Quinoa Quality Inspection

Artificial Vision

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***Abstract*—The current document presents an innovative solution through an artificial vision system to enhance the quality control of quinoa. It aims to address the persistent issue of unwanted contaminants, such as stems and pebbles, which often accompany quinoa cultivation. Leveraging advanced artificial vision techniques, this approach offers a comprehensive solution to this challenge. Starting with the acquisition of a diverse set of quinoa images to train the artificial vision model, meticulous image preprocessing is carried out for consistency and noise reduction. The crucial step of data labeling aids the model's ability to distinguish regions of interest, enabling it to differentiate between quinoa and those regions with impurities. Convolutional Neural Networks (CNNs) are employed as a powerful tool for precise segmentation and detection. The training phase ensures the model can accurately identify and segment quinoa from foreign particles. Post-training validation and fine-tuning ensure optimal performance, and the integration of the trained model into the production line, whether online or offline, ensures real-time impurity removal. This comprehensive approach promises increased efficiency, reduced human errors, and a consistent, high-quality quinoa product, marking a significant advancement in quinoa quality control.**

***Index Terms*—Artificial vision, Convolutional Neural Networks, Quinoa.**

I. Introduction

Given the growing demand for innovative solutions to improve the quinoa separation process, especially in increasingly rigorous production environments, the adoption of cutting-edge artificial vision techniques has emerged as a compelling avenue to enhance efficiency and accuracy.

This approach promises to streamline the process and ensure the production of pure quinoa products, with a focus on studying Quinoa Real, a specific quinoa variety. Subsequently, for better adaptation of the CNN, we diligently assembled the images for the primary dataset, using specific lenses for quality enhancement. Additionally, to ensure a diverse dataset and comprehensive analysis, an additional dataset is presented alongside the main dataset. This strategic choice will allow us to explore the full spectrum of quinoa quality attributes, paving the way for more effective and adaptable solutions to meet the current demand, which is not sustainably met, and improving the Gross Domestic Product of the Plurinational State of Bolivia.

II. Problem

The paramount challenge at present revolves around the separation process to obtain pure quinoa, which is exacerbated by the substantial quantity of quinoa processed daily within production lines. This issue is further compounded by the diminutive size of quinoa grains, which makes their differentiation from other unwanted elements, such as branches and pebbles, a daunting task. The prevailing method employed to tackle this issue relies on manual separation, wherein operators meticulously remove these contaminants from the incoming quinoa. However, this approach is fraught with inefficiencies; it consumes a considerable amount of time and labor, resulting in increased operational costs, while still not delivering the optimal results for achieving high-purity quinoa. As a result, there is a growing need for innovative solutions, like artificial vision techniques, to streamline and enhance the quinoa separation process, offering a more efficient and accurate means of achieving a pure quinoa product in the increasingly demanding production environments.

Regarding quinoa production, the intensification of quinoa production in the South Altiplano region of Bolivia has been primarily oriented towards its export. Over time, export opportunities increased and multiplied from the year 2000 onwards. By the end of 2013 and the beginning of 2014, international prices for this grain tripled, leading to increased production and export volumes. [1]

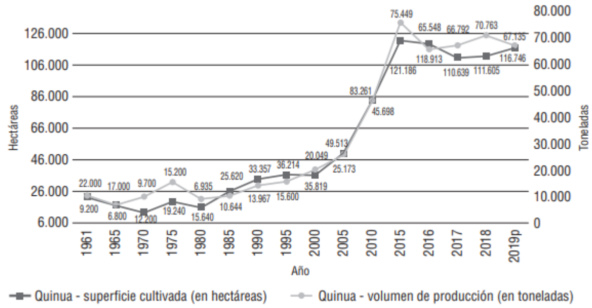

Figure 1. Comparison of quinoa production in Bolivia. [1]

The main exporters in 2020, Peru takes the lead with a value of 124.7 million dollars and an exported quantity of 50,998 tons, followed by Bolivia with a value of 92.4 million dollars and an exported quantity of 37,298 tons. Taking into account that, when adding the percentage shares of Peru and Bolivia, it is observed that they hold a 71% share of total exports, widely leading the global quinoa market as price influencers. [2]

III. Related Work

In the quest for relevant papers pertaining to the project, it is crucial to highlight that the primary focus is on Real Quinoa as the subject of the study. We initiated the literature search by leveraging the documents generously supplied by the engineer, which served as a valuable foundation for further exploration. We also took into account the publication dates of the papers, although it's worth noting that not all of them align perfectly with the desired outcome. All of these documents, along with their summaries and key takeaways crucial to the project, can be conveniently accessed in the uploaded folder on the provided drive, as well as via the link within the GitHub repository. The following section provides concise summaries and essential insights from each of these papers, offering a comprehensive overview of the knowledge base underpinning the project.

