AGRICULTURAL ENGINEERING (ENGENHARIA AGRÍCOLA)

Revista Brasileira de Ciências Agrárias
ISSN (on line) 1981-0997
v.18, n.1, e2586, 2023
Recife, PE, UFRPE. www.agraria.pro.br
DOI: 10.5039/agraria.v18i1a2586 - Protocol 2586
Subm. 09/05/2022 • App. 06/02/2023 • Pub. 14/03/2023

Effectiveness of a cherry coffee sorter prototype with image recognition using machine learning

Miguel Angel Valles-Coral[1]*, Carlos Ivan Bernales-del-Aguila[2], Elmer Benavides-Cuvas[2], Lenin Cabanillas-Pardo[2]

[1] Universidade Universidad Nacional de San Martín, Tarapoto, San Martín, Peru. E-mail: mavalles@unsm.edu.pe
[2] Asociación Valle Grande, Moyobomba, San Martín, Peru. E-mail: ivan3262@hotmail.com; vallegrande2018@gmail.com; lpardocab@unsm.edu.pe

ABSTRACT: The production of specialty coffees is the main objective of coffee growers worldwide and depends on the selection of optimal grains; however, especially in Latin America, they are processed manually and are influenced by subjectivity. The objective of the article was to verify the effectiveness of a cherry coffee sorting prototype with image recognition using machine learning in real time compared to the traditional method in the Valle Grande Association, Peru. Covolutional neural network processing was used. 24,000 images labeled in the LabelImg program of green, ripe, pinton, over-ripe and dry Catimor grains were trained with the YOLOv3 algorithm. The results describe the mechanical-electronic design and assembly procedure of the prototype with the necessary technical specifications for its replication; In addition, they demonstrate their effectiveness in reducing the selection time by approximately 3 hours, with a precision level of 94.0% in four samples of 100 kg of coffee. It is concluded that the prototype is a potential alternative, reducing cost, saving time and providing a useful tool to guarantee the selection of grains that allow obtaining quality higher than 83 SCAA points.

Key words: Catimor; CNN; computer vision; YOLO

Efectividad de un prototipo seleccionador de café cerezo con reconocimiento de imágenes usando machine learning

RESUMEN: La producción de cafés especiales es el objetivo principal de los caficultores a nivel mundial y depende de la selección de granos óptimos; sin embargo, especialmente en Latinoamérica, son procesados de manera manual y está influenciado por la subjetividad. El objetivo del artículo fue comprobar la efectividad de un prototipo seleccionador de café cerezo con reconocimiento de imágenes usando machine learning en tiempo real frente al método tradicional en la Asociación Valle Grande, Perú. Se empleó el procesamiento de redes neuronales covolucionales. Se entrenaron con el algoritmo YOLOv3 24.000 imágenes etiquetadas en el programa LabelImg de granos Catimor verde, maduro, pintón, sobre-maduro y seco. Los resultados describen el procedimiento de diseño y ensamblaje mecánico-electrónico del prototipo con las especificaciones técnicas necesarias para su replicación; además, demuestran su efectividad respecto a la reducción del tiempo de selección en 3 h aproximadamente, con un nivel de precisión del 94,00% en cuatro muestras de 100 kg de café. Se concluye que el prototipo es una alternativa potencial, reduciendo el costo, ahorrando tiempo y proporcionando una herramienta útil para garantizar la selección de granos que permita obtener calidad superior a 83 puntos SCAA.

Palabras clave: Catimor; CNN; visión artificial; YOLO

* Miguel Angel Valles-Coral - E-mail: mavalles@unsm.edu.pe (Corresponding author)
Associate Editor: Edna Maria Bonfim Silva

Introduction

Although coffee (*Coffea arabica* L.), due to commodities such as oil, gold, and other minerals, has gone from occupying 60.0% of exports during the 1970s to only 5.0% in the current decade, it remains the historically most traded tropical product in Latin America (Pineda et al., 2019). Its consumption and economic relevance is undeniable and constitutes an important livelihood for millions (Briceño-Martínez et al., 2020), so much so that European countries encourage alternative systems of production and trade that are environmentally sustainable and equitable in the distribution of the profits it generates (Estevez et al., 2018).

