Assessment of Beer Quality Based on a Robotic Pourer, Computer Vision, and Machine Learning Algorithms Using Commercial Beers

Claudia Gonzalez Viejo, Sigfredo Fuentes, Damir D. Torrico, Kate Howell, and Frank R. Dunshea

Abstract: Sensory attributes of beer are directly linked to perceived foam–related parameters and beer color. The aim of this study was to develop an objective predictive model using machine learning modeling to assess the intensity levels of sensory descriptors in beer using the physical measurements of color and foam-related parameters. A robotic pourer (RoboBEER), was used to obtain 15 color and foam-related parameters from 22 different commercial beer samples. A sensory session using quantitative descriptive analysis (QDA®) with trained panelists was conducted to assess the intensity of 10 beer descriptors. Results showed that the principal component analysis explained 64% of data variability with correlations found between foam-related descriptors from sensory and RoboBEER such as the positive and significant correlation between carbon dioxide and carbonation mouthfeel ($R = 0.62$), correlation of viscosity to sensory, and maximum volume of foam and total lifetime of foam ($R = 0.75$, $R = 0.77$, respectively). Using the RoboBEER parameters as inputs, an artificial neural network (ANN) regression model showed high correlation ($R = 0.91$) to predict the intensity levels of 10 related sensory descriptors such as yeast, grains and hops aromas, hops flavor, bitter, sour and sweet tastes, viscosity, carbonation, and astringency.

Keywords: artificial neural networks, beer color, beer foam, robotics, sensory analysis

Practical Applications: This paper is a novel approach for food science using machine modeling techniques that could contribute significantly to rapid screenings of food and brewage products for the food industry and the implementation of Artificial Intelligence (AI). The use of RoboBEER to assess beer quality showed to be a reliable, objective, accurate, and less time-consuming method to predict sensory descriptors compared to trained sensory panels. Hence, this method could be useful as a rapid screening procedure to evaluate beer quality at the end of the production line for industry applications.

Introduction

Beer is the most consumed alcoholic beverage worldwide in terms of volume, representing 78% of total volume sales. Moreover, consumers are constantly looking for new options of beer; hence the industry focuses heavily on the development of new products or improving existing ones (Euromonitor-International, 2016). However, this brewage is very complex in terms of specific sensory descriptors due to the diversity of ingredients used in the manufacturing process, such as malt, hops, and yeast, as well as the possible addition of adjuncts such as other cereals, flavors, fruit juices, among others (Delcour & Hoseney, 2010). The assessment of sensory attributes of beer is relevant as they are indicators of beer quality, especially the visual characteristics such as foam-related parameters, which, at the same time are closely linked to flavors; tastes such as bitter, sour and sweet; aromas due to the capacity of foam to release them; and mouthfeel given by the carbonation and foamability (Baert, De Clippeleer J, De Cooman, & Aerts, 2012; Cooper, Husband, Mills, & Wilde, 2002; Gonzalez Viejo et al., 2016; Gonzalez Viejo, Fuentes, Torrico, Howell, & Dunshea, 2017)

The raw materials used for beer brewing contribute chemical compounds such as proteins, carbohydrates, alcohol, and others, which affect the sensory characteristics of the final product (Bamforth, 2011). Hops are one of the crucial ingredients of brewing, contributing the characteristic bitter taste from iso-alpha acids. These iso-alpha acids as well as malts contribute to the characteristic color of different styles of beer and may lead to specific astringency levels. Additionally, iso-alpha acids have specific tensio-active properties, which contribute to foam formation, stability, and lacing. Hops also contain essential oils that contribute to the complexity of aromas and flavors found in beer (Bamforth, Russell, & Stewart, 2011; De Keukeleire, 2000).

The type of fermentation (top, bottom, or spontaneous), the type of yeast used, alongside with the original gravity and degree of attenuation (which defines the alcohol content), determine the sweetness level of the final product. These two parameters have an inverse relationship: the lower the alcohol content, the higher the sweetness, as they depend on the amount of fermentable sugars consumed by yeasts. As yeasts consume sugars, carbon dioxide is produced. Therefore, a higher amount of fermentable sugars in the wort can lead to a higher carbonation in the final beer. Proteins and carbohydrates derive mainly from malt, and they contribute almost solely to the body or viscosity of beers, which, at the same time, is highly linked with the foam stability (Delcour

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& Hoseney, 2010). The interest in studying foamability in beers relies on the influence of foam formation and stability over other critical sensory components. Foam plays a fundamental role in releasing aromas and preserving flavor and taste, since with reduced foamability, the beer comes in direct contact with the oxygen from the air and thus it starts to oxidize during consumption, which results in the appearance of off—flavors (Gonzalez Viejo et al., 2016, 2017; Okada et al., 2008; Ortiz, Muela, & Ortiz, 2003).

