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Improving craft beer style classification through physicochemical determination and the application of deep learning techniques

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Abstract

The consumption of craft beer at fairs and festivals is a phenomenon that keeps growing in the world. For this reason, it is important to control the quality characteristics of the different styles. This study aimed to analyze the different styles of beer, classify them according to their physicochemical parameters, and propose a predictive pattern-based model known as deep learning that best defines the styles that are presented at festivals. Physicochemical analyses of final gravity, color, alcohol, bitterness, and α-acids were carried out on eight styles of beer. The first four parameters are those that characterize the styles according to the Beer Judge Certification Program style guide. The incorporation of the α-acid determination allowed a more realistic classification that considers the brewers' new tendencies. This study will lay the foundations to improve local recipes, implement standardization, and provide training to local brewers.

Keywords: physicochemical attributes; beer; predictive analysis.

Practical application: the predictive analysis offers alternatives for brewers to catalog their styles.

1 INTRODUCTION

Festivals and fairs selling craft beer have long been held around the world being the Oktoberfest, in Munich, Germany, the oldest one among them (Harrington et al., 2017). In these events, craft beers with established styles, such as the well-known IPA (Indian Pale Ale), Stout, and Porter, as well as the distinctive styles of each region where the events take place, are sold (Jaeger et al., 2020). Each style is mainly known for its physicochemical parameters such as the original gravity (OG), final gravity (FG), alcoholic degree, color, and bitterness, being the style guide published by the Beer Judge Certification Program (2021), a clear example of this (Chan et al., 2019). This guide follows the accepted international parameters for each style, and it allows judges to score a beer according to these specifications (Moura-Nunes et al., 2016).

This activity is more recent in Argentina, where the oldest one is the National Beer Festival held in Villa General Belgrano-Córdoba. It offers more than 80 styles of craft and industrial beers, typical food, and shows on two different stages (Mongi, 2019). In the city of Resistencia (Chaco, Argentina), this type of event is even newer. Recently, 41 local brewers participated in a regional festival that was attended by 25,000 people and where 25,000 L of beer were sold (Chaco Día por Día, 2019). Resistencia is the capital city of Chaco province, and this event, which has already been established in the province, provides genuine work opportunities for several local producers who sell this type of product. At the same time, it boosts the consumption of other main gastronomic products that complement the sale of craft beer. These events that take place in different parts of the world are very important as they promote tourism and regional development (Harrington et al., 2017). However, despite the positive aspects mentioned, the styles that are sold at the festivals do not always reflect the traditional styles that craft beer consumers demand. Thus, for example, an IPA, known for its pronounced bitterness, and so promoted, is far from the bitter parameters for that style.

For the festivals that take place in the city, the Municipal Bromatology Department requires brewers to carry out a physicochemical control of their beers by the Argentine Food Code (Código Alimentario Argentino, 2007), which includes parameters such as acidity, pH, and alcohol, among others. These parameters give an idea of the physical and chemical aptitude of the beers, but it does not take into account the beer styles, to help the brewer to provide the consumer with a quality product. For this purpose, another type of analysis would be necessary, such as the determinations proposed in this study. The most relevant physicochemical parameters to characterize the different styles are FG, color, alcohol, and bitterness. Bitterness is mainly provided by hops, which also act as an antimicrobial and provide aroma, through the α-acids it contains. α-acids are converted to iso-α-acids during the boiling process (Dietz et al., 2021). However, in craft beers, a new trend toward more aromatic rather than bitter beers leads brewers to perform practices known as dry hopping, which consists of adding hops during the cold stages of the process

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(fermentation and maturation), in order to avoid isomerization (Lafontaine et al., 2018). This practice is not contemplated in the style guide and could be a factor that would contribute to more adequately characterize the styles studied.

