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Image processing and recognition for controlling a greenhouse tower mechanism focused on ergonomics and acceleration in substrate placement for sugarcane germination

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ABSTRACT

Objective: To make the process of placing substrate in greenhouse towers for sugarcane germination faster and easier, through an automated prototype that uses image processing to reduce work time and physical effort.

Design/methodology/approach: A small-scale prototype was built to test how it works and to see if it could be used in real conditions. The system used a camera to recognize and locate points inside the work area, allowing smoother and more accurate movement of the mechanism.

Results: The tests showed that the system detected positions correctly and responded well to control commands, even with small changes in the environment. It also helped reduce working time and the operator's physical effort, improving both efficiency and comfort.

Limitations/implications: During testing, changes in lighting and small vibrations affected the accuracy of the system at times. These issues were mostly caused by the materials used in the prototype and the light conditions around it. Still, the results show that the system can be improved to work with greater precision and stability.

Findings/conclusions: The prototype proved to be a good option to make substrate placement in greenhouse towers faster and more efficient, while reducing physical strain for the operator.

Keywords: Image processing; ergonomics; automation; sugarcane; vertical greenhouses.

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INTRODUCTION

The Sugarcane (*Saccharum officinarum*) is one of the main crops grown in tropical and subtropical regions across Latin America, especially in Mexico, which ranks as the sixth-largest producer worldwide according to Sentíes *et al.*, (2018). Besides being an essential source of sugar, sugarcane is also used to produce biofuels like ethanol, animal feed, paper and biodegradable plastics. It plays an important socioeconomic role in several rural areas and stands out for its high biomass production and ability to capture CO_2.

Traditionally, sugarcane is propagated through the manual planting of cuttings and substrate preparation. These tasks require significant physical effort and take a long time to complete, especially during the germination stage. Improving the way the substrate is prepared and placed is key to making the process faster and easier for workers.

Greenhouse towers and controlled germination systems have become effective alternatives to improve the sugarcane productivity based on Martínez *et al.*, (2018). However, most of the work related to filling and placing the substrate is still done by hand. This causes variations in quality, longer working times, and physical strain from repetitive movements. For that reason, introducing automation can make the process more precise, consistent and comfortable for the operator.

In recent years, technology has played a growing role in agriculture industry, helping to make many production tasks faster and more accurate. Martinez *et al.* (2018) designed a vertical greenhouse that used electronic tools to monitor and control environmental conditions, showing how automation can improve agricultural environments. Likewise, Sotomayor *et al.* (2021) developed a computer vision system to analyze crop images and identify plant features more effectively. Furthermore Kamilaris *et al.* (2018) developed exhaustive research about computer vision through Deep Learning to detect plants and fruit classification.

Although these studies show progress and technological innovation in agricultural automation, most of them focus on later stages of the crop, such as monitoring plant growth or environmental control. Limited attention has been given to early stages like germination and substrate preparation. This project takes a different approach by applying image processing and recognition techniques to control the positioning of an automated mechanism that improves both accuracy and ergonomics when placing the substrate in vertical greenhouse towers.

The main goal of this study is to design, build, and test an image-based positioning system for a small-scale greenhouse tower prototype. The system aims to make substrate placement faster, more accurate, and less physically demanding for the operator. Also, it evaluates how the system performs under different lighting and environmental conditions to explores its potential for real greenhouse use.

In the long term, this work seeks to support the development of smarter, more efficient agricultural systems that make early-stage processes easier, more accurate, and better adapted to the needs of both production and workers.

MATERIALS AND METHODS

The development of this work, focused on the image processing and recognition for a greenhouse tower positioning prototype, was carried out using an experimental approach divided into three main stages:

1. Structural design of the prototype.
   1.1. Fabrication and picking of structural components.
2. Development and Integration of control system and image processing.
3. Functional and ergonomic validation of the prototype.