The current demand for higher quality beers worldwide has increased the need for new and more effective methods to assess their sensory descriptors and quality traits. Descriptive sensory tests such as quantitative descriptive analysis (QDA®) and Spectrum™ have been used as tools to evaluate quality of beers and to ensure the uniformity amongst different batches (Medoro et al., 2016). However, these tests require a panel of 10 to 16 people with extensive training, which is time consuming and expensive (Piper & Scharf, 2004). Rapid sensory methods such as Napping® and sorting have been reported to give reliable data without the requirement of a trained panel. However, these methods are used to find similarities or differences within a set of samples that need to be evaluated in a single session and require a limited number of samples (Antúnez et al., 2015; Giacalone, Ribeiro, & Frøst, 2013).

Artificial neural networks (ANN) are a type of machine learning algorithm that have the ability to simulate the processing techniques of the human brain, giving it the capacity to find nonlinear relationships within a set of parameters and targets (Lin, Groves, Freivalds, Lee, & Harper, 2012). This method has been actively applied for a wide range of purposes such as diagnostic of diseases (Khan et al., 2001), prediction of weather (Kuligowski & Barros, 1998; Tokar & Johnson, 1999), among others. It has also been proposed as an alternative way for more objective beer classification according to quality traits such as alcohol content, pH and CO_2 (Garcia, Argüeso, Garcia, & Diaz, 1995), according to fermentation type (Gonzalez Viejo et al., 2016), and to predict specific compounds in beer, such as acetic acid (Zhang, Jia, & Zhang, 2012). Furthermore, ANN has been used to develop models to predict volatile fingerprinting using gas chromatography (Cajka, Riddellova, Tomaniova, & Hajslova, 2010), to predict chemometrics such as pH, alcohol content, maximum volume of foam and Brix using near-infrared absorbance values within 1600 and 2400 nm as inputs (Gonzalez Viejo et al., 2017), and to predict alcohol content and real extract using mid- and near-infrared (Iñón, Garrigues, & de la Guardia, 2006). In those three studies, the ANN models were compared with other methods such as partial least squares regression and linear discriminant analysis, being ANN the most accurate method in all cases. Therefore, appropriate models based on these types of algorithms can be based on rapid measurements of beer parameters such as foamability and color, which can be obtained using the RoboBEER.

This paper discusses the development of machine learning modeling techniques, specifically, ANN to predict 10 related sensory descriptors in beer using 15 parameters including foamability, alcohol, carbon dioxide (CO_2), and color measured using a robotic pourer, RoboBEER (Gonzalez Viejo et al., 2016). The objective of the machine learning models developed is to allow more efficient assessment of samples at the end of the production line to have accurate results for sensory descriptors such as viscosity, carbonation, astringency, bitterness, sourness, sweetness, and aromas such as yeast, hops, and grains to use as a rapid method to assess beer quality.

Materials and Methods

A set of 22 beer samples (Table 1) from three types of fermentation (eight from top, seven from bottom and seven from spontaneous) were used for sensory descriptive analysis. Each beer was sampled in triplicate to measure all foam-related parameters to reduce bias due to sealability and/or other packaging related variability.

Foamability assessment

To measure all foam-related parameters using computer vision algorithms from pouring videos, a robotic pourer RoboBEER was used. RoboBEER is able to pour a constant amount of beer (80 ± 10 mL) and monitor liquid temperature, alcohol and CO_2 release in real time using sensors controlled by Arduino boards® (Arduino, Italy). In parallel, videos of the pouring process and up to 5 min afterwards are recorded using an iPhone 5S (Apple Inc., Cupertino. CA, U.S.A.). The post analysis of videos is based on customized computer vision algorithms written in Matlab® ver. 2016a (Mathworks, Inc., Matick. MA, U.S.A.). This robotic pourer is capable of giving a total of 15 parameters related to foamability and color of beer, such as maximum volume of foam (MaxVol), total lifetime of foam (TLTF), lifetime of foam (LTF), foam drainage (FDrain), number of large (LgBubb), medium (MedBubb) and small bubbles (SmBubb) in the foam, CO_2 release, alcohol content (OH), and beer color parameters in both scales CieLab (L, a, b) and RGB, respectively.

The analysis from the RoboBEER consists of three parts, (i) data acquisition from the sensors (temperature, alcohol and CO_2) using the CoolTerm terminal application ver. 1.4.3 (Meier), (ii) processing of one frame at the peak pouring volume obtained from the video to analyze the average color of a section of the center region of the liquid in both scales (RGB and CieLab), and (iii) analysis of foam and bubble related parameters from the pouring video. To analyze the foamability, the video was first processed using a semi-supervised algorithm that consists on the initial scaling to convert height into volume followed by the manual selection of foam height every 1 s (30 frames), this allows the code to automatically calculate volume of foam and liquid. After this process, the code calculates the resulting volumes into TLTF, LTF, MaxVol, and FDrain by analyzing the area below the curve of foamability and relevant parameters. Finally, the frame with the maximum volume of foam obtained from the video is analyzed based on the “Hough Transformation” algorithm to obtain bubble size and distribution within the visible foam in the glass wall (Condé et al., 2017). A more detailed description of the RoboBEER methodology and performance is found in work from Gonzalez Viejo et al. (2016).