Deep learning is one of the foundations of artificial intelligence. Deep learning techniques have improved the ability to classify, predict, recognize, detect, and describe data. This tool allows us to improve the classification and prediction software using new algorithms. It facilitates the implementation of learning models increasing accuracy. The system uses new classes of neural networks to extract patterns and data, easily. Deep learning improves the construction of neural network structures with many deep layers. It provides programmers with more computing power software. The use of neural networks is inspired by the human brain and tries to replicate the process of elaboration and classification similar to humans (Opperman, 2019). The main objective of an automatic recognition system is to discover the underlying nature of a phenomenon or object, describing and selecting the fundamental characteristics that allow it to be classified into a certain category (Bowles, 2020). In the case of beer, the physicochemical parameters of the different styles overlap, making manual classification difficult. This study aimed to analyze the different styles of beer, classify them according to their physicochemical parameters, and propose predictive models that best define the styles that are presented at festivals. In addition, the concentration of α-acids (the non-isomerized fraction of hops) is also analyzed as another attribute to consider when evaluating styles, and ranges of variation of this parameter are also proposed for each style analyzed.

2 MATERIALS AND METHODS

2.1 Physicochemical attributes

The international standards Mitteleuropäische Brautechnische Analysenkommission (MEBAK, 2013) were taken as a reference, according to the technique used: alcoholic degree (MEBAK, 2.9.5) by refractometry and pycnometry, following the correlation proposed in the international methodology and expressed in % ABV (alcohol by volume). For the determination of the refractive index, used in the calculation of the alcoholic degree, a manual refractometer (MLAT, China) was used, previously calibrated with distilled water. The FG was determined by pycnometry at 20°C; it was relative to water at the same temperature (MEBAK, 2.9.2.2). Iso-α acids (IBUS – International Bitterness Unit) and α-acids (MEBAK, 2.17.2) were extracted from beer with isooctane. The concentration was determined by spectrophotometry at different wavelengths and expressed in mg/L. The color was determined by spectrophotometry (MEBAK, 2.12.2), and the value was expressed on the Standard Reference Method (SRM) scale from the American Society of Brewing Chemists (ASBC). The methodology was used previously by Gómez Pamies et al. (2021).

The beer samples were taken by the same craft brewers and packaged in caramel-colored bottles. They were kept in a refrigerator at 4°C until the moment of analysis.

2.2 Predictive technique

A predictive model based on patterns using artificial neural networks (ANNs) (Zyner et al., 2018) was applied, and the representative characteristics of each style of beer were expressed in classes. For such purposes, Tensor Flow libraries (Gulli & Pal, 2017), using the Python language, were employed to classify algorithms.

For the classification analysis, a training file was used, selecting 320 experimental samples obtained from the local breweries, and 40 samples of each style were selected. A total of 240 samples were used for the training process and 80 for the validation process. The complete information was obtained from the files called Supplementary Material 1. This file contains the input data and the output data of the classification samples.

The parameters of the beers were taken from the style guide (Beer Judge Certification Program, 2021). The styles selected were those with the highest production among brewers in the region: 1—British Golden Ale (12 A), 2—English IPA (12 C), 3—American Pale Ale (18 B), 4—Irish Red Ale (15 A), 5—American Amber Ale (19 A), 6—American Porter (20 A), 7—American Stout (20 B), and 8—Dorada Pampeana (X1), an Argentinian style. The acronym used corresponds to the style guide (Beer Judge Certification Program, 2021).

Table 1 shows the ranges of variation of the characteristic parameters: FG, alcohol, color, and IBU of the eight styles of the craft beers selected. In addition, Table 1 also shows the

Table 1. Physicochemical parameters according to the style guide published by Beer Judge Certification Program (2021) and α-acid range proposed for the styles analyzed.

Styles	Alcoholic degree (% ABV)		Final gravity		Bitterness (IBU)		Color (SRM)		α-acid (mg/L)	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
12 A. British Golden Ale	3.8	5.0	1,006	1,012	20	45	2	5	1.0	9.0
12 C. English IPA	5.0	7.5	1,010	1,015	40	60	6	14	15.0	35.0
18 B. American Pale Ale	4.5	6.2	1,010	1,015	30	50	5	10	3.0	15.0
15 A. Irish Red Ale	3.8	5.0	1,010	1,014	18	28	9	14	5.0	13.5
19 A. American Amber Ale	4.5	6.2	1,010	1,015	25	40	10	17	2.0	10.0
20 A. American Porter	4.8	6.5	1,012	1,018	25	50	22	40	5.0	16.0
20 B. American Stout	5.0	7.0	1,010	1,022	35	75	30	40	16.0	24.0
X 1. Dorada Pampeana	4.3	5.5	1,009	1,013	15	22	3	5	1.0	9.0

Alcoholic degree: alcohol-by-volume (ABV); final gravity (FG): dimensionless, relative to water at 20°C × 1,000; IBUs: International Bitterness Unit (mg/L); SRM: Standard Reference Method from the American Society of Brewing Chemists (ASBC); α-acid: mg/L.

proposed variation ranges of α-acids for each style analyzed based on the data obtained for the 320 samples of the training and validation processes.

