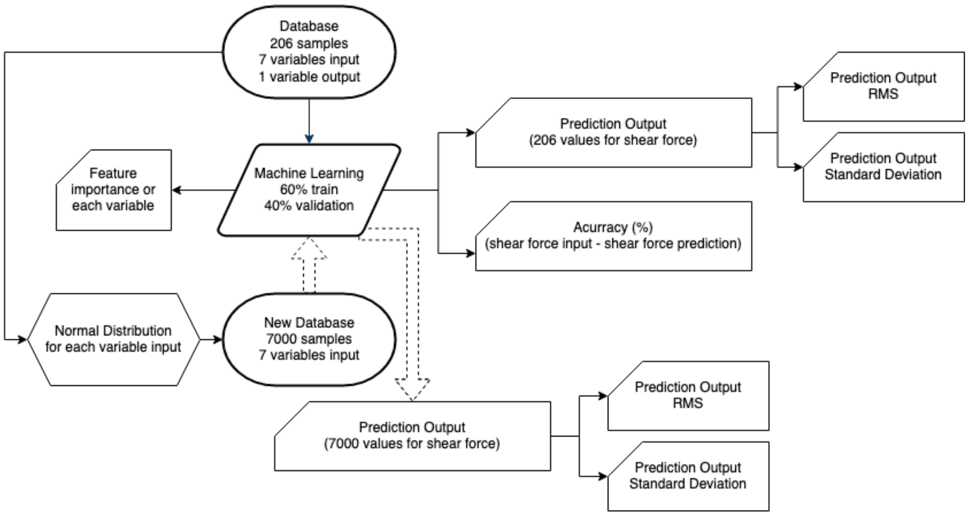


Figure 1. Evaluation Workflow for Machine Learning Prediction

Samples	206		7000	
	MEAN	STD	MEAN	STD
pH	5,81	0,26	5,81	0,27
Animal_Sex	0,21	0,41	0,29	0,45
Animal_Weight	260,44	51,74	261,13	51,98
Number_of_Teeth	1,29	1,24	1,34	1,16
Medial_Loin_Area	66,93	12,90	67,12	13,07
Loin_Area	25,83	2,47	25,86	2,41
Flesh_Color	4,52	1,55	4,53	1,53

Table 1. Values of Mean and Standard Deviation for each variable used on workflow development

generated by the Normal Distribution, where the Machine Learning predictions were validated by comparing the RMS of the predictions with the RMS value of the laboratory samples.

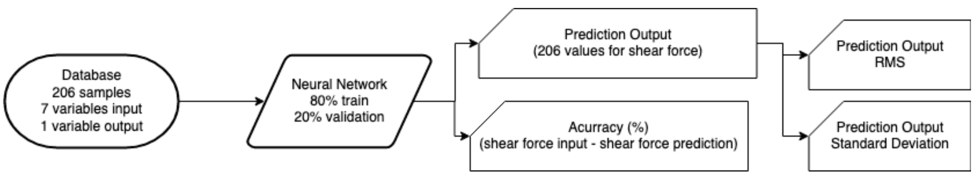
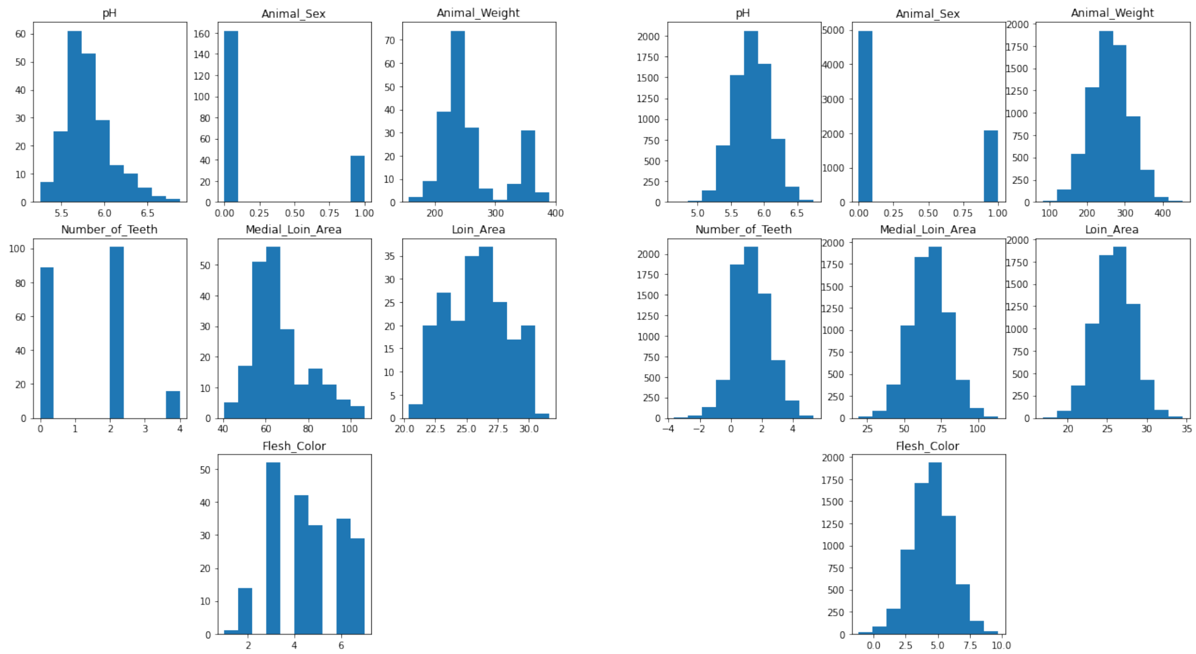