A. Aplicación Web para Clasificar los Granos de la Quinua según la Norma Técnica Peruana Aplicando Machine Learning

The main idea of the project is focused on the actual method to separate quinoa of many other impurities. Usually it is done manually by an expert, but it takes a lot of time.
Into the project, the grains are evaluated by an app that was developed by the person that has done the project, it uses a classifier IA and create a sample report about the photo. It has many characteristics to take on account to determine if a grain is size that is required, if the grain is complete not broken, type and size. The parameters that are also available on the app, it takes seven parameters to ensure which type of grain is, and tree others for the size of it.
The classification of the grain was made in python code, using the tool OpenCV, for the CNN, they use TensorFlow with a trained model. The tool used for taking the samples of images was a camera, it has a 1600X resolution. All the images were taken by the autorn and also for each type of quinoa were taken 1000 images. [3]

B. Sistema de visión computacional móvil en la identificación de la calidad de quinua blanca

For this system, the images are taken by cell phones in the case of the thesis, all the images were taken by five different cell phones, the best option being the Samsung S9 camera. According to this, the preprocessing performed by the author includes techniques such as noise reduction and smoothing, histogram processing, edge enhancement, and contour detection. Additionally, it has a low-cost implementation, but the accuracy depends on the image quality of the used cell phone. Therefore, the main contribution is the fact that they were implemented in a single classification and also in a multiple classification for the grains. This has only been seen before in individual targets, not in multiple targets as can be read in the thesis. However, it has a noticeable problem, which is trying to manually classify the quinoa grains.
They took 385 samples evaluated for SVCM, they received 370 result true positives, they reached 96.1] of efficiency in prediction of class. [4]

C. Clasificación automática de tipos de semilla de quinua a través de descriptores de color

The study in question involved the identification and classification of wheat and quinoa seeds using computer vision techniques. In the case of wheat seeds, a dataset of 1080 grayscale images was collected, with 120 images for each variety. These images were acquired under controlled lighting conditions using a ring fluorescent light. On the other hand, for quinoa seed classification, 360 images were captured with varying backgrounds using a SONY Cyber-Shot DSC-S750 camera mounted on a 40x stereoscope.
To enhance the image quality for quinoa seed classification, it was applied several image processing filters such as Medianblur, Gaussianblur, and general blur to correct and standardize the color representation. Additionally, the Otsu method was used for segmentation, aiming to improve feature extraction for subsequent classification.
One of the principal contributions of this research is the novel approach of using color descriptors to differentiate between different types of quinoa seeds. Unlike previous studies that predominantly focused on shape and texture descriptors, this study introduced the utilization of color information as a distinguishing factor for seed classification, breaking new ground in the field.

This paper stands out from other research endeavors due to its pioneering exploration of color descriptors in seed classification, which has been relatively unexplored in the existing literature. By doing so, the authors aim to address the challenge of accurately classifying various seed types using computer vision techniques, with potential applications in seed quality control and breeding programs.
To assess the performance of the computer vision systems, a 10-fold cross-validation approach was employed. The evaluation metrics included precision, recall, and F1 score, which provided a comprehensive analysis of the classifiers' effectiveness in seed classification.
Looking ahead, the authors recommend that future research should concentrate on enhancing classifier accuracy by incorporating advanced feature extraction techniques and delving into the potential of deep learning algorithms. Furthermore, they underscore the necessity for additional exploration in the realm of color descriptors for seed classification, as this remains a largely untapped area within the existing literature. This call for further investigation emphasizes the ongoing potential for innovation and improvement in the domain of seed classification using computer vision. [5]