Sensory evaluation

A sensory session for descriptive analysis was carried out to assess all beer samples. The sensory session and training were carried out in the sensory lab facilities of the Faculty of Veterinary and Agricultural Sciences of The Univ. of Melbourne, Australia (FVAS – UoM). A questionnaire using a 15 cm nonstructured scale was implemented through a biometric-sensory application (bio-sensory App) (Torrico et al., 2017) designed for Tablet PCs (Android) and developed by the sensory group belonging to the School of Agriculture and Food within the FVAS – UoM. A sensory panel of 12 participants, who were prescreened to be regular beer consumers, able to verbalize descriptors, and with previous experience in similar tests, was used to conduct the session. These panelists were trained to detect basic tastes and aromas using the International Standard methodology (ISO 8586-1: 1993E Sensory

Table 1–Beer samples used classified by type, subtype, and country of origin with their respective abbreviation.

Type/subtype	Country of origin	Label/code	Packaging type/net content	Alcohol content
Top fermentation				
Abbey Ale	Belgium	L	Brown glass bottle 330 mL	6.6%
India Pale Ale	Australia	IP	Brown glass bottle 330 mL	6.2%
Porter	Poland	Z	Brown glass bottle 330 mL	9.5%
Kolsch	Australia	P	Brown glass bottle 330 mL	4.6%
Red Ale	USA	RT	Brown glass bottle 330 mL	5.8%
Steam Ale	Australia	SA	Brown glass bottle 330 mL	4.5%
Aged Ale	Scotland	IG	Brown glass bottle 330 mL	6.6%
Sparkling Ale	Australia	CS	Brown glass bottle 375 mL	5.8%
Bottom fermentation				
Lager	Mexico	C	Clear glass bottle 355 mL	4.5%
Lager	Mexico	XX	Green glass bottle 330 mL	4.5%
Lager	USA	BL	Brown glass bottle 355 mL	5.2%
Lager	Netherlands	H	Green glass bottle 330 mL	5.0%
Lager	Czech Republic	BC	Green glass bottle 330 mL	5.0%
Lager low alcohol	Germany	BB	Green glass bottle 330 mL	0.3%
Pilsner	Czech Republic	PU	Green glass bottle 330 mL	4.4%
Spontaneous fermentation				
Lambic Cassis	Belgium	LC	Green glass bottle 375 mL	3.5%
Lambic Framboise	Belgium	LF	Green glass bottle 375 mL	2.5%
Lambic Gueuze	Belgium	LG	Green glass bottle 375 mL	4.5%
Lambic Kriek	Belgium	LK	Green glass bottle 375 mL	3.5%
Lambic Kriek	Belgium	OK	Green glass bottle 375 mL	6.0%
Lambic Gueuze	Belgium	OG	Green glass bottle 375 mL	6.0%
Lambic Gueuze	Belgium	OT	Green glass bottle 375 mL	6.5%

analysis – General guidelines for the selection, training and monitoring of selected assessors and expert sensory assessors, and quality control procedures) (ISO 1993), this training was conducted in five sessions of 60 min each. The general training consisted of basic tastes using sodium chloride for salty, sucrose for sweet, caffeine for bitter, monosodium glutamate for umami and citric acid for sour taste using the dilutions suggested in the above mentioned International Standard. Furthermore, the training included the familiarization with different aromas generally found in beer using the Le Nez du Vin®: Wine Aroma kit (Le Nez du Vin, France) including aromas such as fruity (lemon, cherry, apple, orange), floral (acacia, honey, rose, violet), vegetal and spicy (yeast, cedar, pine, cut hay, clove), animal notes (butter, leather), and roasted notes (toast, caramel, coffee, smoke), among others.

The selection of descriptors for the test was carried out using the quantitative descriptive analysis (QDA®) method in blind tasting sessions using the different beer samples to generate consensus and agreement on a set of the most relevant attributes. For the QDA®, the training sessions and selection of descriptors consisted of seven sessions of 60 min each and divided as follows: (i) two sessions were dedicated for top fermentations beers, (ii) two sessions for bottom fermentation, (iii) two sessions for spontaneous fermentation samples, and (iv) one more session for a mix of all types of beers. To assess the panel performance during the training, a combination of cluster analysis, standard deviation, ANOVA and spider chart (data not shown) were developed to assess significant differences within the panelists for each descriptor.

A single double-blind sensory session was conducted to evaluate the intensity of the different descriptors for the 22 beer samples used in this study (Table 1). The samples were served at refrigeration temperature (~4 °C) and covered with aluminum foil by an independent person that did not participate in the session, which codified each sample with a three-digit random numerical codes with the tasting order semi-randomized (two blocks of 11 beers each) (Gonzalez Viejo et al., 2016). All beer samples were served just after beer bottles were opened in International Standard Wine Tasting Glasses Luigi Bormioli and one at a time for an independent assessment. A total of 21 descriptors were evaluated, however, for this paper only 10 descriptors were used (Table 2) as these are the attributes affected by or related to foamability. For this study, only one replicate was analyzed as the results from the standard error of the mean (SEM) were between 0.17 and 1.49 (Table S2). Furthermore, an ANOVA and least significant differences (LSD) test ($\alpha = 0.05$) were conducted using the SAS® 9.4 software (SAS Institute Inc., Cary, NC U.S.A.) to find significant differences between samples for each descriptor. There were significant differences between samples for all descriptors, which indicates that the range of beer samples was adequate for modeling purposes. These results can be found in the supplementary material (Table S2).