During 1994 to 2013, Brazil, Colombia, and Peru were the Latin American countries that accounted for the largest share of international coffee trade, and it was also in those years that Peru managed to increase its relative share (Sanchez Arevalo et al., 2016). In addition, in Peru until 2018, coffee was in first place as a percentage of the agro-export sector, with the European Union (EU) as the main destination because of the Acuerdo Comercial Perú - EU, followed by the United States.

According to Díaz Vargas & Willems (2017) in their "Baseline of the coffee sector in Peru", the perennial crop planted in the inter-Andean valleys and with greater coverage in the high jungle, is the main agricultural export product in Peru. However, the deficient competitiveness of the sector has a direct impact on the low yield and productivity of coffee plantations, and this has a negative impact on the quality of life and socioeconomic level of coffee growers and producers.

According to Ramos Giraldo et al. (2015), the need for manual intervention in all stages of the process represents the highest costs and consequently affects the competitiveness of the sector compared to countries that have high levels of mechanization and technification of the crop. Although Peru and Colombia are the main exporters of coffee at the South American level, processing is still still done manually without taking advantage of the opportunities provided by machine learning based agricultural technologies (Liakos et al., 2018).

Exporting coffee to the best markets, requires ensuring the quality of the product based on its organoleptic characteristics related to the size, smell, and color of the fruit, in addition to 850 other identified compounds (Gutiérrez G. & Barrera B., 2015) that are evaluated during the selection phase (Rosas-Echevarría et al., 2019). A rigorous selection method during coffee processing will allow better values to be obtained during cupping and tasting in order to obtain a better perspective of the properties of the coffee produced (Suarez-Peña et al., 2020). However, human error in the selection process requires the application of statistical methods, protocols, and standardized analysis that can only be acquired through experience in the field.

The Valle Grande Association in the Alto Mayo area, in the province of Moyobamba, has a low production of specialty coffees, with cup quality averages of less than or equal to 83 points according to the sensory evaluation method of the Specialty Coffee Association of America (SCAA) according to the association expert cupper. This does not allow it to be competitive in the market and achieve better prices because, as indicated by Buendía-Espinoza et al. (2020), cup quality is necessary to generate alternatives that ensure the quality and differentiation of coffee. One factor that causes this is the manual selection process of cherry coffee, with a high degree of subjectivity and error (Rosas-Echevarría et al., 2019), reaching 15.0% over-ripe beans, 2.0% dry beans, and 3.0% green beans.

It is necessary to evaluate or design equipment that automates the process to ensure the selection of the best coffee bean, applying statistical methods based on numerical measurements of physical properties that can be performed by devices, with reproducible results and minimum margins of error as the design of Suarez-Peña et al. (2020) who apply machine learning, as well as Oliveira et al. (2016) build an artificial vision system that classifies coffee beans according to their color. Among other examples of devices and applications related to coffee selection, we find the work of Huang et al. (2020), Pinto et al. (2017), and Wiggers et al. (2022) who apply computer vision methods based on covolutional neural networks.

According to El Wahabi et al. (2020), using machine learning processes increases the economic performance of companies and those that do not do so due to the need to include them in their industrial processes will see their growth deteriorate and even melt out of existence in the next five years. Therefore, machine learning - a branch of artificial intelligence - generates algorithms with the ability to learn in a supervised or unsupervised manner without the need to program them explicitly (Sandoval, 2018); and complemented with computer vision that emulates the functioning of human vision, they are tools that allow performing mathematical operations quickly and learning patterns for image recognition with the objective of extracting specific attributes (Parra et al., 2018).

The objective is to test the effectiveness of a cherry coffee selection prototype with real-time image recognition through the application of machine learning versus the traditional selection method, in order to obtain homogeneous ripe cherry coffee and maintain cup quality in the Alto Mayo valley, department of San Martin. This made it possible to innovate the selection process by developing and applying technology at the prototype level, making it more efficient in order to increase the quality of the grain measured in terms of the SCAA sensory evaluation method.