Finally, 80 samples, which did not fall within the range of Table 1, were used for the prediction model. The styles of these last 80 samples were proposed by the brewers, but they did not fit the physicochemical properties of the style. Consequently, the predicted model obtained in the first part of this study was used for the last samples to propose more convenient styles according to the real physicochemical values. The complete information for the last samples was obtained from the files called Supplementary Material 2. This file contains the input data and the output data of the out-of-style samples.

2.3 Data preparation

A matrix of 320 rows and six columns was established. The rows represented the samples obtained experimentally. The first five columns constituted the chemical properties of the beers and the last one constituted the class. The input data were indicated by the first five columns and the output data were indicated by the last one. Subsequently, they are used to perform the training and test tasks in a neural network.

2.3.1 Neural network architecture and data entry

The neural network model was of the deep learning type, and it was configured with the structure shown in Figure 1. The input and output data were placed in the input layer of the neural network. The hidden layer is made up of 40 neurons. The prediction model was built to classify eight beer styles; for that reason, there are eight output neurons.

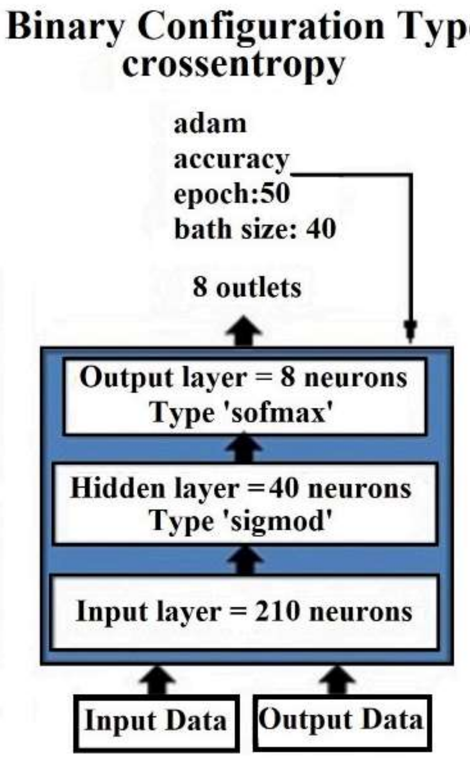

Figure 1. Neural network with deep learning structure.

2.3.2 Network training

The neural network was trained using the TensorFlow tool (Bowles, 2020) and the Python programming language. The source code used in training tasks is presented in Supplementary Material 3. Figure 2 shows the stability of the model after iteration 17 with an approximate accuracy of 0.96. Losses stabilize at iteration 17.5 with an approximate value of 0.11.

3 RESULTS AND DISCUSSION

Figure 3 shows the receiver operating characteristic (ROC) curve (Gulli & Pal, 2017). The plot is widely used to visualize the sensitivity versus specificity plots for a classifier system as the discrimination threshold varies. The source code used in the ROC curve plotting tasks is presented in Supplementary Material 4.

The ROC curve is used to summarize the performance or effectiveness of the predictor used. The diagonal line is called the non-discrimination line. Any response from the classifier that traverses such a line is called a random classifier. The area under the ROC curve is called the area under the curve (AUC) and represents the performance of each predictor. This area has a value between 0.5 and 1, where 1 represents a perfect classification and 0.5 represents a random classification. That is, if the AUC value for a test is 0.80, it means that there is an 80% probability of success. As a guide for interpreting the ROC curves, the following intervals have been established for the AUC values: 0.5 (random), 0.5–0.6 (bad test), 0.61–0.68 (regular test), 0.75–0.8 (good test), and 0.8–0.97 (very good test). The class represents the styles of beers, and the numerical value represents the degree of accuracy of the predictor for that class. In this way, it is possible to establish the performance of the predictor according to the style of beer. From the result observed in Figure 3, it can be observed that only one style (American Pale Ale) had a good test and all the other styles were very good tests with more than 88% probability of success. These studies allowed a very good classification of the different styles and allowed the use of this predictive technique for a better classification of the styles that do not fit within the range of Table 1. This procedure was used in the following section of this study.