Table 2–Sensory descriptors obtained by agreement of a trained sensory panel, which are directly related to foamability properties of beer and their abbreviation.

Descriptor	Abbreviation
Bitter taste	TBitt
Sweet taste	TSweet
Sour taste	TSour
Aroma grains	AGrains
Aroma hops	AHops
Aroma yeast	AYeast
Viscosity	CVisc
Astringency	MAstr
Carbonation mouthfeel	MCarb
Flavor hops	FHops

Multivariate data analysis

A multivariate data analysis based on principal components analysis (PCA) was performed using a customized Matlab® code (Fuentes, Unpublished). Factor loadings for the two major principal components used to construct the PCA can be found in Table S3 as supplementary material. A correlation matrix was

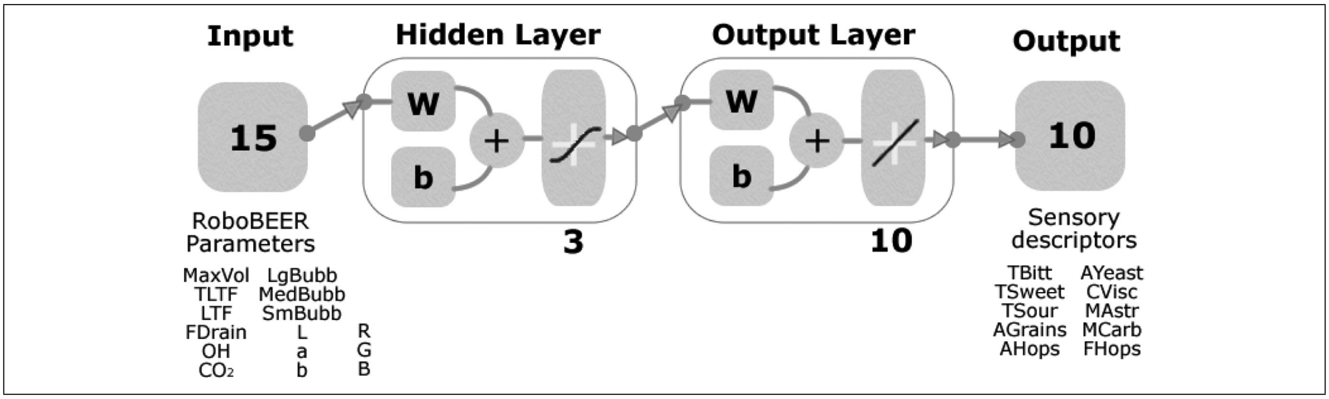

Figure 1–Feedforward network model diagram with two layers and sigmoid functions using three hidden neurons and ten outputs for regression models. A total of 15 inputs from RoboBEER: (i) MaxVol, (ii) TLTF, (iii) LTF, (iv) FDrain, (v) LgBubb, (vi) MedBubb, (vii) SmBubb, (viii) CO_2, (ix) OH, (x) L, (xi) a, (xii) b and (xiii) R, (xiv) G, and (xv) B and ten targets from sensory descriptors (Table 2) were used to create the ANN model.

developed in Matlab® to find significant correlations ($P < 0.05$) between the 15 parameters measured with RoboBEER and the 10 sensory descriptors (Table 2). Mean values of the parameters measured with RoboBEER and from sensory descriptors can be found in the supplementary material (Table S1 and S2). For the parameters measured with RoboBEER the SD between the three bottles of each sample are presented.

Artificial neural networks

The Matlab Neural Network Toolbox™ 7 (Mathworks, Inc., Matick, MA, U.S.A.) fitting tool was used to develop an ANN regression model to predict the sensory descriptors (Table 2) intensities using 15 parameters as inputs: MaxVol, TLTF, LTF, FDrain, LgBubb, MedBubb, SmBubb, CO_2, OH, L, a, b and R, G, B, obtained using the RoboBEER and values for sensory descriptors as targets from Table 2. For this model the Levenberg-Marquardt training algorithm was used along with a random data division of 70% ($n = 46$) used for training, 15% ($n = 10$) for validation with a mean squared error performance algorithm and 15% ($n = 10$) for testing using a default derivative function. After testing different number of neurons (10, 7, 5, and 3), the model was developed using three hidden neurons as the results using the four options were similar (Figure 1). Statistical data used to evaluate the accuracy of these models consisted in the correlation (R) and determination (R^2) coefficients, mean squared error (MSE), slope and P-value obtained using Matlab®.