Materials and Methods

The research was carried out at the Valle Grande Association collection center, located in the district of Soritor, province of Moyobamba, Peru. The area is also known as the Alto Mayo valley, located at 637 m above sea level. It has an average temperature of 19 °C, with a relative air humidity of 77.0% and average annual rainfall of 1,477 mm. As for the type of study, it was a technological development study based on

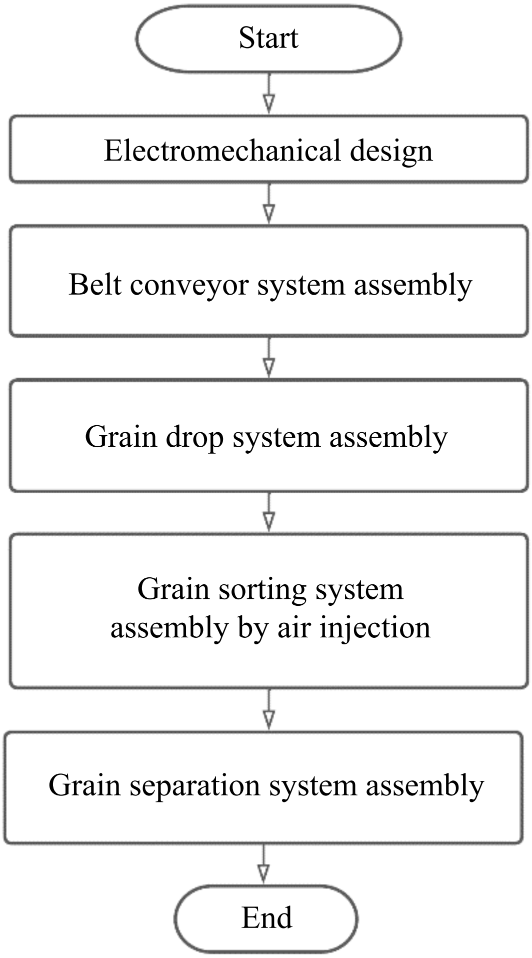

Figure 1. Flow chart of the prototype assembly procedure.

the proposal of Ramos Giraldo et al. (2015), which proposes a structured methodology for the design of a selective coffee harvesting system. The prototype assembly procedure followed the steps shown in Figure 1.

The assembly of the belt and vacuum conveying system was installed by gravity drop according to the proposed prototype dimension of 2 t batch/h, ensuring that the drop system serves for the machine vision system to focus accurately. For the assembly of the grain selection system, air injection connected to the artificial viewer that integrated the sorting algorithm was used. Finally, the separation system pushes the grains to the corresponding sections to be dropped into trays to be transported to the next sub-processes. Upon completion, the final proposal was adjusted to 0.5 t batch/h.

Image recognition and machine learning

Images were taken in the same environment as the prototype channels under normal grain passage conditions. Manually over six months, 24,000 images were separated and labeled, of which 80.0% were for training and 20.0% for random testing. The images were captured in RGB format, then transformed to BGR for use by the YOLOv3 algorithm, which internally transformed them into HSV for processing.

The imaging equipment was a 30 FPS 5 Mpx camera, which was used to capture the moving images of the objects, the same equipment that has been used in the reading of images for the identification of the type of grain. Image labeling was performed to indicate what type of grain each photograph is in order to move on to training. For this purpose, the LabelImg program was used to generate a .txt file containing the labels (type of grain) and to record the coordinates of the image. The labels identified were green, ripe, pinto, over-ripe, and dry (Figure 2).