D. Discrimination of foreign bodies in quinoa (Chenopodium quinoa Willd.) grains using convolutional neural networks with a transfer learning approach

In this study, the authors manually selected quinoa grains and foreign bodies to acquire images. These images underwent pretreatment, including resizing and color space conversion, to prepare the dataset for analysis.
The primary contribution is the development of a Convolutional Neural Network (CNN)-based system for detecting foreign bodies in quinoa grains, aiming to improve product quality and safety.
This paper stands out by focusing on CNNs and transfer learning for quinoa grain foreign body detection, a unique approach in the field. The authors aim to address the issue of foreign body contamination in quinoa, which poses health risks to consumers.To evaluate their system, they used metrics like accuracy, precision, recall, and F1-score.
For future research, the authors suggest improving CNN models and emphasizing the need for standardized datasets for food product foreign body detection. [6]

E. Determination of physical characteristics of quinoa (Chenopodium quinoa Willd.) seeds by digital processing of images

The authors obtained new images for their research using both a digital camera and a scanner. These images underwent pre-processing steps, including image thresholding, morphological operations, and edge detection to enhance their suitability for analysis.
The primary contribution of this study is the development of a computer vision system capable of accurately determining the physical characteristics of quinoa seeds, encompassing attributes like size, shape, and color.
Distinguishing itself from other research projects, this paper specifically focuses on these physical characteristics of quinoa seeds, using a combination of digital camera and scanner images for analysis.
The authors aim to address the critical challenge of accurately determining these physical characteristics, which holds significance for the production and commercialization of high-quality quinoa seeds.
To assess their computer vision systems, the authors compared results with manual measurements and analyzed the accuracy and precision of their measurements.
Looking ahead, the authors propose future research to enhance the accuracy and speed of the computer vision system. They also suggest exploring alternative imaging techniques, such as X-ray imaging, and emphasize the need for further investigation into the relationship between physical characteristics and seed quality. [7]

F. Mobile Computational Vision System in the Identification of White Quinoa Quality

The authors collected new images of 5g portions of white quinoa from Peru, specifically La Libertad. To enhance these images, they applied techniques like contour detection using the Canny algorithm, as well as morphological operators such as ”closure” and ”dilation” to remove noise and highlight details. Additionally, segmentation methods, including thresholding and region descriptors, were used for feature extraction.
Their primary contribution is the development of a mobile computational vision system designed to identify the quality of white quinoa. This system leverages algorithms and functions from the OpenCV and TensorFlow library, offering a unique approach in the field.
Distinguishing itself from other research projects, this paper concentrates on the identification of white quinoa quality using a mobile computational vision system, while others may focus on different crops or utilize distinct methods.
The authors' goal is to address the challenge of accurately determining the quality of white quinoa, a crucial factor for commercialization given that product costs in national and international markets vary based on quality. The evaluation of their computer vision systems involved assessing efficacy, sensitivity, and specificity.
In terms of future research, the authors propose the development of a mobile application for identifying white quinoa quality and the exploration of deep learning algorithms for more accurate identification. They also highlight a research gap in the limited studies focusing on the identification of

quinoa quality using computer vision systems. [8]

G. Survey of Seed Classification techniques

The authors acquired new images of 5-gram white quinoa samples from Peru's La Libertad region. They used pre-processing techniques like contour detection, morphological operations, and segmentation methods.
Their primary contribution is a mobile computational vision system for white quinoa quality identification, using OpenCV and TensorFlow libraries. This paper distinguishes itself by focusing on white quinoa quality using a mobile computational vision system. Their goal is to address the challenge of accurately assessing white quinoa quality, which impacts market pricing.They evaluated their systems based on efficacy, sensitivity, and specificity.
Future research directions include developing a mobile app, exploring deep learning algorithms, and emphasizing the need for more studies on quinoa quality assessment using computer vision. [9]