When the above model was used to predict styles that best represent those ones, made by local brewers, a very interesting variation was found. In Figures 4A–4E, the experimental data used for the verification model and the data used for the predictive model can be observed comparatively.

The generality of the samples is that, at least, one or more parameters deviate from the expected range. This can be attributed to not only various general causes but also particular ones. In Resistencia, Chaco, there are no beer supply distributors, so craft brewers are forced to purchase raw materials by making long-distance orders from different stores (more than 1000 km away from the production area). This causes damage to performance in the brewing process due to the loss of quality of the inputs. Transport and poor storage of inputs could be two of the possible reasons why regional craft beers fail to achieve the ranges stipulated by the BJCP, as shown in Table 1.

Another general cause that can be attributed to the variation in the parameters is the lack of standardization in the process carried out by each brewer and the absence of fidelity to the recipe for each style.

For the 80 samples that do not fit the range of Table 1, the following analysis could be done. It can be observed in Figure 4A that 27.5% of the color parameter values fell within the expected range of variation, 67.5% outside, and 2.0% below the range. Besides, it is noteworthy that the darkest styles, such as the Irish red, American Amber Ale, American Porter, and American Stout, are the ones that presented the greatest variations. This could have been caused by defects in the raw material or errors in the process. The type of malt used determines the color. Besides, the mashing that has not been carried out properly could have favored the greater extraction of pigments, achieving darker colors. Likewise, longer cooking times could cause greater development of dark colors due to the well-known Maillard reaction (Howe, 2019). The more the wort is heated, the more the caramelization is achieved and the more it is colored (Howe, 2019). Another possible cause could be attributed to the storage of the beer before being marketed. It may mainly be due to the oxidation of the wort (Bamforth, 2009), non-uniform storage periods, and/or incorrect temperature controls which could have darkened the beer. These are some of the most influential factors that can be corrected by conscious control of the processing conditions. This is important, as it allows the brewers to know that although it is only a visual aspect because it impacts color,

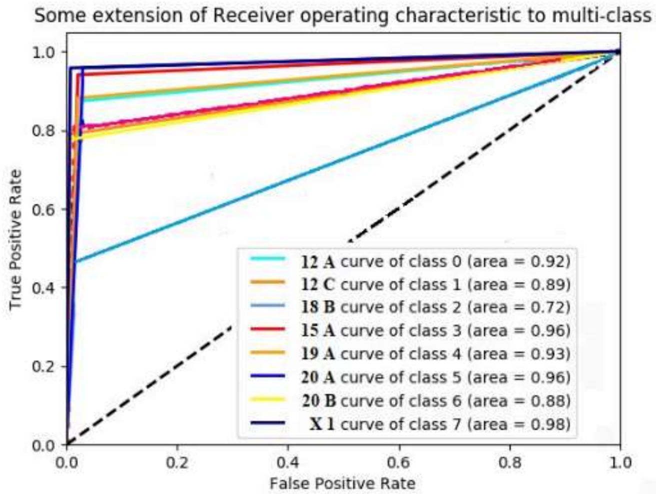

Figure 3. Behavior of the predictor response for each class using the ROC curve.