Focusing specifically on the main objective of this work (the development and integration of the control system and image-processing module), it was subdivided into 5 stages:

1. Creation of frame.
2. Creation of ROI within the frame.
3. Detection of inserts by colors.
4. Calculation of offset error.
5. Correction and advance.

The development of the prototype followed a structural design process, electronic integration, and functional validation. However, the main focus of this work was the implementation of an image processing and recognition system, responsible for detecting specific positions and assisting in the automated positioning control of the mechanism. This module proved essential for achieving the highest possible positioning accuracy and reducing manual intervention during the substrate placement process.

Structural design of the prototype

As the first step in the structural design, the dimensions of a full-sized greenhouse tower (Figure 1) were obtained to create a scaled-down version. The measurements considered included the length of the tower, its diameter, the total number of inserts, and their respective diameters.

Once the dimensions of the greenhouse tower were obtained, the design and 3D printing of the same in scale size was conducted.

The tower design was conducted in the Fusion 360 software, since according to Sánchez *et al.* (2022) it is one of the most complete and intuitive simulation software that can be found on the market today, software that was used for the design of the components that

Figure 1. Full-sized greenhouse tower made of PVC material. The tower measures 1.5 m in height and 16 cm in diameter, with a total of 270 inserts.

were part of the final structure of the prototype, Figure 2 shows the design and printing of the greenhouse tower, the dimensions of the aforementioned were scaled so that the tower was congruent in relation to the size, quantity and dimension of the tower inserts to scale.

After the scaled greenhouse tower was printed, the prototype's structural design was made. Figure 3 shows that the design has a DC motor, a stepper motor, and a number of 3D-printed pieces that make up the framework. Sanchez *et al*. (2022) say that these designs can be utilized to make simulations that let you guess how different kinds of activities, processes, and/or mechanisms will work in the real world.

Figure 2. 3D-printed scaled greenhouse tower. This piece measures 16 cm in height, 1.68 cm in diameter, and contains a total of 270 inserts

Figure 3. Prototype design and simulation created in Fusion 360, showing the structural components (DC motor, stepper motor, lead screw, rigid coupling, and guide rod).

Once the design and simulation of the mechanism were completed, the prototype was fitted with the structure components printed, including an inclined base designed to support the tower at a 45° angle, as shown in Figure 4.

Taking the mechanism of a linear motion guide with a high-precision ball screw as a reference for our mechanism, a bearing was designed to avoid any vibration and/or offset, as shown in Figure 5. A vertical base was coupled to the bearing to add support and avoid unnecessary movements. Moreover, a rigid coupling was implemented for the same reason.

Figure 4. Conditioned prototype for the tower with the components printed, which include the rigid coupling, the tower base and the inclined base.

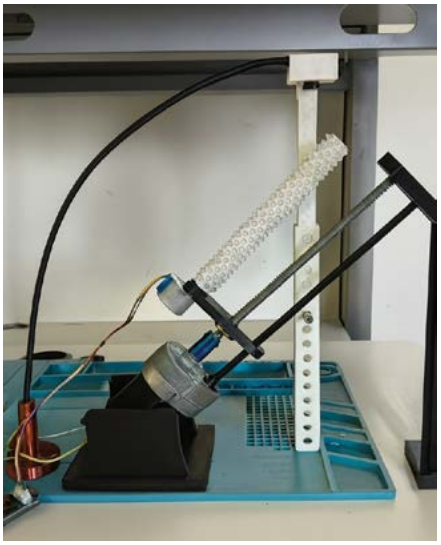

Figure 5. The webcam is equipped with the fitted prototype, which includes the bearing with its base, the blue rigid coupling, and the both structures of the camera, for which the vertical base was designed for positional and height adjustment to ensure the greenhouse tower is captured correctly.

Once the greenhouse tower was equipped and fitted, a USB camera was adapted to develop the image positioning system. A base for the camera was designed and printed, which was divided into 2 pieces; the red one was designed to support the camera's cable, and the design of a desk lamp was taken as reference. The second base was designed to provide additional support for the camera by allowing adjustments to its height and position. All these structures are shown in Figure 5.