H. A robust quinoa grain recognition system using a multi-feature fusion approach

The study aims to address specific challenges in the realm of quinoa grain recognition. It identifies that previous systems, primarily based on a single feature, tend to be imprecise under varying lighting conditions, different grain orientations, and noise presence in images. Furthermore, these systems appeared sensitive to variations in the grains' inherent features like color, shape, and texture and often couldn't distinguish between different quinoa varieties.
To enhance the recognition accuracy and robustness, the study proposes a multi-feature fusion methodology, integrating aspects of color, shape, and texture of the grains. In doing so, it not only seeks to elevate the overall accuracy but also the system's ability to function under non-ideal conditions. A key component in this approach is the utilization of an image database containing grains from diverse quinoa varieties, thereby ensuring a broader and versatile recognition capability.
The paper suggests that this multi-feature system might be valuable across various applications. In the food industry, for instance, it could be employed to classify grains from different varieties, thereby ensuring product quality and uniformity. From an agricultural perspective, it could be utilized to research the characteristics of different quinoa varieties, aiming to enhance both the grain's production and quality. In the realm of precision agriculture, the system could prove useful for real-time monitoring of crop growth and health, contributing to more efficient farming.
In addition to the proposed solutions, the study also identifies and acknowledges existing gaps in current research on quinoa grain recognition. These gaps revolve around the reliance of past systems on a singular feature type and the lack of ability to recognize different grain varieties. Through thorough evaluation, the paper showcases that its system achieves an impressive 99 per cent of accuracy. [10]

I. A quinoa grain recognition system using a hybrid deep learning approach

The tesis discusses a system for identifying quinoa grains using a hybrid deep learning method. This system integrates two deep learning techniques: Convolutional Neural Networks (CNN) and Supervised Machine Learning (SML). CNNs, suitable for image processing, learn to discern features relevant for classification, such as size, shape, color, and texture of quinoa grains. On the other hand, SML uses algorithms that learn from labeled data, in this case, images of quinoa grains labeled according to their type.
The system proposed in the paper employs a CNN to extract features from images of quinoa grains, and an SML algorithm to classify the grains based on these features. The system was evaluated using a dataset composed of 10,000 images of different varieties of quinoa, achieving an accuracy of 99 per cent, which highlights it as an effective tool for identifying quinoa grains.
To acquire new images, the authors used a high-resolution digital camera capturing quinoa grains of various varieties. They applied several preprocessing methods to the images, including resizing to a fixed size, normalizing the pixel intensity, and noise removal.
The main contribution of this work is the development of an accurate, robust, and efficient system for quinoa grain recognition. This system, distinct from other research projects, benefits from a hybrid deep learning approach and utilizes the largest dataset to date for this task, achieving the highest accuracy reported in quinoa grain recognition.
The central problem addressed by the paper is quinoa grain recognition, a crucial task for the production and processing of quinoa, which can be used to control its quality, classify it into different varieties, and separate quinoa from impurities.

J. application of machine vision for detection of foreign matter in wheat grains

All 1000 samples were imaged using a three-chip charge coupled device (CCD) color camera with a zoom lens of 10-120 mm focal length, a personal computer (PC Pentium 3), color frame-grabbing board, and a diffuse illumination chamber. The illumination was provided by a fluorescent light source of 300 mm diameter, 35 W circular lamp. The images were acquired at a speed of 30 frames per second and digitized into three 8-bit 256 by 256 digital images as tagged image file format images using a frame grabber installed in the PC.

that robust machine vision algorithms were developed and tested to extract morphological, color, and textural features of wheat grains and dockage content.
the text explains that the study used machine vision algorithms to extract morphological, color, and textural features of wheat grains and dockage content. The extracted image features were then used for classification purposes. The results of the study indicate that classification was reduced from about 97% for wheat mixed with stones to 96% for wheat mixed with rice and 93% for wheat mixed with barley (at 5.0% admixture). This trend indicates that the features of 1.0% foreign matter admixture started overlapping with other classes (of admixture). [11]

IV. Exploratory Data Analisis

For the EDA we used a similar dataset, because there is no free dataset to work on, but this dataset is perfect to make an EDA on it. The entire code can be found in the following colab. Also the data-set has been downloaded in the next link of roboflow: https://universe.roboflow.com/zubair-abdullah-zpa7a/wheat-grain-growth/dataset/13. We tried to make the work that we will do on our dataset, we are going to ensure all the images are properly taken, also we will classify and change if there could be an image that will not be used or processed.

