ProfilePrint

A.I. Powered Coffee Cupping and Grading

More Accurate and Consistent Rapid A.I. Technology

profileprint.ai
@profileprint.ai
profileprint

ADDRESS
20 Lengkok Bahru
#01-14 Enabling Village
Singapore 159053

CONTACT
info@profileprint.ai
+65 8769 0918

> In 2020/2021, almost 10 million tonnes of coffee were consumed worldwide[1]

Demand for coffee has been increasing steadily, with the global coffee market valued at USD 102.02 billion in 2020[2]. As consumers are getting more conscious about the products they are purchasing, there's a surge in demand for certified coffee products to ensure the reliability of their purchase. The most important determinant of coffee quality is its flavour profile, which is largely due to the perception of taste and aroma molecules.

The complexity of coffee flavour is due to biochemical and chemical changes from harvesting to final processing. Generation of the final coffee flavour happens during the roasting process, which encompasses a series of complex chemical reactions that have yet to be fully elucidated[3]. Therefore, evaluation of coffee quality is usually done by roasting of the green coffee, grinding of roasted beans, preparation of coffee liquid and generation of cupping scores by trained professionals.

Current quality evaluation methods are time-consuming and subjective

Working with trained graders, we have found that their scores are significantly different from one another. This is further backed by research findings, which show that there's high variability between different cuppers, with low inter-rater reliability[4,5]. Another study also found that the interpretation of each sensory descriptor is subjective among the graders, therefore scores cannot be used interchangeably[6]. Training of experts can be tedious and expensive, yet there's still no universal standard of quality control of coffee due to its subjective nature[7].

As such, there has been increase in studies in using AI to improve sensory data, particularly in interpretation of cupping scores[8,9]. Here at ProfilePrint, we believe that AI technology must work hand-in-hand with the trained experts in order to bridge the gap in quality evaluation. Selection of the right statistical tools and models can help to reconciliate some of these differences and generate a more representative result.

Additionally, processing of the green coffee beans is needed for quality evaluation. This includes roasting, cooling and grinding. Each of the processes has parameters that requires strict control, such as temperature and time, which will impact the final quality of coffee itself. This makes the entire evaluation process onerous and tedious. Many studies conducted on coffee and its flavour profile used roasted coffee beans as well, and most of the experiments required separation techniques such as gas-chromatography mass-spectrometry (GC-MS), which can take around one hour per sample to generate a spectrum.

Table 1. Model Metrics from Trained Model of Cupping Scores

	Ground green beans		Whole green beans	
	CV R2	Calibration R2	CV R2	Calibration F
Fragrance | Aroma	0.951	0.997	0.951	0.994
Flavor	0.929	0.992	0.955	0.997
Aftertaste	0.959	0.994	0.954	0.995
Acidity | Salt	0.928	0.993	0.940	0.996
Body	0.931	0.992	0.940	0.996
Balance	0.957	0.994	0.948	0.997
Overall	0.953	0.993	0.952	0.997

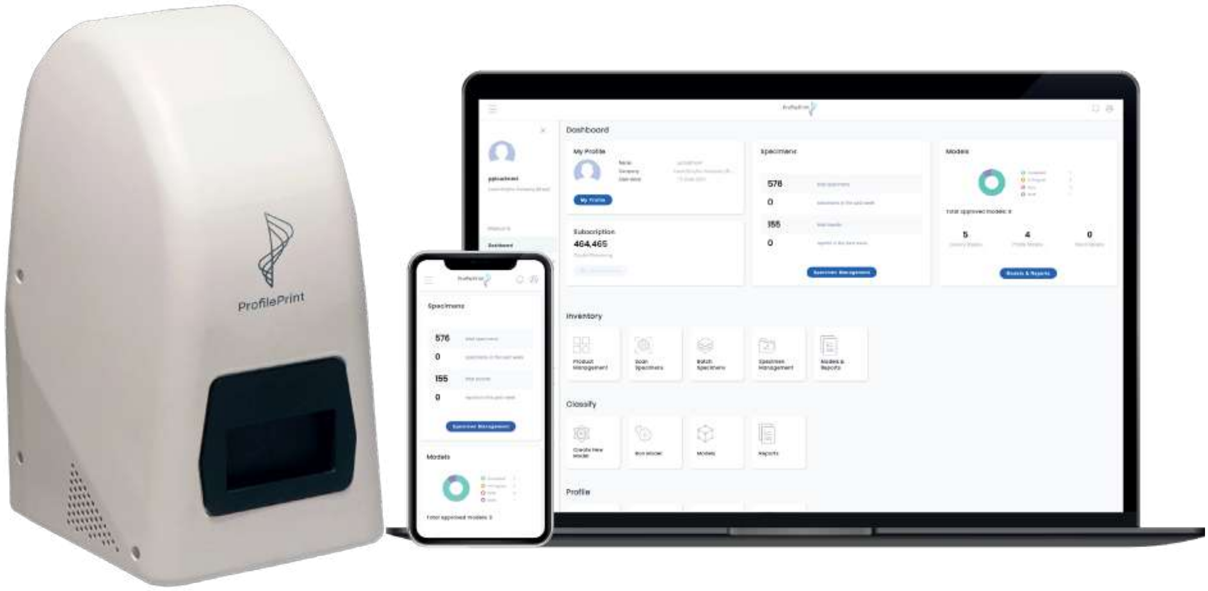
From the experiments we have conducted, we have found that the fingerprints of green coffee beans obtained from our technology were correlated with the cupping scores (Table 1). Despite having little aroma that's characteristic of the final product, green beans contain all the necessary precursors for flavour generation during the roasting process. The type and quantity of precursors are influenced by genetics, environment, coffee maturation, post-harvest processing and storage[10]. Quality scores of coffee brews were also found to be correlated with proportion of caffeine, protein, chlorogenic acids and sucrose[11].