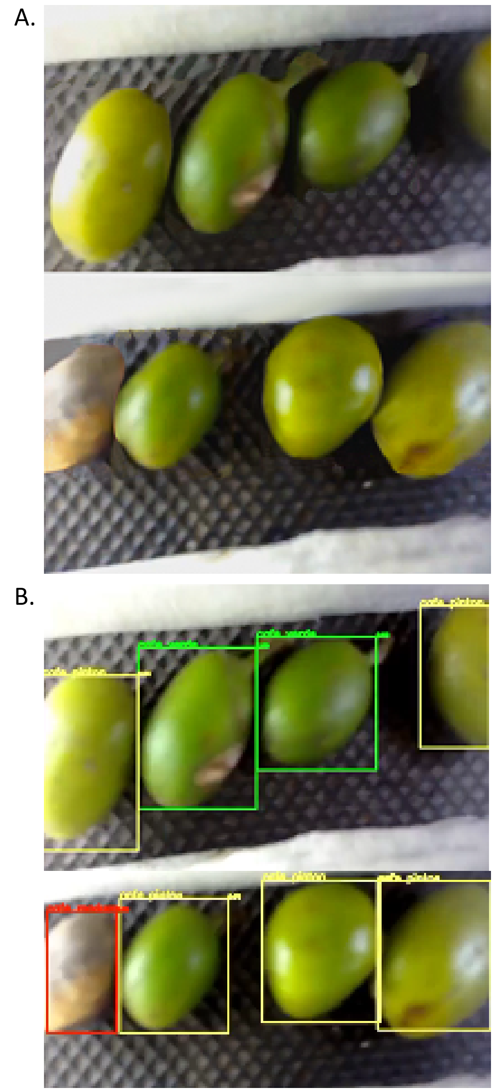

Figure 2. Coffee beans on the band of the prototype (A) original and (B) identification YOLOv3.

A literature review was conducted to determine the most feasible machine learning-based image recognition algorithm to implement. Covolutional neural network (CNN) processing was selected because it is a machine learning model for image or video recognition capable of training data at high speed without much computational capacity that, when compared to other models, presents advantages in terms of performance and accuracy (Sandoval, 2018; Wiggers et al., 2022).

The labeled images were trained with the YOLOv3 (You Only Look Once) algorithm, which is based on CNN named Darknet for image classification that adds the detection part in frames indicating the object coordinates (Bazame et al., 2021;

Wiggers et al., 2022). The source code for this technique is in Python, which has 80 network weights and 53 default neural network layers. During training, 133 epocs were performed, an acceptable level of accuracy, which had an efficiency of 75.0%.

The deployment of the predictive model was performed on a computer with 16 Gb RAM, eight-core processor and 8 Gb graphics card with CUDA support from Nvidia. This was saved in a .pth file, which was then loaded on the PC and a program made in Python was run where it captures the video and makes the comparison to identify the type of grain and generate the air injection action. Algorithms can be requested from the corresponding author.

Functional testing and data analysis

The possible synchronization and real-time image calibrations were performed. The processing target of 0.5 t batch/h, since it was supported by five rails. A 6 hours functional test was performed to know the operation of the air rails and solenoid valves, in order to identify possible imperfections to correct and adjust the electronic part of the selector.

The prototype was used to process 100 kg of coffee per four replicates using a single rail. The results of the selection were organized in Excel. The final quantity (%) of green, ripe, pinto, over-ripe, and dry beans, and the precision of selection (%) were recorded, as well as the processing time (minutes), which were then compared with the information from the traditional selection of coffee beans at the Valle Grande Association. In addition, the selected mature (optimum) grain was sensorially evaluated to measure its influence on quality.

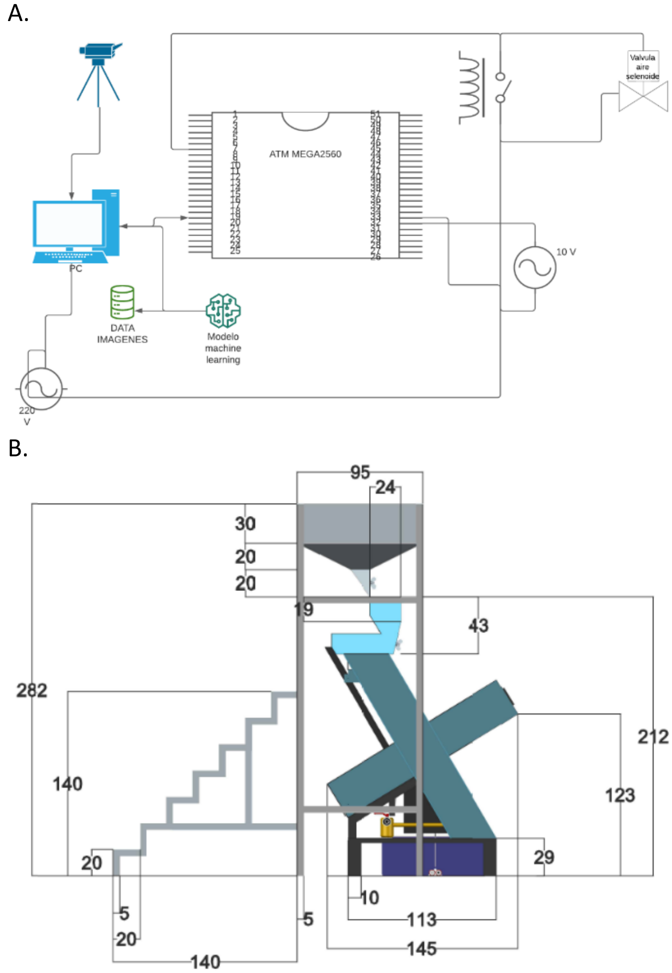

Figure 3. Prototype selector (A) prototype sketch and (B) structural design.