Figure 2. Evaluation Workflow for Neural Network

Using the database of 206 samples 7 variables from the laboratory data, the neural network had its structure built using 80% of the data for training and 20% for validation with a series of network configurations, which allowed accuracy of 78, 5%, and an RMS value very close to the laboratory data and those presented by Machine Learning.

2.1 Results

In this section, the results for a approach using a Machine Learning and Neural Network and a mathematical approach to build a new database for variables has been shown. To build a new database for each variables, a normal distribution was used with same mean and standard deviation values.(Table 1)



(a) 206 samples (b) 7000 samples

Figure 3. Distribution of variables used to input on Machine Learning and Neural Network

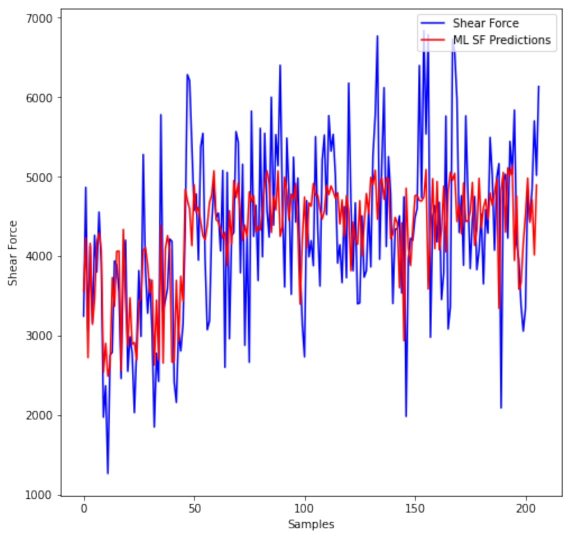


Figure 4. Comparasion Values of Shear Force Measure vs Prediction

In order to make a comparison between the results presented by Machine Learning and Neural Network, even with the lack of real Shear Force values for the 7000 samples generated, the objective function was defined to parameterize the analysis and facilitate the comparison. Thus, the RMS was calculated for laboratory, Machine Learning and Neural Network data: Laboratory: 65.57 on RMS; Machine Learning(data, lab): 65.79 on RMS; Machine Learning (generated data): 65.90 on RMS and Neural Network: 65.53 on RMS. The importance of each variable in the prediction was also presented by Machine Learning in the form of a tree, where: pH: 51.54%, Animal_Sex:7.41%, Animal_Weight: 14.46%, Number _of_Theeth: 1.35%, Medial_Loin_Area: 9.08% Loin_Area: 6.93% and Flesh_Color: 9.22%.

Trained Machine Learning was used for the Shear Force prediction of the new entries. RMS was calculated for the new Shear Force data. Where the same average and values presented were obtained, where the assertiveness of the Machine Learning and Neural Network methods can be compared.

3 Conclusions

Recent advances in computational methods and meat sciences can provide methods to predict the quality of the meat and some important variables to measure to determine the tenderness of the meat. In this work has been shown the prediction of the values for shear force using computational methods is efficient, obtaining an accuracy of 86.69% between real shear force values and predicting machine learning values using 206 samples from Database. With the real values of shear force from 206 samples meat, can be obtained the RMS of 65.57 used to compare the different methods of prediction. Using machine learning with 206 original samples can determine an RMS of 65.79. With a new set of values with 7000 samples determined with a normal distribution, a Machine Learning RMS for prediction shear force is 65.90, and using a Neural Network Method, post training with original 206 samples, obtain 65.53 on RMS.

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