With the prototype and USB camera fully prepared, work proceeded on the development of the image processing system.

Image processing and recognition

According to Torres (1996), digital image processing has acquired an important role in information and computing technologies in recent years. Currently, it is the foundation for a growing variety of applications, including medical diagnosis, remote sensing, space exploration, computer vision, and others. It is for this reason that this type of technology was chosen for application in the agricultural industry.

One of the goals of the mechanism is to accelerate substrate placement. To achieve this, the motion of an auger was used as a reference, consisting of linear advance, retraction, and rotation —was used as a reference.

The first mechanism (linear advance and retraction) of the greenhouse tower will be executed by the DC motor, where its direction and speed will be programmed.

The second mechanism (rotational) will be executed by the stepper motor, where its direction and number of steps will be programmed to control the greenhouse tower's rotational speed.

Figure 6 shows a graphical representation of the final mechanism designed for the greenhouse tower.

Figure 6. Movement projection of the greenhouse tower. The colored lines indicate its trajectory, which follows a spiral path.

As shown in Figure 6, the greenhouse tower's movement consisted of linear advance, retraction, and rotation (spiral). Using the camera, each insert will be detected, and its alignment error relative to the camera's center will be calculated. Depending on the direction of the misalignment, it will be corrected by the actuators (DC motor and stepper motor).

Several image-processing methods could have been used for the purpose of this work (insert detection). The advantages and disadvantages of each were validated to select the most optimal choice for the primary objective. Table 1 will present the main image processing methods, their descriptions, advantages, and disadvantages.

As shown in Table 1, there are 3 image processing methods. Saini (2017) shows the importance of color detection through an Artificial Intelligence (AI) system that detects and follows objects by color in real time, applicable in robotics and automation. Considering the aforementioned factors, the complexity of the project and the available resources, color detection was the most suitable option for the project. Therefore, each spiral of the greenhouse tower was dyed a different color to facilitate the development of the image processing system, as shown in Figure 7.

Once the prototype aims mechanism was understood, the development of the image processing system was conducted. The system was developed in the Visual Studio Code programming environment, using the Python programming language due to its versatility and broad compatibility with computer vision libraries.

The implementation was conducted on a Raspberry Pi 4, selected for its superior processing capacity and for integrating a complete operating system that allows the simultaneous execution of acquisition, processing, electronics and control tasks.

Unlike microcontroller-based platforms like Arduino, Raspberry pi 4 offers an arquitecture more robust for real-time image processingfurt, native support to camera interfaces and network communication, as well as more efficient memory and data

Table 1. Different methods of detection of inserts, description, advantages and disadvantages.

Methods	Description	Advantages	Disadvantages
Objects detection (based on automatic learning or neural networks).	It uses trained models (YOLO, SSD, Faster R-CNN, etc) to recognize and locate objects through learned features.	High accuracy in complex environments; adaptable to multiple types of objects.	It requires a large amount of training data and high computational consumption, in addition to sensitivity to variations in lighting and angle.
Shapes detection (based on contours or hough transforms)	It uses edge extraction and specific geometries.	Useful for objects with well-defined shapes and lighter processing.	Sensitive to visual noise and shadows, limited to variations in color or texture.
Color detection (based on color thresholds in RGB or HSV spaces)	It identifies regions of interest (ROI) through segmentation of previously defined color ranges.	Low computational cost, easy to implement, high processing speed, good accuracy in controlled environments.	Sensitive to extreme variations in lighting or shadows, requires calibration of color ranges.

Martín Pérez *et al*. (2023).

Figure 7. Greenhouse tower with spirals of inserts differentiated by colors.

management. These features make it in an optimal to the development of self-assisted control system using artificial vision in experimental or prototyping environments.