Results and Discussion

Prototype design and assembly

According to the requirements and proposals for the design and assembly of the prototype, the sketch, structural design, and 3D design were made in AutoCAD 2020 software (Figure 3). The design consisted of a hopper system and a pre-picker that transports the coffee beans through channels to be selected and generate their separation by air injection, which is driven by an electronic panel connected to cameras and a computer that interprets the type of bean based on the YOLOv3 algorithm.

Regarding the electromechanical assembly procedure, the general structure had four 1½ × 3/16 in. angles, with a height of 2.80 m. In addition, a 1/8 fluted iron ladder of 1.3 × 1.4 m was attached. A 1.2 mm thick stainless steel hopper was assembled with dimensions of 96.0 × 1.3 m with a depth of 85.0 cm. It was assembled with 1.2 mm thick die-cut INOX plates, rolled with a diameter of 39.0 cm and a cylinder length of 1.0 m, which is rotated at 35 r/min by a 1 HP motor reducer, having its own frame made of 1.5 × 1.5 in. INOX tubes.

A two-phase rotation system was assembled for the output of small grains and the output of large grains, in order to standardize the size of the samples for the selection by images with artificial vision. The system was designed to support free-fall belt speeds, where the grain must pass to be inspected by a camera, and this sends the video in real time to process the images and use the machine learning image processing algorithms, which in turn sends a pulse (command) via serial connection to the ATM board and the relay that activates the solenoid to inject air and fire according to the color.

The air system was used to separate grains and divert them to other channels, understanding that the classification is by green, ripe, pinton, over-ripe and dry type. A 1,100 W air compressor was used, which drifts to another cylinder with air, which through hoses directs to solenoids that have small needles that point to the free-fall channel rail. The part that activates the air output is by means of a relay up to 250 V of 10 A capacity from an electronic board.

Effectiveness of the prototype

Table 1 shows the summary of coffee bean selection with the prototype. The average of the four replicates was 8.25% pinton, 79.00% ripe, 6.75% green, 5.88% over-ripe, and 0.13% dry. The selection accuracy was based on the expertise of the technical, agro-industrial and agronomist team of the Valle Grande Association, with an average of 94.00%. The average processing time was 39 minutes, which is directly related

Table 1. Data collected from the selection of cherry coffee beans with the prototype.

Repetition	Final amount (%)					Accuracy (%)	Time (minutes)
	Pinton	Mature	Green	Over-ripe	Dry		
1	10.00	75.00	6.00	8.50	0.50	93.00	40
2	7.00	81.00	7.00	5.00	0.00	95.00	39
3	8.00	78.00	6.00	8.00	0.00	95.00	39
4	8.00	82.00	8.00	2.00	0.00	94.00	39

to the delay activation to drive the air injector through the arduino and the fixed standard speed (7 r/pm) of the girdle (1.22 m).

Compared to the manual selection of cherry coffee beans at the Valle Grande Association, the average final quantity of ripe beans selected from 100 kg ranges from 68.0 to 75.0%. Regarding accuracy, a maximum average of 85.0% is obtained, and the approximate selection time is 4 hours. These results demonstrate the effectiveness of the prototype compared to the traditional selection, whose referential cost of assembly (Figure 1) amounts to eleven thousand dollars with a useful time according to technological risk of three years.

Rosas-Echevarría et al. (2019) corroborate the results of the present study, who by designing a quality control system with standardized parameters of coffee beans applying segmentation and RGB to HSV transformation, managed to reduce the selection time from 50 kg (2 hours) by approximately one hour. However, it has compared the YOLOv3 algorithm, a reduction of up to approximately 3 hours is obtained in the selection of 100 kg of coffee beans, being a promising alternative as it is considered one of the fastest current techniques to recognize images prior training (Redmon & Farhadi, 2018).