This is not surprising as sugars in green coffee can undergo caramelization process to generate furans, while it can also participate in the Maillard reaction with amino acids to generate pyrazines, aldehydes and ketones. Caffeine is commonly associated with bitterness, while chlorogenic acids will be broken down to caffeic and quinic acid which further contributes to the bitterness and astringency. Moreover, the carotenoids in green coffee is also converted to (E)-beta-damascenone, which contributes to the fruity aroma of coffee. Therefore, green beans contain much of the information necessary for the prediction of the final coffee quality.

Rapid and reproducible quality evaluation by ProfilePrint

ProfilePrint uses broad spectrum region including visible and NIR to generate a unique fingerprint for each specimen, which is essentially spectral information from the second and third overtone region[12]. The data is then stored and fed into an AI-algorithm in ProfilePrint's SaaS platform, and a model is generated, which can be used to make the intended predictions. For instance, predicting cupping scores is one of our key focus areas. More recent research has been conducted to relate sensory data with spectral data of coffee beans and results have generally been positive[13,14]. This is because the information embedded in the spectra tells us about the bonds present in the sample, which relates to the sugars, proteins, lipids and other compounds that contributes to the profile of roasted coffee. We have built several models on the cupping scores, with cross-validation R2 of up to 0.95.

What discerns ProfilePrint from traditional methods is our patented technology that leverages on advancement in A.I. methodologies onto the overtone metabolomic signatures, including both visual peaks as well as non-visual patterns. The method is non-destructive and does not require further sample dilution (due to high absorption) compared to methods like Fourier Transform Infrared Radiation (FTIR). We have also found that increasing sample homogeneity by grinding the green coffee samples (Table 1), the respective model performance of ground coffee and whole beans were comparable. Additionally, our SaaS platform provides an easy way for model generation that does not require experts to use, empowering the democratisation of A.I. technologies in a traditional industry.



Classification models can also be built, especially for defect detection, origin classification etc. For instance, one common defect of coffee is known as the aging defect, which results in a flattening of the flavour profile. Instead of evaluating its cupping score, one can generate a pass/fail model to determine if the green bean's quality have indeed deteriorated over time. This is due to the fact that quality losses from prolonged storage were caused by lipid oxidation as well as moisture content of the beans and these changes can be picked up by the range of the ProfilePrint analyser[15,16]. We have trained and evaluated a model with both calibration and validation accuracy of 1.

Other defects not due to storage can also be determined. Part of ProfilePrint's range includes the visible light, which can also detect colour changes of the beans, which have been found to be a marker for quality changes not due to prolonged storage[17]. The usefulness of the visible light range used in the ProfilePrint analyser, which is not found in conventional NIR machines, has not been well documented in literature. However, it is validated to be therefore useful in this aspect. Additionally, it can also detect the precursors of aroma, such as carotenoid, which is highly correlated to the fruity aroma of the coffee.

What's Next?