The electronic applied to the prototype works were derived from the motors, each motor needs its respective driver to program the speed, time and/or direction of rotation. As shown in Figure 8, the DC motor used an L298N H-bridge driver and the stepper motor used a ULN2003A driver, both powered by a 12V and 5V power supply and connected to a breadboard with jumper wires to allow the prototype to operate freely.

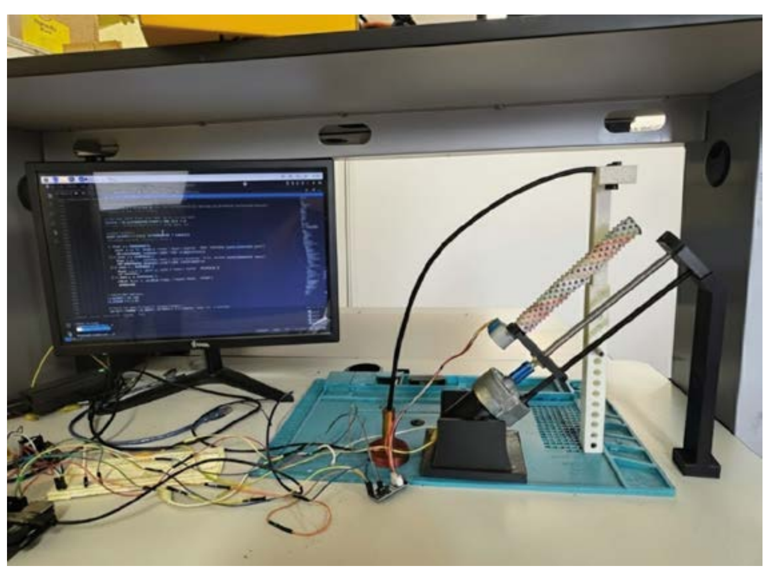

Figure 8. Image of the complete prototype, showing the connection of the functional prototype with the electronics coupled with the Raspberry Pi 4 and a monitor where its interface is displayed.

The methodology followed for the development of the system is listed as follows:

1. **Creation of frame**: Once the camera was tested, the next step was to create a frame. A frame refers to the specific image within a sequence of moving images (Frank, 2019). The frame allows visualization of the area that will be available for the initial position of the prototype. Figure 8 shows a frame created to adjust the position and height of the camera.
2. **Creation of ROI within the frame**: A region of interest (ROI) is a portion of an image that is to be filtered or manipulated. An ROI can be represented as a binary mask image. In the mask image, pixels belonging to the ROI are set to 1, and pixels outside of it are set to 0. This process simplifies processing because detecting multiple insets in the same frame would drastically affect the system and cause significant instability. By filtering the frame within an ROI, insets are detected only in a single region of the frame.

As shown in Figure 9, a second frame was programmed, but it was not used practically throughout the project. It was programmed for visualization purposes, to display what the ROI detects and thus delimit its size for practical use.

3. **Detection of inserts by colors**: For color detection, the OpenCV tool was used, according to Khurana *et al.* (2023). OpenCV is an open-source computer vision library that presents a fundamental approach to motion and color detection (as in this case), encompassing frame acquisition, noise reduction, object tracking, color thresholding, etc.
4. **Calculation of offset error**: Once the insert-detection module was implemented, the phase error with respect to the ROI was calculated in pixels (px). Depending on the direction in which each insert is phased, the type of error and therefore the type

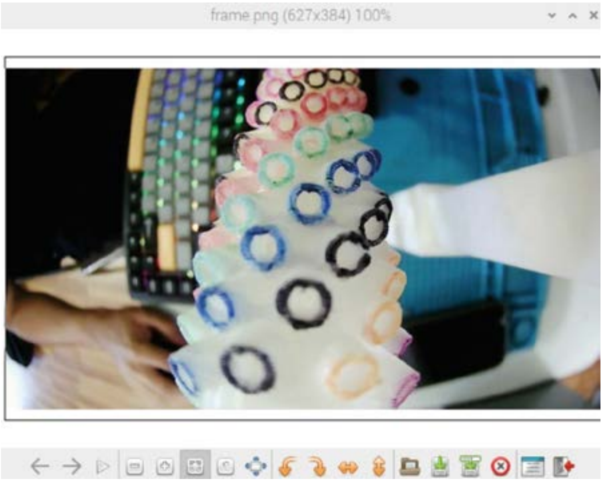

Figure 9. USB camera test execution, creating a frame and adjusting the position and orientation of the camera with respect to the position of the prototype and the greenhouse tower.

of actuator that will correct the insert is determined. Figure 10 shows the graphical logic of the system.