The accuracy of the prototype for bean selection is in the acceptable range (greater than 80.0%) as well as the report of Herrera et al. (2016), who determined a level of effectiveness of 87.0% of an automatic coffee fruit selection system that applied Bayesian algorithms based on the minimum error rule. The results also agree with the research of Portugal-Zambrano et al. (2016), where the classification of physical defects of green coffee beans with a computer vision system achieved 98.8% effectiveness using the White-Patch algorithm, color histograms as feature extractor and SVM for the classification task.

Oliveira et al. (2016) demonstrated that neural networks applied to the evaluation of green coffee bean color articulated to a machine vision system classifying beans into off-white, cane green, green, and blue-green, achieved a generalization error of 1.15% and the Bayesian classifier had 100.0% accuracy of all samples. Close results were found by Huang et al. (2019), who by developing an automatic system for picking coffee beans according to good or bad states with image processing technology through CNN obtained an approximate accuracy of 93.34%.

We infer that neural networks of machine learning based algorithms coupled to a robust technological infrastructure are effective solutions for coffee bean selection, as reflected in the % accuracy in Table 1, and noted by Bazame et al. (2021), stating that YOLO has high processing speed, as it processes images in a single step and predicts object boundaries and probabilities of belonging to classes. Likewise, its implementation was based on YOLOv3 because of its modernity, compared to YOLO and YOLOv2, which is low cost and provides ease of computational design for the detection and classification of coffee beans.

On the other hand, the results of the sensory analysis of the samples of ripe coffee beans (optimum) selected by the prototype, had higher averages of 84 points according to the SCAA standard, reflecting improvements with respect to the 82 points normally obtained in the Valle Grande Association with the traditional selection process. According to Buendía-Espinoza et al. (2020), ensuring the quality of coffee requires standardizing and guaranteeing the selection of ripe or optimal beans that are considered special when processed, an action that the prototype helps to contribute to the Association by reducing selection time, labor and cost optimization.

Although the research is at a prototype level, its effectiveness has been determined in the selection of coffee beans with image recognition using machine learning in real time, specifically with the YOLOv3 algorithm, at an accuracy level of 94.0%, according to green, ripe, pinton, over-ripe, and dry labels, based on the training of 24,000 images of coffee beans of the Catimor variety. Thus contributing to the statement of Bazame et al. (2021), who by applying YOLOv3-tiny achieved an average accuracy for the immature, ripe, and over-ripe Catuaí 144 coffee fruit classes of 86.0, 85.0, and 80.0%, respectively. These results allow the application of machine vision techniques to be extended to other harvest and postharvest processes in agriculture (Guevara-Sánchez et al., 2022), and the Valle Grande Association to use the prototype for its other coffee varieties.

Conclusions

The machine learning based selection prototype is a potential alternative for postharvest coffee, reducing the cost of manual selection processing by 70.0% per campaign from four to five months approximately, saving time and providing a useful tool to guarantee the adequate selection of beans to obtain raw material with a coffee flavor in cup with quality averages higher than the current 83 points.

For the operation of the prototype, a selection software based on the CNN model has been built. The overall effectiveness of the screening prototype was 94.0%. The prototype for selecting coffee beans in real time by applying machine learning is expected to increase productivity in the coffee sector, and its investment would guarantee profitable trade in areas with low technological penetration.

Acknowledgment

To the engineers Lloy Pinedo and Jorge Raul Navarro-Cabrera, of the Universidad Nacional de San Martín, for their support in data processing, systematization of the information, review of the draft, and correction of the final version of the article. In addition, to the bachelor in engineering Milquisaet Jimenez, for his collaboration in the modeling and training of the algorithm.

Compliance with Ethical Standards

Author contributions: Conceptualization: LCP, CIBA; Data curation: LCB, MAVC, EBC; Formal analysis: MAVC, LCB, CIBA; Methodology: LCB, MAVC; Project administration: EBC; Resources: CIBA; Supervision: LCB, EBC; Validation: EBC, MAVC; Writing – original draft: MAVC, LCB; Writing – review & editing: MAVC, LCB.

Conflict of interest: The authors declare that they have no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Financing source: Programa Nacional de Desarrollo Tecnológico e Innovación - ProInnóvate for the financing of the project “Desarrollo de un prototipo seleccionador de café cerezo, con reconocimiento de imágenes usando machine learning en tiempo real, con fines de obtener café cerezo maduro homogéneo y mantener la calidad de taza” under Contract No. 283-INNOVATEPERU-PIEC1-2019.

