International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

IJSRA

(Review Article)

Check for updates

Exploring computer vision, machine learning, and robotics applications in banana grading: A review

Joshua Kyle Beltran, Dominee Kyle Ibarlin *, Mark Ivan Mapa and Edwin Romeroso Arboleda

Department of Computer, Electronics, and Electrical Engineering, Cavite State University, Indang, Cavite, Philippines 4122.

International Journal of Science and Research Archive, 2024, 11(01), 1159–1166

Publication history: Received on 22 December 2023; revised on 30 January 2024; accepted on 02 February 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.11.1.0180

Abstract

This paper presents a literature study on the applications of Artificial Intelligence (AI) in banana grading. The traditional approach of banana grading, primarily dependent on manual labor, is not only time-consuming but also receptive to subjective variations. The need for more accurate and efficient solutions has become increasingly necessary. With the help of AI technology, we can better address the evolving challenges and demands in automating the grading processes of banana-related agriculture. The study focuses on three sub-domains of AI: Computer Vision, Machine Learning, and Robotics. This research reviews the application of AI techniques in Banana Grading to help individuals understand the significant development of banana-related agricultural systems in the past few years.

Keywords: Artificial Intelligence; Banana Grading; Computer Vision; Machine Learning; Robotics

1. Introduction

In the growing trend of Artificial Intelligence, or AI, one cannot deny that it is the new innovation that is set to change lives, particularly in the agricultural industry. Performance in the agricultural industry has improved with the aid of this technology, through which different AI driven techniques can be applied. These technologies have helped address the excess use of water, pesticides, herbicides, maintain the fertility of the soil, also help in the efficient use of manpower, elevate the productivity, and improve the quality [1]. At the present time, the integration of artificial intelligence in agricultural crops, for instance, banana grading, not only changes the process of evaluating and categorizing crops, but also serves as a key in transforming agricultural activities, supporting livelihoods, and contributing to GDP development [2].

Agriculture has the potential to profit greatly from the application of technology such as the Internet of Things (IoT), sensors, smart devices, Big Data Analytics, Machine Learning (ML), and a wide range of Artificial Intelligence (AI) approaches [3]. It is clear that there is a rising interest in using AI and data science in the field of agriculture to assist the adoption of disruptive technologies, with the goal of increasing productivity, lowering costs, integrating systems, and promoting sustainable agricultural and food production practices [4].

The manual grading and sorting processes in banana grading are laborious, time-consuming, and dependent on manpower to inspect outer appearances for freshness, to check products for freshness, which leaves room for error. The reliance on human vision for classification leads to subjective decisions and increases the risk of biased predictions. Traditional methods are also required to be labor-intensive, handmade feature extraction techniques, which can differ depending on the kind of images employed for testing and training [5].

* Corresponding author: Dominee Kyle Ibarlin

This literature study covers significant contributions in which AI techniques were employed for banana crops to encounter the discourses for innovation in this field. Three important AI methods were evaluated as concentrated areas in this study, particularly Computer Vision, Machine Learning, and Robotics. This research focuses on the application of AI techniques in Banana Grading in order to make the individuals understand the significant development of banana-related agricultural systems in the past few years.

2. Artificial Intelligence Applications in Banana Grading

2.1. Computer Vision

Computer vision is a technology that involves the automated retrieval, interpretation, and comprehension of valuable information from images. Logically and algorithmically dependents are involved to accomplish an automated visual perception. Computer vision systems are practicable to classify and analyze a wide variety of items, such as fruits, and vegetables, into particular grades, detect deficiencies, and assess characteristics or qualities, including color, structure, scale, surface defects, and contamination [6]. Moreover computer vision technology, as an emerging technology, exhibits promising potential in the agriculture sector. This automation using this sub-domain of Artificial Intelligence decreases the reliance on manual labor and improves the speed and consistency of grading. In the future, computer vision intelligence technology, built on large-scale datasets, will be employed in every aspect of agricultural production management and will play a more significant role in deciphering current agricultural problems [7].