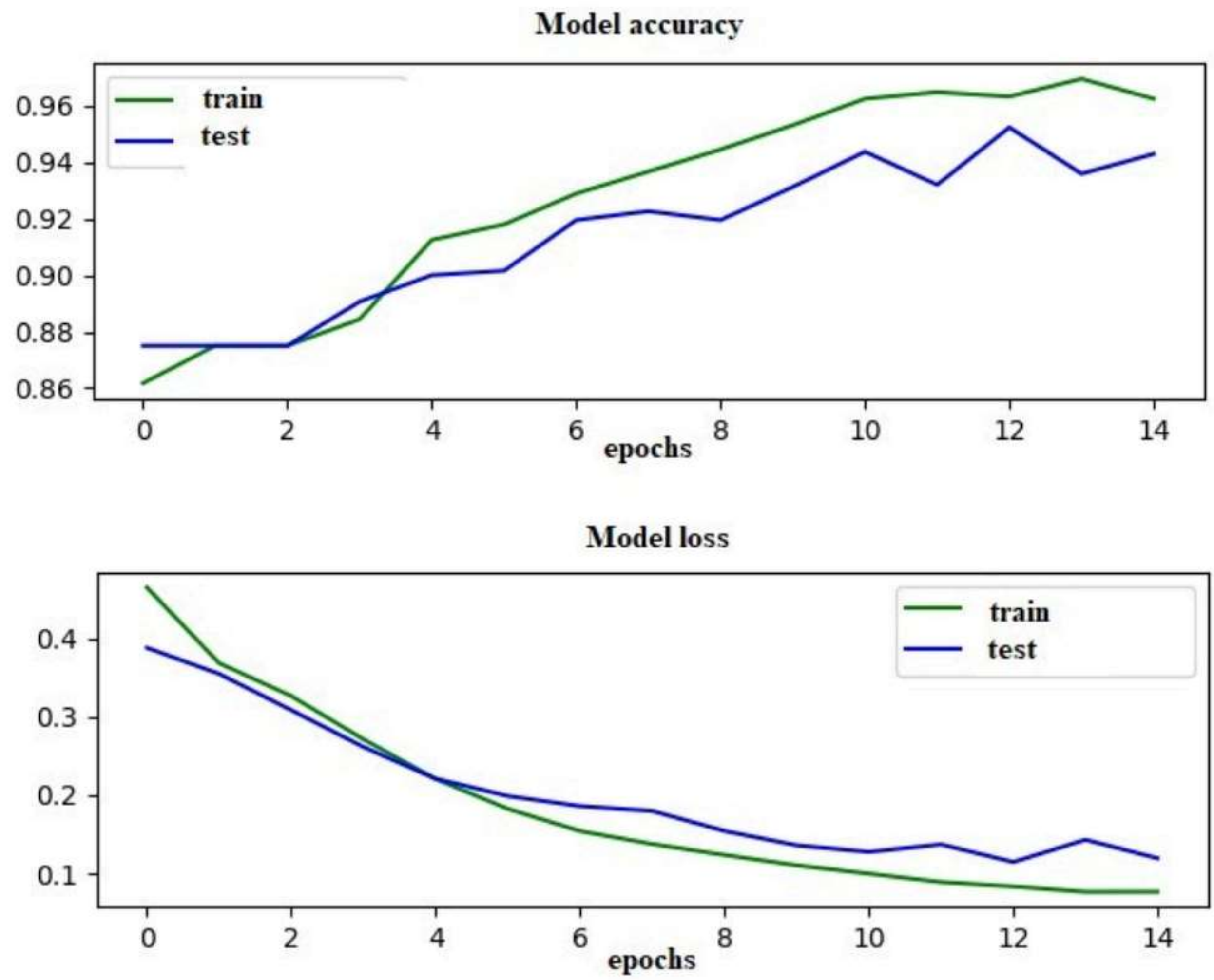

Figure 2. Response of the deep learning structure network training.

it undoubtedly has a strong influence on the taste of the drink. From the results obtained, it is possible to make adjustments to the recipes to improve the quality of the beers.

When observing the data of the final densities (Figure 4B) and alcohol (Figure 4C) of the different styles of beer, it can be said that almost all the values are below the ones established in the BJCP guide. FG values were 70% lower, and none were higher than the expected range. As regards alcohol, 55% of the values were lower and 2% were higher than the expected range.

These parameters are closely related because the FG directly impacts the beer body, the mouthfeel, and the alcohol degree (Bamforth, 2003). The correct handling of pH and mashing temperature are key factors in producing a beer according to the expected style (Holbrook, 2019). However, low FG, associated with low alcohol content, may mean that craft brewers were using less malt for their recipes to reduce costs, or that it was of low quality. This type of procedure should be regulated to produce economically viable processes without losing the distinctive attributes of each style. With this procedure (model and prediction), the problem could be detected and most of the brewers could be able to improve their recipe.