Results and Discussion

Multivariate data analysis

Figure 2a and 2b show the PCA and correlation matrix using 15 RoboBEER parameters: (i) MaxVol, (ii) TLTF, (iii) LTF, (iv) FDrain, (v) LgBubb, (vi) MedBubb, (vii) SmBubb, (viii) CO_2, (ix) OH, (x) L, (xi) a, (xii) b and (xiii) R, (xiv) G, and (xv) B and 10 sensory descriptors (Table 2). The principal component 1 (PC1) represented 40.1% of data variability, while principal component 2 (PC2) accounted for 23.4%, thus the PCA represented 64% of total data variability. From the PCA in Figure 2a and factor loadings in Table S3, PC1 is characterized mainly by yeast, hops, and grains aromas as well as color lightness on the positive side of the axis, and sweet and sour tastes along with the color parameters (a, R, and G) on the negative side. On the other hand, the PC2 is characterized by bubble size and foam drainage on the positive side, and foam-related parameters from both the RoboBEER and sensory descriptors (MaxVol, TLTF, OH, MCarb, and CVisc) on the negative side. However, a weakness found in this analysis was that the scores of the factor loadings were within a range of 0.02 to 0.29 for PC1 and 0.01 to 0.37 for PC2 which are considered as weak or poor scores (Comrey & Lee, 2013).

Figure 2a shows a separation of the samples according to the type of fermentation (top: circles and dotted line; bottom: squares and dashed line; two groups of spontaneous: triangles, and solid and long dashed lines) that, however, have differences among them. These results and the differences found in the ANOVA (Table S2) indicate that the samples have a wide range of characteristics in terms of foamability, color, and sensory descriptors that allow the modeling of the data. It is important to note as a limitation of the study, that only one replication was made for the descriptive sensory session, therefore, the reliability of the panel cannot be assured. However, when combining all sensory results with the RoboBEER parameters, the relationship between the parameters and the separation of samples are in accordance with literature.

As seen in Figure 2a, the group of bottom fermentation beers had more foam drainage and therefore, lower foam stability and CO_2 than the top and spontaneous fermentation, this is mainly due to the differences in the process (fermentation time, temperature and filtration, carbonation), and type of yeast (Bamforth et al., 2011). Top fermentation beers presented higher bitterness, hops aroma and flavor, and astringency, which are common attributes in this type of beers (Perozzi & Beaune, 2012a; Perozzi & Beaune, 2012b). On the other hand, the first group of lambic beers (LG, LC, LF, and LG) had more sweetness and sour taste, whilst the group of OG, OT and OK present sour taste and a higher MCarb, and CVisc and, therefore, more foam stability and volume (MaxVol, TLTF, LTF). The separation into two groups for spontaneous fermentations might be due to the differences in alcohol content as the first group (LG, LC, LF, and LG) had lower alcohol content (2.5% to 4.5%) compared to the second group (6.0% to 6.5%). Another reason for the differences within this type of beers might be due to the fermentation that uses wild yeast from the environment of the region where the beer is produced, which makes it more difficult to have very similar descriptors among different breweries (De Keersmaecker, 1996).

The positive and significant ($P < 0.05$) correlation between the viscosity (CVisc) and foam-related parameters such as MaxVol, TLTF and LTF ($R = 0.75$, $R = 0.77$, and $R = 0.53$, respectively), and the negative correlation with FDrain ($R = -0.77$) can be