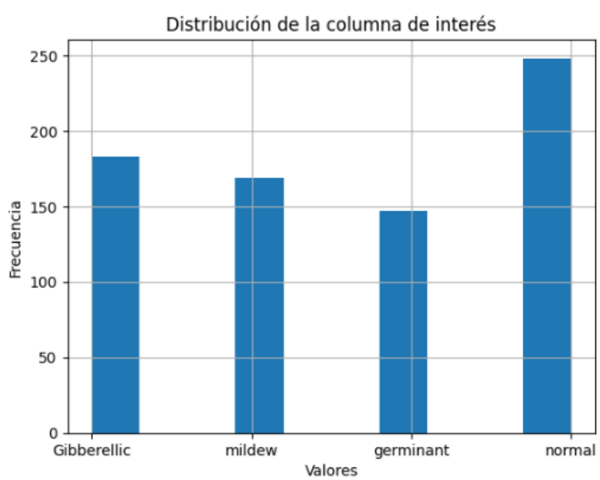

Figure 2. Block Diagram

V. Methods

The described model architecture entails a 3-layer convolutional neural network (CNN) for image classification. Each convolutional layer incorporates Rectified Linear Unit (ReLU) activation and MaxPooling to introduce non-linearity and spatial down-sampling, respectively. The final layer employs softmax activation, suitable for multi-class classification problems. The Adam optimizer is utilized to adaptively adjust learning rates during training, enhancing the robustness of the model. Data augmentation is applied to the dataset, a technique involving artificial expansion of the training data through transformations like rotation and flipping. This approach aids in real-time detection by exposing the model to diverse variations of input data. The training process involves 10 epochs, each representing a complete pass through the training dataset. The model achieves a commendable accuracy of 92.27 percent with a corresponding loss of 0.20. The trained model is saved in Hierarchical Data Format (HDF5) with a ".h5" extension, facilitating future use for predictions on new data.

In summary, the described CNN architecture, optimization strategy, data augmentation techniques, and training details collectively contribute to a robust image classification model. The reported accuracy and loss metrics suggest effective learning and generalization capabilities, making the model suitable for real-time detection tasks. The use of the HDF5 format for model storage ensures accessibility and ease of deployment for future applications, in this case would be applied in a real application such as the detection of quinoa on a conveyor belt.

A. Expected Solution

The proposed solution to the core issue of quinoa separation involves the implementation of cutting-edge artificial vision methods. Specifically, the system is designed to pinpoint and address the presence of "garbage" - those tiny pebbles and branches originating from the quinoa plant that often contaminate the crop during processing. This approach is geared towards swiftly and accurately identifying these contaminants and subsequently triggering an output signal to remove them from the production line. This not only translates to significant time savings but also enhances overall productivity in quinoa processing.
Furthermore, the proposed solution extends its capabilities to enhance the accuracy in identifying and extracting information related to image noise. This noise is essentially any element within the image that doesn't correspond to quinoa grains. By characterizing these non-quinoa elements, the system can precisely locate their positions within the image and facilitate their removal. This feature ensures a more refined and thorough quality control process, further contributing to the production line's efficiency and the delivery of a high-quality, pure quinoa product. The integration of artificial vision technology promises to be a transformative solution to the prevailing challenges in quinoa separation, streamlining the process and significantly improving its effectiveness.

VI. Experiments

To evaluate the model's efficacy in real-world scenarios, a series of trials were conducted using diverse images containing both quinoa and non-relevant objects resembling garbage. The model's ability to discern and accurately classify these distinct elements was scrutinized. The convolutional neural network (CNN) demonstrated a noteworthy capacity to detect quinoa within varied environmental contexts. However, challenges were encountered when discerning between quinoa and objects resembling garbage, underscoring the importance of refining the model's specificity in differentiating between relevant and non-relevant elements. These trials shed light on the model's strengths in quinoa detection, yet also highlighted the need for further optimization to enhance its precision in discriminating between target and non-target items, especially those sharing visual similarities with garbage. Ongoing efforts to fine-tune the model's discriminatory capabilities aim to bolster its performance across a broader spectrum of real-world scenarios, ensuring reliable and accurate detection in practical applications.