The bitterness revealed that 72.5% of the data was lower and none was above the expected value. The bitterness of the beer also depends on the percentage of α-acids found in the hops used in production. Percentage U% is the proportion of α-acids that are converted to iso-α-acids. The conversion percentage varies between 0 and 40% according to a large number of factors (Briggs et al., 2004). The longer the boiling time of hops is, the higher the possibility of isomerization will be. Also, the fact that the extraction of α-acids from pellets is higher than the proportion in flowers is due to the modifications that take place during the pelletization process, and the fact that the hops disintegrate better exposes the α-acids for their isomerization. The higher the FG, the lower the U% is because the solubilization of iso-α-acid decreases. Regarding the fermentation process (the amount of yeast used) and clarification (the addition of coagulants), they can affect the levels of iso-α-acid precipitation. In short, concerning bitterness, many factors could influence the development of this parameter. Therefore, becoming aware that there is a problem in different styles will allow regional brewers to modify their recipes to increase bitterness in those styles that may require it. Regarding bitterness, it is important to mention that the problem arises in the styles with the highest bitterness, such as the American Porter and American Stout. In turn, there has been a significant

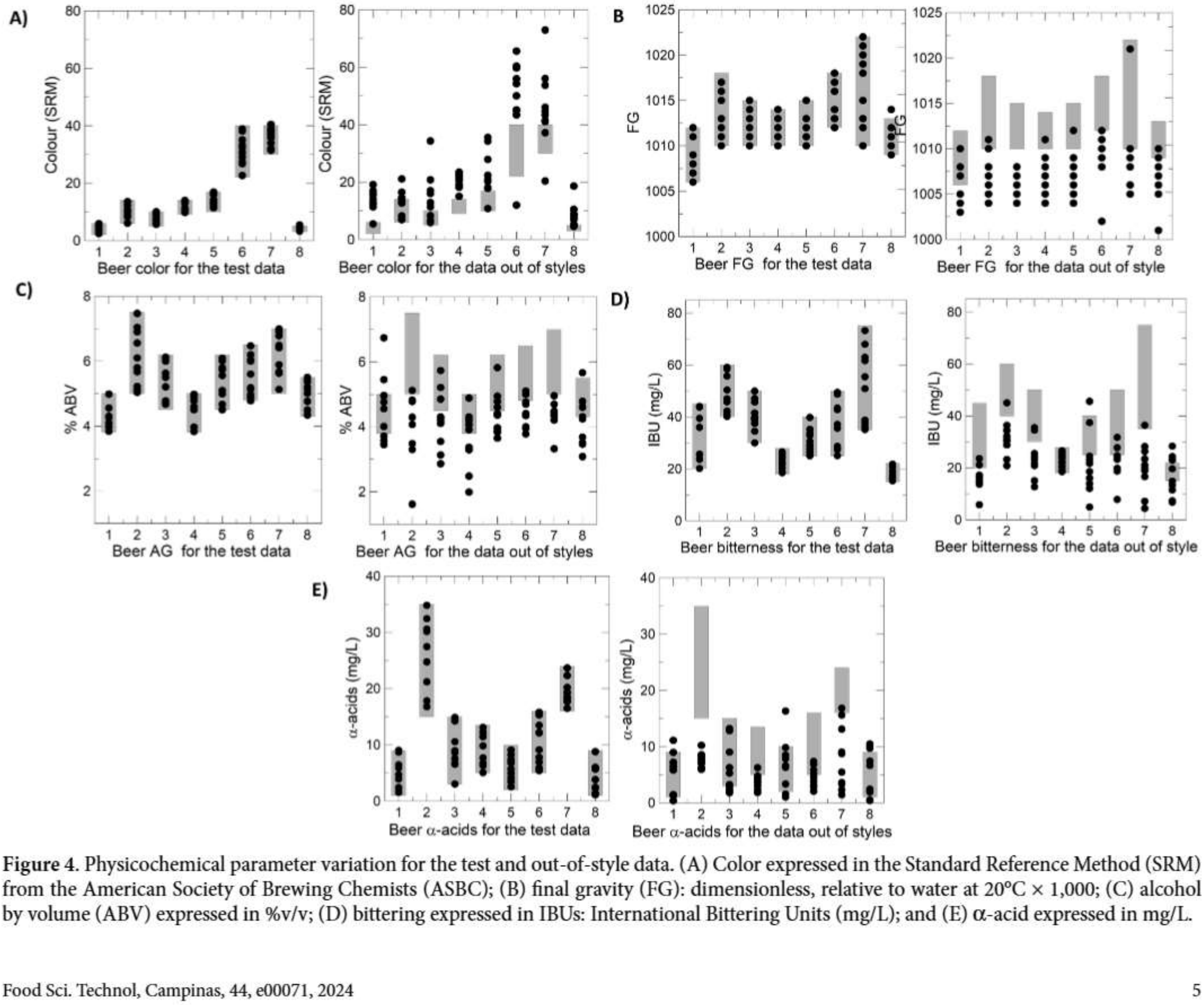

Figure 4. Physicochemical parameter variation for the test and out-of-style data. (A) Color expressed in the Standard Reference Method (SRM) from the American Society of Brewing Chemists (ASBC); (B) final gravity (FG): dimensionless, relative to water at 20°C × 1,000; (C) alcohol by volume (ABV) expressed in %v/v; (D) bittering expressed in IBUs: International Bittering Units (mg/L); and (E) α-acid expressed in mg/L.

change in the way of producing the well-known English IPA style because, although the characteristic bitterness is notable, there was a significant trend toward the production of a style with a greater aroma. The aroma parameter is not listed in the style guide. However, the current trend among local brewers is to produce more aromatic beers. The aroma and flavor parameters are associated with the proportion of α-acids present in beers and they are desirable attributes in the final product (Oladokun et al., 2017). Nowadays, brewers use different techniques to improve this value (Gasiński et al., 2022). Figure 4E shows the range of α-acid variation for the experimental data, and it