Literature Cited

Bazame, H. C.; Molin, J. P.; Althoff, D.; Martello, M. Detection, classification, and mapping of coffee fruits during harvest with computer vision. Computers and Electronics in Agriculture, v.183, e106066, 2021. https://doi.org/10.1016/j.compag.2021.106066.

Briceño-Martínez, B.; Castillo-Calderón, J.; Carrión-Jaura, R.; Díaz-Sinche, D. Propuesta de implantación de invernadero de secado de café con cubierta parabólica y estructura modular adaptada. Ingenius, n.24, p.36-48, 2020. https://doi.org/10.17163/ings.n24.2020.04.

Buendía-Espinoza, J. C.; Maldonado-Torres, R.; Amador-Atlahua, L.; Álvarez-Sánchez, M. E. Identification of discriminatory elements to characterize *Coffea arabica* L. using main components. Revista Mexicana de Ciencias Agrícolas, v.11, n.1, p.1-12, 2020. https://doi.org/10.29312/remexca.v11i1.2207.

Díaz Vargas, C.; Willems, M. C. Línea de base del sector café en el Perú. Lima: PNUD, 2017. 56p. https://www.undp.org/sites/g/files/zskgke326/files/migration/pe/Libro-cafe_PNUD_PE.pdf. 17 Feb. 2022.

El Wahabi, A.; Baraka, I. H.; Hamdoune, S.; El Mokhtari, K. Design of a mini robot for the automation of 3D winding machines axes and self-correction by artificial vision using deep learning. In: Ezziyyani, M. (Ed.). Advanced intelligent systems for sustainable development. (AI2SD’2019). Cham: Springer, 2020. p.210-223. (Advances in Intelligent Systems and Computing, v. 1105). https://doi.org/10.1007/978-3-030-36674-2_23.

Estevez, C. L.; Bhat, M. G.; Bray, D. B. Commodity chains, institutions, and domestic policies of organic and fair trade coffee in Bolivia. Agroecology and Sustainable Food Systems, v.42, n.3, p.299-327, 2018. https://doi.org/10.1080/21683565.2017.1359737.

Guevara-Sánchez, M.; Guevara-Sánchez, K. E.; Quispe-Cubas, N.; Valles-Coral, M. A.; Navarro-Cabrera, J. R.; Pinedo, L. Drying effect by infrared radiation on sensory quality in special coffees (*Coffea arabica*) cup. Revista de la Facultad de Agronomía de la Universidad del Zulia, v.39, n.3, e223936, 2022. https://produccioncientificaluz.org/index.php/agronomia/article/view/38365. 25 Aug. 2022.

Gutiérrez G., N.; Barrera B., O. M. Selección y entrenamiento de un panel en análisis sensorial de café Coffea arabica L. Revista de Ciencias Agrícolas, v.32, n.2, p.77-87, 2015. https://doi.org/10.22267/rcia.153202.15.

Herrera, J. C.; Medina, S. M.; Beleño, K.; Gualdrón, O. E. Diseño de un sistema automático de selección de frutos de café mediante técnicas de visión artificial. Revista UIS Ingenierías, v.15, n.1, p.7-14, 2016. https://doi.org/10.18273/revuin.v15n1-2016001.

Huang, N. F.; Chou, D. L.; Lee, C.A. Real-time classification of green coffee beans by using a convolutional neural network. In: International Conference on Imaging, Signal Processing and Communication (ICISPC), 3., 2019, Singapore. Proceedings... Singapore: IEEE, 2019. p.107-111. https://doi.org/10.1109/ICISPC.2019.8935644.

Huang, N. F.; Chou, D. L.; Lee, C.A.; Wu, F.P.; Chuang, A.C.; Chen, Y. H.; Tsai, Y.C. Smart agriculture: real-time classification of green coffee beans by using a convolutional neural network. IET Smart Cities, v.2, n.4, p.167-172, 2020. https://doi.org/10.1049/iet-smc.2020.0068.

Liakos, K.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: a review. Sensors in Agriculture, v.18, n.8, p.2674, 2018. https://doi.org/10.3390/s18082674.