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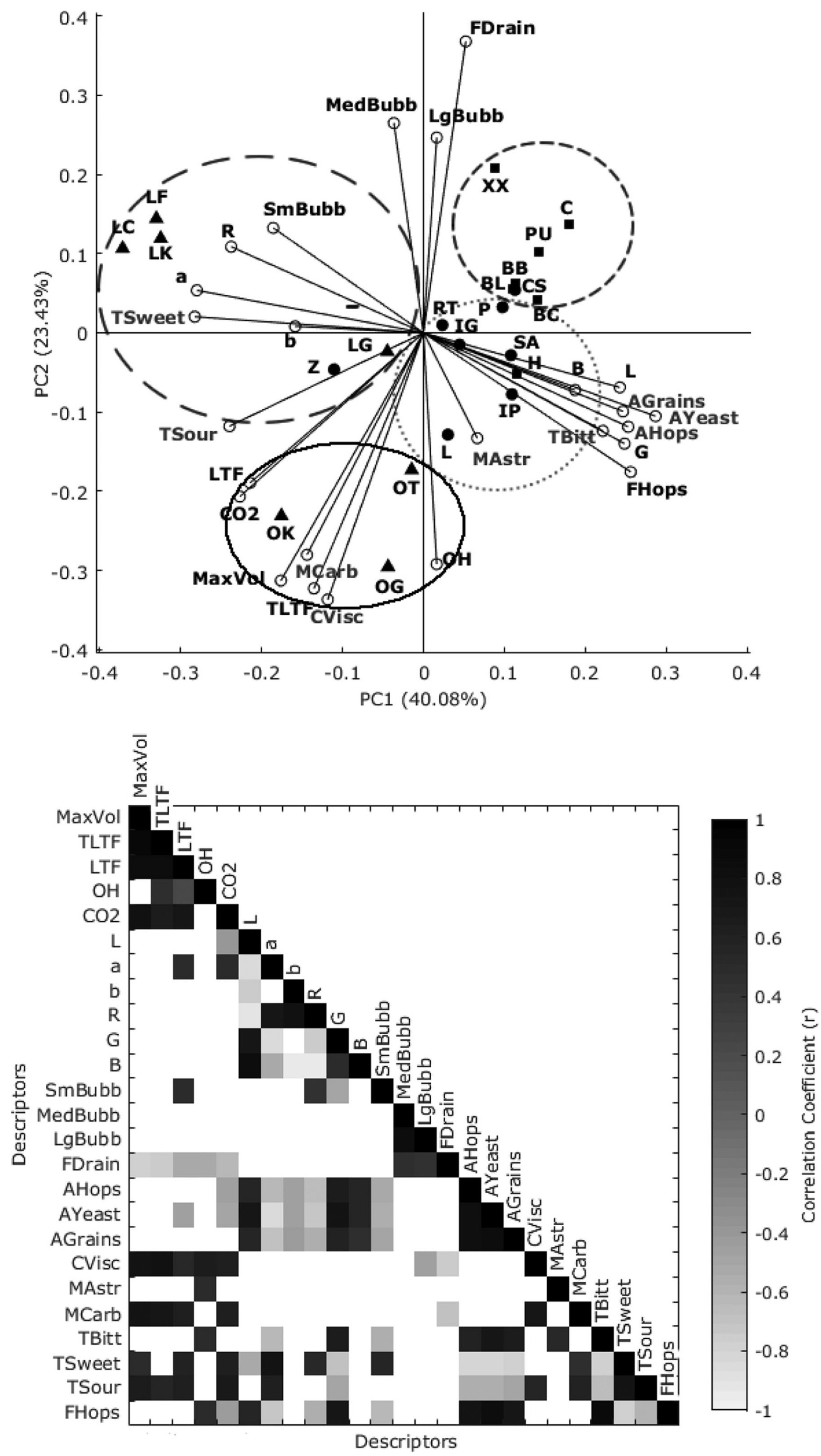

Figure 2–Multivariate data analysis showing: (a) PCA from the RoboBEER foam and color parameters: (i) maximum volume of foam (MaxVol), (ii) total lifetime of foam (TLTF), (iii) lifetime of foam (LTF), (iv) foam drainage (FDrain), (v) number of large (LgBubb), (vi) medium (MedBubb), and (vii) small bubbles (SmBubb) in the foam, (viii) CO_2, (ix) alcohol content (OH), and color parameters in both scales (x, xi, xii) CieLab (L, a, b) and (xiii, xiv, and xv) RGB. The samples abbreviations are listed in Table 1 and grouped by type of fermentation (top: circles, bottom: squares and spontaneous: triangles), *x*-axis represents principal component 1 (PC1) and *y*-axis represents principal component 2 (PC2); and (b) correlation matrix showing the descriptors in both axes and the significant correlation values in the color bar in which black represents positive and light gray negative correlations. Dark gray descriptors represent the RoboBEER parameters, while the light gray descriptors represent the sensory attributes studied (Table 2).

attributed to the fact that the surfactant substances, such as proteins and carbohydrates, contained in beers are able to increase the viscosity of the liquid and, therefore, contributing to foam stability, hence, the higher the viscosity the higher the foam stability and the lower foam drainage (Figure 2b) (Delcour & Hoseney, 2010; Depraetere, Delvaux, Coghe, & Delvaux, 2004). Furthermore, there was a positive correlation between TSweet, and the MaxVol and LTF ($R = 0.49$ and $R = 0.58$, respectively); likewise, TSweet had a positive correlation with SmBubb ($R = 0.56$), which at the same time was positively correlated with LTF ($R = 0.50$); all this