Mohamedon, M. F. et al. developed a mobile application using computer vision to identify banana ripeness. They adopted transfer learning to extract edges from images of a pre-trained model for classification, employing TensorFlow Lite and the Model Maker library to simplify adapting and converting a pre-trained model. The study revealed an accuracy of 98.25% in identifying banana ripeness through banana live images, and displaying the ripeness level [8].

Mazen, F. M. A. et al. introduced an automatic computer vision system for identifying the ripening stages of bananas. The proposed system, when compared, outperformed other techniques, together with SVM, Naive Bayes, KNN, decision tree, and discriminant classifiers, which achieved a recognition rate of 97.75% [9].

Athiraja, A. et al. conducted a study on early detection of banana diseases. They standardized and filtered images to detach noise by means of pre-processing techniques. Then, feature extraction techniques for assessing color, shape, and texture. Subsequently, employing Adaptive Neuro-Fuzzy Inference System and case-based reasoning algorithms. Receiver Operating Characteristics (ROC) curve analysis showed the dominance of the Adaptive Neuro-Fuzzy Inference System when compared to the case-based reasoning algorithm in the presented system [10].

Kimpli, K. et al. innovatively created an expert system technique for evaluating the freshness of banana fruit. This program utilized the Google Cloud Platform to transmit a sample banana image, leveraging the Google Cloud Vision programming interface to extract attribute values from the image. The obtained analytical results were then compared to the application's database of attribute datasets to assess the ripeness of the banana sample image. The integration of various components, including image processing and data mining, led to the development of a highly accurate classification model for banana maturity, achieving an impressive accuracy rate of 96.15%. This approach signifies a significant advancement in assessing the freshness of banana fruit, showcasing the potential of expert systems and cloud-based technologies to contribute to the improvement of fruit quality evaluation processes [11].

Dewi, C. et al did an evaluation of the non-destructive assessment of banana maturity using banana fruit imaging and computer vision techniques. The study presented a comprehensive and extensive assessment of the literature on the type of picture utilized and the steps of the identification process, beginning with feature extraction, dimension reduction, feature selection, and classification. The analysis found significant possibilities for using digital imaging and computer vision methods to automatically determine banana ripeness [12].

Darapaneni, N. et al., utilized banana fruit to build a computer vision model targeting three use cases: identifying bananas in images, determining sub-family or variety, and assessing banana quality. The researchers developed a Convolutional Neural Network (CNN) and adjusted a MobileNet model for the highest level of performance using a dataset of 3064 images. The model achieved 93.4% accuracy in sub-family/variety classification and a perfect 100% accuracy in assessing banana quality [13].

Haque, et al suggested a Convolutional Neural Network (CNN)-based computer vision model that accurately classifies five strains of bananas: cavendish, lady finger, shabri, green, and red, as well as identifying rotting ones. The researchers successfully implemented the two deep learning models, achieving substantial accuracy while adjusting different parameters. Proponents also used well established assessment criteria including accuracy, recall, F1-score, and ROC. The second model achieved higher accuracy (93.4±0.8%) and identified rotting bananas with 98.3±.8% [14].

The look of fruits and vegetables is an important sensory attribute that influences market value, customer preference, and choice. Although individuals can sort and grade, the process is uneven, time-consuming, variable, subjective, onerous, expensive, and easily influenced by the environment. As a consequence, an expert fruit grading process is necessary. Bhargava and Ansal (2021) provided a complete review of several approaches, such as preprocessing, segmentation, feature extraction, and classification, for assessing fruit and vegetable quality based on color, texture, size, shape, and flaws. The study includes a rigorous evaluation of several algorithms offered by researchers for quality assessment of fruits and vegetables [15].

2.2. Machine Learning

Machine learning, a subset of artificial intelligence, involves the use of algorithms that improve through experience. It has been applied in various fields, from healthcare to finance, and now, it's making waves in agriculture, specifically in banana cultivation and processing. One of the applications of machine learning in banana cultivation is ripening stage detection. Researchers have developed mobile-based deep learning models for detecting ripening levels in bananas. These models can analyze images of banana plants, identify patterns, and provide a diagnosis in real time. Using Convolutional Neural Networks (CNN), a type of deep learning algorithm, researchers have been able to classify the ripening stages of bananas with high accuracy. This can help determine the optimal time for banana harvest and even predict the shelf life of the fruit, leading to reduced waste and increased profits [16].