The program's visual logic, as shown in Figure 11, consists of drawing a Cartesian plane within the ROI, thus indicating its exact center.

The offset of the insert depends on the quadrants of the plane: if it is to the left on the X-axis, the error is negative, and if it is to the right, the error is positive. Similarly, if the insert is above the Y-axis, the error is positive; otherwise, it is negative.

5. **Correction of advance**: Once the error is calculated, as shown in Figure 11, the program adjusts the offset using a stepper motor for the X-axis and a DC motor for the Y-axis, placing the insert in the center of the ROI. To expedite the system's process, a 15% tolerance was programmed; that is, a zone was programmed in

Figure 10. ROI creation within the frame: 2 windows were programmed in which the main window shows the complete frame and the ROI in green, the small window is a frame where only what the ROI detects is shown.

Figure 11. Detection of inserts by colors inside of ROI. The algorithm was programmed to detect different inserts by colors, in the color black, as this figure shows.

which the insert is allowed to be offset within a certain error range. If the sum of the offsets on both axes (errors) is within the tolerance, the system considers it centered, as shown in Figure 12. This is done to "center" the inserts as quickly as possible and thus speed up the process.

As explained in the previous step, although the system detects a misalignment error on both axes —an error of -9 px on both axes in Figure 13— the total error is below the tolerance, so the system detects the insert as centered. In addition, a 3-second delay was programmed into the system, simulating the time it would take the operator to place the substrate in the insert, displaying the message "placing the insert."

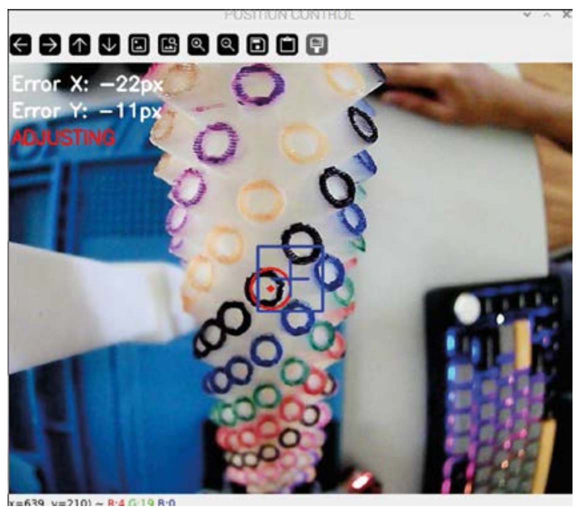

Figure 12. Error calculation and offset adjustment of the inserts, displaying on screen the error on the X and Y axes and a "adjusting" message while the correction lasts.

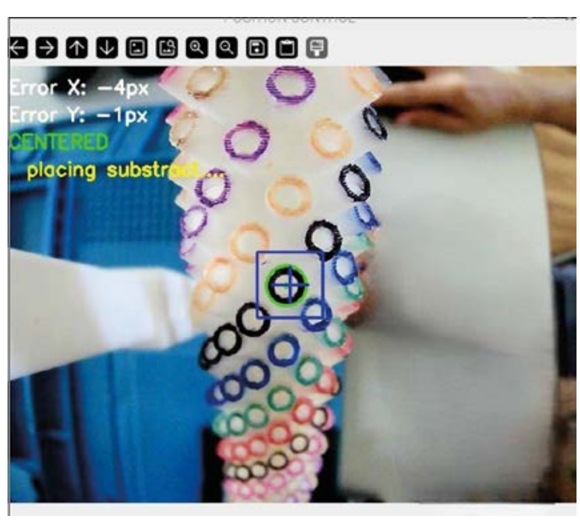

Figure 13. The insert has been corrected by the system, displaying error X and error Y on the screen, a "centered" message indicating the insert has been corrected, and a "placing insert" message simulating the actual placement of the substrate.