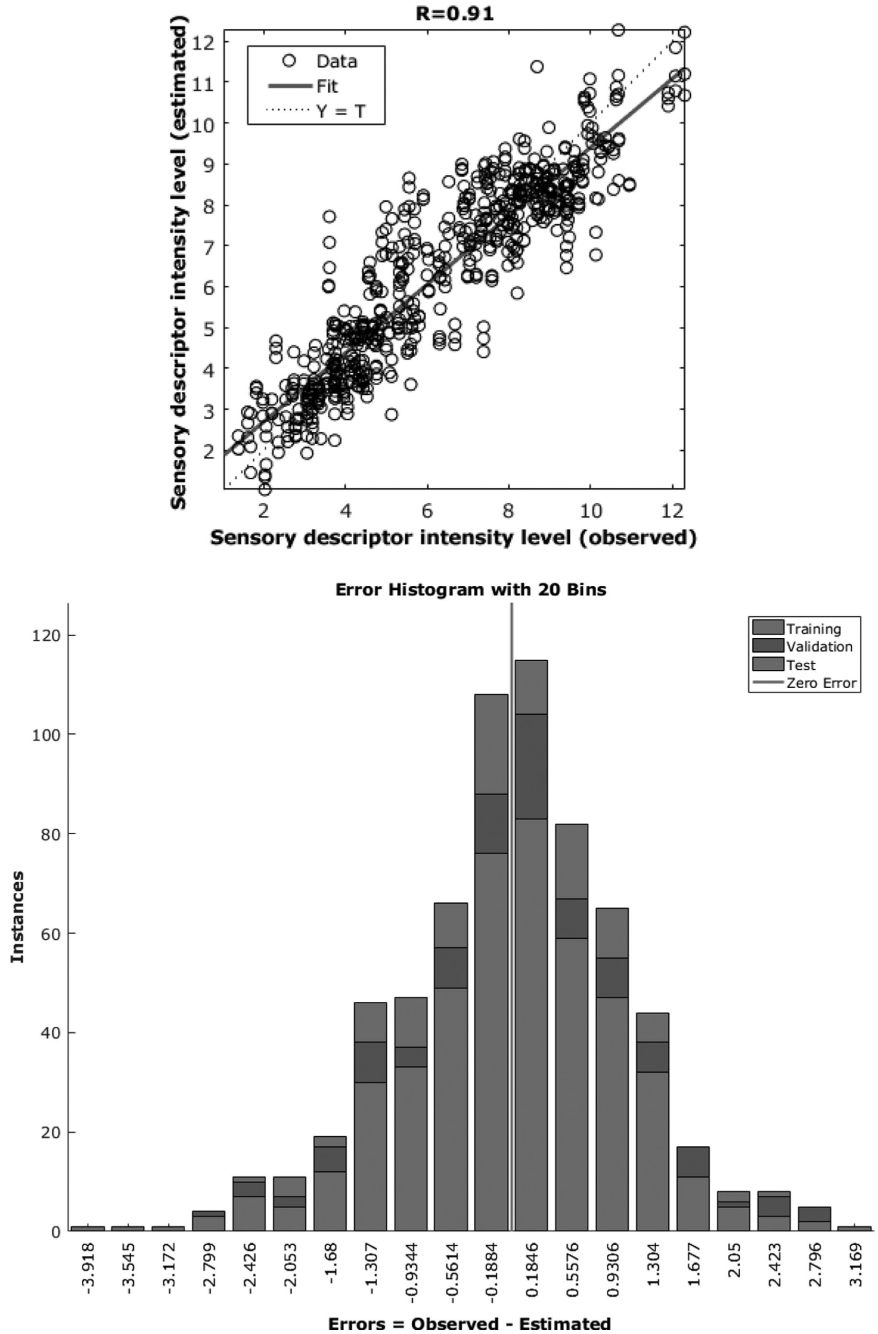

Figure 3–Results from artificial neural networks showing (a) the overall model obtained with a high correlation ($R = 0.91$). Both axes represent the 15-point scale used for the 10 sensory descriptors with the *x*-axis corresponding to the data from the trained sensory panel (observed) and the *y*-axis the ANN modelled data (estimated). (b) The error histogram that presents a normal distribution in which the *x*-axis represents the errors calculated as observed minus estimated.

is related to the contribution of carbohydrates to foam stability, which is achieved because sugars are able to increase the viscosity of the bulk phase and reduce the rate of liquid drainage in the lamella (Badui, 2006; Bamforth et al., 2011). In the case of small bubbles, these contribute to foam creaminess, which give a higher foam stability (Depraetere et al., 2004). On the contrary, large bubbles produce a coarse foam, which, at the same time, decrease the viscosity and cause an increased rate of foam drainage that coincides with the negative correlation between CVisc and LgBubb ($R = -0.45$) and the positive correlation between FDrain and LgBubb ($R = 0.43$) (Bamforth, 1985). The positive correlation between TSour and MaxVol ($R = 0.64$), TLTF ($R = 0.56$), and LTF ($R = 0.62$) is related to the influence that pH has on the foamability in beer as, the closer the protein to its isoelectric pH, the higher the foam stability (Badui, 2006; Gonzalez Viejo et al., 2017).

The release of CO_2 had a positive correlation ($R = 0.62$) with the carbonation mouthfeel (MCarb), which would indicate that the amount of carbonation in the beer was accurately perceived by the trained panel. The positive correlation of TSweet with red color (R and a) ($R = 0.52$ and $R = 0.76$, respectively) were consistent with results found by Abeytilakarathna, Fonseka, Eswara, and Wijethunga (2013) in which Brix content had a direct correlation with red color in fruits, as the red colored beers used in this study have red fruits juice within their ingredients. Finally, the correlation between the AGrains and AHops with color

Table 3–Statistical data for the artificial neural networks model showing the correlation (R) and determination (R^2) coefficients and means squared error (MSE) for the training, validation and testing stages, and overall model.