Coffee is a complex field of study – the relationships among different coffee compounds are not fully understood. Being a natural product, inter-sample variation will definitely be present[18], and thus conducting a one-time research may not be representative of the findings. This is where AI accelerates the transformation. Learning is a continuous process, and using AI and ProfilePrint's rapid fingerprinting technology, information will be regularly updated and quality of the models can be continuously improved.

References

[1] Conway, P., & 4, F. (2021, February 04). Global coffee consumption, 2020/21. Retrieved April 27, 2021, from https://www.statista.com/statistics/292595/global-coffee-consumption/

[2] Coffee market - Growth: Trends: Forecast (2021 - 2026). (n.d.). Retrieved April 27, 2021, from https://www.mordorintelligence.com/industry-reports/coffee-market

[3] Wei, F., & Tanokura, M. (2015). Chemical changes in the components of coffee beans during roasting. In Coffee in health and disease prevention (pp. 83-91). Academic Press.

[4] Worku, M., Duchateau, L., & Boeckx, P. (2016). Reproducibility of coffee quality cupping scores delivered by cupping centers in Ethiopia. Journal of Sensory Studies, 31(5), 423-429.

[5] Giacalone, D., Steen, I., Alstrup, J., & Münchow, M. (2020). Inter-rater reliability of "clean cup" scores by coffee experts. Journal of Sensory Studies, 35(5), e12596.

[6] Di Donfrancesco, B., Gutierrez Guzman, N., & Chambers IV, E. (2014). Comparison of Results from Cupping and Descriptive Sensory Analysis of C olombian Brewed Coffee. Journal of Sensory Studies, 29(4), 301-311.

[7] Feria-Morales, A. M. (2002). Examining the case of green coffee to illustrate the limitations of grading systems/expert tasters in sensory evaluation for quality control. Food Quality and Preference, 13(6), 355-367.

[8] Tham, H. J., Tang, S. Y., Teo, K. T. K., & Loh, S. P. (2016, June). A review on intelligent sensory modelling. In IOP Conference Series: Earth and Environmental Science (Vol. 36, No. 1, p. 012065). IOP Publishing.

[9] Livio, J., & Hodhod, R. (2018). AI Cupper: A fuzzy expert system for sensorial evaluation of coffee bean attributes to derive quality scoring. IEEE Transactions on Fuzzy Systems, 26(6), 3418-3427.

[10] Poltronieri, P., & Rossi, F. (2016). Challenges in specialty coffee processing and quality assurance. Challenges, 7(2), 19.

[11] Barbosa, M. D. S. G., dos Santos Scholz, M. B., Kitzberger, C. S. G., & de Toledo Benassi, M. (2019). Correlation between the composition of green Arabica coffee beans and the sensory quality of coffee brews. Food chemistry, 292, 275-280.

[12] Barbin, D. F., Felicio, A. L. D. S. M., Sun, D. W., Nixdorf, S. L., & Hirooka, E. Y. (2014). Application of infrared spectral techniques on quality and compositional attributes of coffee: An overview. Food Research International, 61, 23-32.

[13] Baqueta, M. R., Coqueiro, A., & Valderrama, P. (2019). Brazilian coffee blends: A simple and fast method by near-infrared spectroscopy for the determination of the sensory attributes elicited in professional coffee cupping. Journal of food science, 84(6), 1247-1255.

[14] Tolessa, K., Rademaker, M., De Baets, B., & Boeckx, P. (2016). Prediction of specialty coffee cup quality based on near infrared spectra of green coffee beans. Talanta, 150, 367-374.

[15] Kurzrock, T., Kölling-Speer, I., & Speer, K. (2005). Effects of controlled storage on the lipid fraction of green Arabica coffee beans. In ASIC 2004. 20th International Conference on Coffee Science, Bangalore, India, 11-15 October 2004 (pp. 161-168). Association Scientifique Internationale du Café (ASIC).

[16] Rendón, M. Y., Salva, T. D. J. G., & Bragagnolo, N. (2014). Impact of chemical changes on the sensory characteristics of coffee beans during storage. Food chemistry, 147, 279-286.

[17] Selmar, D., Bytof, G., & Knopp, S. E. (2008). The storage of green coffee (Coffea arabica): decrease of viability and changes of potential aroma precursors. Annals of Botany, 101(1), 31-38.

[18] Caporaso, N., Whitworth, M. B., Cui, C., & Fisk, I. D. (2018). Variability of single bean coffee volatile compounds of Arabica and robusta roasted coffees analysed by SPME-GC-MS. Food Research International, 108, 628-640.