Once the 3-second delay has elapsed, the system will resume searching for the next nearest insert detected in the ROI. The system will repeat this process with all single-color inserts, thus performing the spiral mechanism. Once the system detected all single-color inserts, the tower will return to its original place and the system does the same process with the rest all single-color inserts, the color sequence was predefined in the source code.

RESULTS AND DISCUSSION

The experimental tests were repeated 3 times under similar lighting and environmental conditions to ensure consistency. Each trial measured the time and precision of substrate placement using the image-based control system. Additionally, a comparative evaluation was conducted against the manual placement method, where the operator performs the task while standing, typically taking about 90 minutes per tower, as shown in Table 2. In contrast, the automated prototype completed the same task in approximately 40-45 minutes (6-7 minutes per spiral). Although the study primarily focused on functional validation and did not include a full statistical analysis, the results remained consistent, with minimal variation observed between trials. Moreover, future research will include statistical analysis.

The comparison with the manual method showed that the automated system reduced total operation time by nearly 50%, lowering the duration from 90 minutes to approximately 40-45 minutes per tower. The performance of the image recognition and positioning modules remained consistent between tests, with only minor variations attributed to lighting changes. While no quantitative ergonomic analysis was performed, Observational assessment indicated a clear reductionin repetitive movements and physical effort compared to manual operation.

To evaluate the positioning accuracy of the system, ten consecutive measurements were collected to quantify the deviation between the target position and the final position reached by the mechanism. The results showed an average error of 5.3 mm with a standard deviation of 0.94 mm. Using these values, a 95% confidence interval was computed, yielding a margin of $\pm$0.67 mm. This indicates that the true positioning error of the system lies between 4.63 mm and 5.97 mm under controlled operating conditions. These findings demonstrate that the prototype performs consistently and that the image-processing module provides reliable positional feedback when integrated with the control system.

Although previous studies have explored automation in greenhouse environments, their focus differs significantly from the present work. Martínez *et al.* (2018) concentrated on environmental monitoring and electronic instrumentation within vertical greenhouses, rather than on optimizing substrate placement or ergonomic efficiency. Similarly, Sotomayor

Table 2. Time comparison of detection system with manual colocation.

Test	Detection system time	Manual colocation time
1	41 min 35 sec	1 h 25 min
2	44 min 48 sec	1 h 38 min
3	43 min 23 sec	1 h 28 min

et al. (2021) applied computer vision techniques for the visual analysis of crop textures, addressing post-germination plant evaluation rather than pre-germination operational processes. In contrast, this study introduces an image-processing-based positioning system specifically designed to automate and improve the early-stage task of substrate placement, a process that remains largely manual and underexplored in the literature. This focus on pre-germination automation and ergonomic improvement highlights the novelty and practical relevance of the proposed prototype.

CONCLUSIONS

The results obtained demonstrated that the designed prototype constitutes a viable alternative for the pre-germination of crops and for the automation of greenhouse towers. The integration of an image processing system allows for more precise control over the positioning of the mechanism, improving the dynamics of substrate placement and reducing manual intervention and awkward postures. Although ergonomic improvements were not quantitatively measured, the time reduction of the system and the inserts' automatic detection could demonstrate an ergonomic improvement, given that, according to CENEA (2023), the frequency and the duration of repetitive tasks allow finding out ergonomic improvements in automatic processes, and Sánchez *et al.* (2024) highlight how the reduction of awkward postures and repetitive movements is an indicator of ergonomic improvement in production processes. In a future project, by designing a real-scale mechanism, we could obtain actual measurements of ergonomic improvements.