VII. Conclusion

In conclusion, the developed convolutional neural network (CNN) has shown promising capabilities in detecting quinoa across diverse images, exhibiting adaptability to varying environmental conditions. The model's utilization of ReLU activation, MaxPooling, softmax output, and the Adam optimizer, coupled with data augmentation techniques, has resulted in a commendable accuracy of 92.2 percent and a loss of 0.20 during the training process. However, challenges were observed in accurately distinguishing quinoa from objects resembling garbage, emphasizing the need for continued model refinement. The trials underscore the model's potential and highlight the importance of ongoing optimization efforts to enhance its specificity and robustness in real-world scenarios. The .h5 format ensures the model's accessibility and usability for future applications, and ongoing fine-tuning endeavors aim to address nuanced challenges, ultimately fostering a more reliable and precise tool for quinoa detection in diverse environments.
GitHub: https://github.com/PamePatzi/Quinoa-Quality-Inspection-NDA

VIII. Block Diagram

For the block diagram we made the next figure:

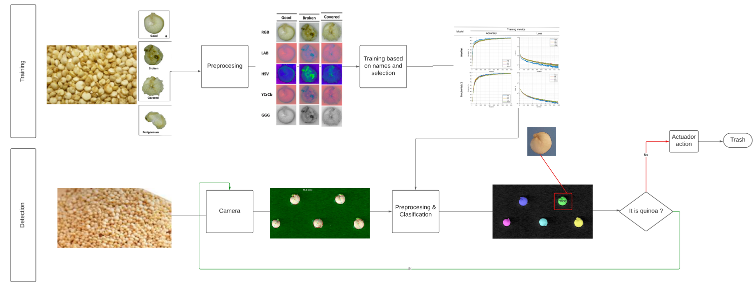

Figure 3. Block Diagram New.

The reference images for the construction of the diagram were taken from the papers [3] [7] [6] and from a database of images created specifically for this project

References

[1] E. Jiménez and A. Romero, "Crisis alimentaria y rol de la producción orgánica y sostenible: la producción de quinua en el altiplano sud de bolivia," *CIDES-UMSA*, 2021.

[2] G. A. ORIS, "Informe de comercio exterior: Quínoa," *Gobierno de la Provincia de Salta*, 2021.

[3] P. A. Q. Valero, "Aplicación web para clasificar los granos de la quinua según la norma técnica peruana aplicando machine learning," *UNIVERSIDAD PERUANA UNIÓN*, 2020.

[4] T. V. D. L. Lecca Pino Percimil, "Sistema de visiÓn computacional mÓvil en la identificaciÓn de la calidad de quinua blanca," *UNIVERSIDAD PRIVADA DEL NORTE*, 2018.

[5] J. C. A.-D. H. I. M.-C. John C. Montalvo-Samame*, Victor A. Tuesta-Monteza, "Clasificación automática de tipos de semilla de quinua a través de descriptores de color," *Universidad Señor de Sipán Pimentel,*, Jan. 2021.

[6] J. S.-G. J. J. C. Q. J. M. P. a. W. C. Himer Avila-George1, Miguel De-la-Torre, "Discrimination of foreign bodies in quinoa (chenopodium quinoa willd.) grains using convolutional neural networks with a transfer learning approach," *PeerJ*, vol. 12, Jan. 2023.

[7] C. A. P. P. Percy Arapa Carcasi, "Determinación de características físicas en semillas de quinua (chenopodium quinoa willd.) mediante procesamiento digital de imágenes," *Revista Venezolana de Ciencia y Tecnología de Alimentos.*, Jan. 2015.

[8] E. M.-R. José Luis Herrera Salazar, "Mobile computational vision system in the identification of white quinoa quality," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 12, No 8, 2021.

[9] D. A. Chaugule, "Survey of seed classification techniques," *TurkishJournalofComputerandMathematicsEducation*, vol. 12, pp. 1–25, Jan. 2021.

[10] J. P. Quiroz, J. L. Flores, and L. A. Rojas, "A quinoa grain recognition system using a hybrid deep learning approach," *IEEE Access*, vol. 11, pp. 157 880–157 893, 2023.

[11] I. Elbatawi and G. Arafa, "Application of machine vision for detection of foreign matter in wheat grains," *Arab Univ.s*, 2008.