Oliveira, E. M.; Samid Leme, D.; Groenner Barbosa, B. H.; Pereira Rodarte, M.; Fonseca Alvarenga Pereira, R. G. A computer vision system for coffee beans classification based on computational intelligence techniques. Journal of Food Engineering, v.171, p.22-27, 2016. https://doi.org/10.1016/j.jfoodeng.2015.10.009.

Parra, P.; Negrete, T.; Llaguno, J.; Vega, N. Computer vision techniques applied in the estimation of the *Cocoa* beans fermentation grade. In: IEEE ANDESCON, 2018, Santiago de Cali. Proceedings... Santiago de Cali: IEEE, 2018. p.1-10. https://doi.org/10.1109/ANDESCON.2018.8564569.

Pineda, J. A.; Piniero, M.; Ramírez, A. Coffee production and women’s empowerment in Colombia. Human Organization, v.78, n.1, p.64-74, 2019. https://www.proquest.com/docview/2193969608. 17 Aug. 2022.

Pinto, C.; Furukawa, J.; Fukai, H.; Tamura, S. Classification of green coffee bean images basec on defect types using convolutional neural network (CNN). In: International Conference on Advanced Informatics: concepts, theory and applications (ICAICTA), 2017, Denpasar. Proceedings... Denpasar: IEEE, 2017. p.1-5. https://doi.org/10.1109/ICAICTA.2017.8090980.

Portugal-Zambrano, C. E.; Gutierrez-Caceres, J. C.; Ramirez-Ticona, J.; Beltran-Castanon, C. A. Computer vision grading system for physical quality evaluation of green coffee beans. In: Latin American Computing Conference (CLEI), 42., 2016, Valparaiso. Proceedings... Valparaiso: IEEE, 2016. p.1-11. https://doi.org/10.1109/CLEI.2016.7833383.

Ramos Giraldo, P. J.; Navarro, M. G.; Hoyos Suárez, J. F.; Oliveros Tascón, C. E.; Sanz Uribe, J. R. Aplicación de una metodología estructurada para el diseño de un sistema de cosecha selectiva de café. Scientia et Technica, v.20, n.1, p.10-19, 2015. https://doi.org/10.22517/23447214.9009.

Redmon, J.; Farhadi, A. YOLOv3: An incremental improvement. Washington: University of Washington, 2018. 5p. https://tethys.pnnl.gov/sites/default/files/publications/Redmonetal.pdf. 10 Aug. 2022.

Rosas-Echevarría, C.; Solís-Bonifacio, H.; Cerna-Cueva, A. Efficient and low-cost system for the selection of coffee beans: an application of artificial vision. Scientia Agropecuaria, v.10, n.3, p.347-351, 2019. https://doi.org/10.17268/sci.agropecu.2019.03.04.

Sanchez Arevalo, J. L.; Arruda, D.O.; Carvalho, J.P. Competitividade no comércio internacional do café: um estudo comparativo entre Brasil, Colombia e Peru. Organizações Rurais & Agroindustriais, v.18, n.1, p.62-78, 2016. http://revista.dae.ufla.br/index.php/ora/article/view/888. 18 May. 2022.

Sandoval, L. J. Algoritmos de aprendizaje automático para análisis y Predicción de datos. Revista Tecnológica, n.11, p.36-40, 2018. http://redicces.org.sv/jspui/bitstream/10972/3626/1/Art6_RT2018.pdf. 25 Sep. 2022.

Suarez-Peña, J. A.; Lobaton-García, H. F.; Rodríguez-Molano, J. I.; Rodriguez-Vazquez, W. C. Machine learning for cup coffee quality prediction from green and roasted coffee beans features. In: Figueroa-García, J.C., Garay-Rairán, F.S., Hernández-Pérez, G.J., Díaz-Gutierrez, Y. (Eds.). Applied Computer Sciences in Engineering. WEA 2020. Cham: Springer, 2020. p. 48-59. (Communications in Computer and Information Science, v.1274). https://doi.org/10.1007/978-3-030-61834-6_5.

Wiggers, K. L.; Pohlod, C. D.; Orlovski, R.; Ferreira, R.; Santos, T. A. Detection and counting of plants via deep learning using images collected by RPA. Revista Brasileira de Ciências Agrárias, v.17, n.2, e1353, 2022. https://doi.org/10.5039/agraria.v17i2a1353.