Stage	Samples	Means squared error (MSE)	Correlation coefficient (R)	Determination coefficient (R^2)
Training	46	0.98	0.92	0.85
Validation	10	1.55	0.87	0.76
Testing	10	1.00	0.93	0.86
Overall	66	0.90	0.91	0.83

parameters coincides with the contribution that malted barley and hops (tannins) have to the color in beers, as the malted barley exposed to high temperatures during kilning in the brewing preprocess goes through the Maillard reaction and, in some cases, the caramelization and pyrolysis of sugars, which cause the brown color to be higher or lower depending on the time and temperatures used during this stage of brewing (Figure 2b) (Piggott, 2011).

ANN model development

As shown in Figure 3a, a high overall correlation and determination coefficients ($R = 0.91$, $R^2 = 0.83$) were obtained using the 15 foam-related and color parameters from the RoboBEER as inputs and 10 sensory descriptors (Table 2) as targets, which is consistent with the levels of correlation found among these parameters (Figure 2a and 2b). The results obtained for the correlation were consistent even after several retraining attempts, furthermore, data were tested both normalized and non-normalized, obtaining similar results (data not shown). Additionally, the MSE, correlation, and determination coefficient values for all stages and overall model are shown in Table 3. Although the MSE values appear to be high, the errors for the model training, validation, and testing stages were normally distributed (Figure 3b). The slope for the overall model was 0.98 and was statistically significant with a P-value <0.0001.

This model would allow prediction of the level of intensity of 10 different sensory descriptors (Table 2) that are representative of beer quality using parameters obtained automatically from RoboBEER. The model developed meets some specifics that the ANN requires to avoid overfitting such as: (i) the number of inputs (inputs = 15) needs to be smaller than the number of samples used for the training stage ($n = 46$), (ii) the network is small enough to avoid having enough power to overfit the model. The advantage of this type of ANN is that it consists of three different stages: (i) training which is used to compute the gradient and update the weights and biases, (ii) validation used to minimize the error and prevent overfitting by monitoring the validation error in the training stage, and (iii) testing which is used to compare different models (Beale, Hagan, & Demuth, 2017).

The advantages of ANN modeling over other linear and nonlinear methods are that it allows to create a single multitarget model function that can be fed with new data to obtain numerical values for the prediction of every single target. Furthermore, the model will learn and find further patterns when more data is included, hence strengthening the accuracy of new predictions and profiling specific styles that are desired by consumers of specific brewing companies. However, it has to be monitored to avoid having a very large database that could cause overfitting. In the industry, it is common that the evaluation of beer quality in terms of sensory is performed mainly by the master brewer who tastes the samples and decides whether the beer meets the expected descriptors or not, but this is highly subjective, usually relies on one or two assessors, and does not provide quantitative and consistent data that can be assessed later by other people within the company. Therefore, the models developed in this study would contribute to reducing the variability from human error as well as to increasing the accuracy of replicability of measurements. Furthermore, the use of RoboBEER to predict intensities of sensory descriptors would provide both physicochemical and sensory parameters, which would give more objective information about the quality of all batches produced. The implementation of this method would be available on request, under data security policies, to small, medium, and large brewing companies, generating a comprehensive database of samples that could contribute to the sustained improvement of existing products and the development of new products to supply a growing brewing market.

Conclusion

The robotic pourer for beer (RoboBEER) coupled with machine learning modeling techniques, is shown to be effective and accurate to assess beer quality in terms of its color, foamability, and related sensory descriptors. Although this method does not intend to completely replace the use of traditional sensory techniques with humans, it can potentially be used as a rapid method at the end of the production line for beer processing to assess samples from every single batch. The ANN model obtained would allow the determination of levels of intensity of the most relevant sensory descriptors investigated straight from the final product. It may be used as a screening method to assess differences between products to decide whether or not to conduct a difference test in case of product development without the need of gathering trained panelists and time-consuming data analysis, which makes the method more reliable and replicable, less time consuming, and more cost-effective. Finally, the RoboBEER can handle repetitive sampling and does not suffer from fatigue as human panelists do, which helps to obtain more consistent, representative, and repeatable results that will help the industry in achieving their specific quality more efficiently.

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Author Contributions

C. Gonzalez Viejo contributed in the design of the RoboBEER specifically for these experiments, to the experimental design, to the data analysis, and to writing of the manuscript.

S. Fuentes devised the RoboBEER and did quality control of data acquisition and processing, helped devise the hypotheses and the machine learning models, including validation and testing, and to the writing.

K. Howell contributed with knowledge on the fermentation and chemistry background information of beers used and writing the paper.

D. Torrico contributed with the sensory training, sensory trial, data acquisition and analysis, and to the writing of the paper.

F. Dunshea contributed in the general planning of the experiments and writing the paper.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Table S1. Means of the 15 parameters measured with the RoboBEER in first row and their standard deviation (SD) in second row.

Table S2. Means, standard error of the means (SME) and letters of significance of the intensity of the 10 sensory descriptors.

Table S3. Factor loadings of the two principal components for each parameter.