Furthermore, the combination of 3D-printed components and metallic elements posed additional structural challenges, suggesting that future versions may benefit from improved mechanical stability and the possible integration of advanced algorithms or AI-based control strategies.

Supplementary Materials / Additional Materials / Corresponding Author

For access to the prototype design files, system source code, and/or additional technical documentation required for its reproducibility or replication of the project, please contact the email correspondence. All materials are available upon request.

REFERENCES

Frank, H. (2019). Frame by Frame: A Materialist Aesthetics of Animated Cartoons [Libro electrónico]. University of California Press. https://doi.org/10.2307/j.ctvr7fd7m

Khurana, N., Bansal, M., Thakur, A., Sai Varshitha, V., Tannu, & Kaur, E. H. (2023). Machine learning-powered real-time motion detection system: A review. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 896-901). IEEE. https://doi.org/10.1109/ICIMIA60377.2023.10426464

Martín Pérez, J. L. (2023). Comparación de técnicas de detección de objetos en imágenes [Tesis de maestria, Universidad Complutense de Madrid]. Repositorio Institucional UCM. https://docta.ucm.es/entities/publication/016117b7-232d-4205-81c8-ccf8bfbca1b6

Martinez-Sibaja, A., Ramos-Tejeda, R., Posada-Gómez, R., Águila-Rodríguez, G., Rodríguez-Jarquin, J.P., Trujillo-Caballero, J.C. (2018). Diseño de un invernadero vertical e integración de herramientas para su instrumentación electrónica. *Agro Productividad, 10*(10), 49-53. https://revista-agroproductividad.org/index.php/agroproductividad/article/view/87

Saini, R., & Saini, S. (2017). Real-time color object detection and tracking using computer vision. *International Journal of Advanced Research in Computer Science, 8*(5), 1234-1240

Sánchez Márquez, J. A., Azael, S. R. T., Gasca, A. G. G., Martínez Jiménez, L. S., Núñez Guía, K. N., Ruelas Rodríguez, M., & Sánchez Ramírez, F. (2022). Optimización del proceso de diseño de prototipos mediante simulaciones de forma en 3D empleando Autodesk FUSION 360 [Trabajo académico, Universidad de Guanajuato]. Repositorio Institucional de la Universidad de Guanajuato. http://repositorio.ugto.mx/handle/20.500.12059/7177

Sentíes-Herrera, H. E. (2018). El mejoramiento genético de la caña de azúcar (saccharum spp.) en México: una historia de éxito con nuevos desafíos. *AgroProductividad, 9*(7). https://revista-agroproductividad.org/index.php/agroproductividad/article/view/778

Sotomayor, J., Gómez, A., & Cela, A. (2021). Sistema de visión artificial para el análisis de imágenes de cultivo basado en texturas orientadas. *Revista Iberoamericana de Producción Académica y Gestión Educativa, 8*(2), 89-101. https://www.redalyc.org/pdf/6887/688773656007.pdf

Yeum CM, Choi J, Dyke SJ. Localización y clasificación automatizadas de regiones de interés para la evaluación visual de infraestructuras civiles. *Monitoreo de la Salud Estructural. 2018;18*(3):675-689. doi: 10.1177/1475921718765419

CENEA. (2023). ¿Cómo evaluar riesgos por movimientos repetitivos en un puesto de trabajo? Centro de Ergonomía Aplicada. Recuperado de https://www.cenea.eu/evaluacion-riesgos-movimientos-trabajos-repetitivos-en-un-puesto/

Sánchez Ortega, J., Chérrez Sandoval, H. P., Barriga Gavilanes, M., & Urquizo Flores, G. K. (2024). Rediseño de Puestos de trabajo Orientado a Criterios Ergonómicos Generales. Una Revisión Bibliográfica. *Ciencia Latina Revista Científica Multidisciplinar, 8*(5), 160-177. https://doi.org/10.37811/cl_rcm.v8i5.13287