can be observed that the English IPA style exhibited higher values for aroma. Additionally, in the other styles analyzed, a pronounced trend can be observed, which could be used for style characterization. Therefore, this study proposes the determination of α-acids as another attribute to be considered when evaluating styles, and it suggests ranges of α-acid concentration variation for each analyzed style (Table 1) based on the data obtained from the 320 samples in the training and validation process.

Furthermore, in Table 2, the data obtained with the prediction program are presented. For better comprehension, it can be mentioned that the program predicts which style would be more convenient based on the experimental physicochemical data obtained for the out-of-style samples. All the physicochemical parameters for each style that do not fit into the expected range can be observed in Table 2, with the new more convenient predicted style. None of the expected styles for 12 A corresponded with this style, 10% corresponded with 12 C, 50% corresponded with 18B, 20% corresponded with 19 A, and 20% corresponded with X1. This analysis not only allows knowing how far a style is from the expected one but also, based on the parameters found, predicting which style corresponds to the actual physicochemical parameters.

4 CONCLUSION

The predictive pattern-based model of deep learning was appropriate and novel for the treatment of the experimental data obtained. It allowed the development of a system to suggest a style that, according to their analytical parameters, best represents the beer. The addition of the α-acid determination enabled a more realistic classification that considers new tendencies for brewers. This study will establish the foundations to improve local recipes by implementing standardization and providing training to local brewers.

Table 2. Correlation between the beer styles expected by the brewers and the styles classified by the predictive analysis adopted.

Expected styles by brewer's recipe	Predicted styles for the samples out of style							
	12 A	12 C	18 B	15 A	19 A	20 A	20 B	X 1
12 A		10	50		20			20
12 C		36.4	63.6					
18 B	18.2	9.1	54.5	9.1	9.1			
15 A	9.1		27.3	27.3	36.3			
19 A		27.3	27.3	9.1	27.3	9.1		
20 A			10		10	70	10	
20 B		8.3			16.7	33.3	41.7	
X 1	40	30	10	10				10

The data are expressed as a percentage, adding 100% per row for each style; 12 A: British Golden Ale; 12 C: English IPA; 18 B: American Pale Ale; 15 A: Irish Red Ale; 19 A: American Amber Ale; 20 A: American Porter; 20 B: American Stout; X1: Dorada Pampeana.

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