Another intriguing use of machine learning is disease detection in bananas. Researchers used CNN to accurately diagnose banana illnesses. Researchers used mobile-based deep learning algorithms to identify illnesses in bananas. These algorithms can evaluate banana plant photos, identify disease-related patterns, and deliver real-time diagnoses. Farmers may now take prophylactic actions to ensure their crops' health and yield [17].

Patel, H. B, et al. applied machine learning and deep learning for automated illness diagnosis and grading in bananas. The methods involve early disease identification using digital images, image preprocessing, fuzzy clustering for segmentation, statistical feature extraction, and an FFNN for classification. The AI system achieves an exceptional 99.8% identification rate, providing a reliable tool for farmers in disease diagnosis and banana sorting, surpassing previous systems and enhancing productivity in the food processing industry [18].

Wang, M., et al. applied different machine learning algorithms. The results showed a high degree of accuracy, with RPD values consistently over 2.0 and a ripeness estimation precision of 97.5%. Real-time dynamic monitoring can be made achievable by the system's integration into an MCU, demonstrating that it has practical applications in agriculture [19].

Ratha, A. K., et al. integrated VGG16 deep features and GLCM texture features using an SVM classifier for banana maturity estimation. In a two-phase machine learning approach, individual evaluations achieved 92.34% accuracy (VGG16 plus SVM) and 89.99% accuracy (GLCM texture feature plus SVM). Parallel feature fusion significantly enhanced performance to 99.87% accuracy, showcasing successful automatic ripeness grading for bananas [20].

Sabilla, I. A., et al. integrate k-NN, SVM, and DT machine learning algorithms to determine banana type and ripeness from peel images, optimizing processing time through PCA for accurate and efficient banana grading. Linear SVM achieved the highest accuracy at 99.1%, surpassing k-NN and DT, with grayscale preprocessing and RGB dominance values emphasized [21].

Kosasih, R., et al. used statistical features and machine learning algorithms, including Naive Bayes and Support Vector Machine (SVM), to classify banana ripeness levels based on texture and color information extracted from images. Naive Bayes achieved 86.67% accuracy, indicating effectiveness in texture-based classification. The study suggests potential for further research, emphasizing increased image data and exploration of deep learning algorithms like convolutional neural networks [22].

Athiraja, A., et al. used multiple machine learning techniques for agricultural applications. For early banana disease identification, image processing, soft computing, and ANFIS were used. In AI disease diagnosis, preprocessing and ANFIS, along with noise removal, enhanced accuracy. In identifying the maturity of bananas, CNN architectures achieved an accuracy rate of over 90%; the first model performed best for both optimizers. Accuracy of transfer learning using VGG19 and VGG16 was comparable to earlier studies. The original architecture that was put forth showed better average recall and precision (0.87) [23].

Paulraj et al. suggested an approach to utilize a neural network and image processing solution to recall and recognize ripe bananas in accordance with their respective colors. The RGB color components of the captured banana pictures serve as the foundation for the suggested system. There were four sets of bananas of varying sizes and maturity. The photographs of bananas were taken everyday in parts, one after the other, till they rotted, and employed a supervised neural network model. The model successfully accomplished an identification accuracy of 96% [24].

Olaniyi, E. O., et al. devised an innovative intelligent identification system aimed at addressing challenges in the field of food production, specifically tackling the potential errors associated with human operators grading bananas. The introduced approach not only eliminates the likelihood of human error but also seeks to enhance the speed and efficiency of labor compared to traditional manual grading methods. Moreover, it is designed to operate effectively in environments where human operators may face limitations. The study presented an intelligent identification technique tailored for sorting bananas, showcasing superior performance when compared to previous designs. Experimental results demonstrated the system's effectiveness in the food processing industry, achieving an impressive 97% recognition rate. This underscores the potential of the technology to significantly improve the accuracy and efficiency of banana grading processes in the food production sector [25].

Bertemes-Filho, P. et al. introduced a banana ripening classification test that utilizes a support vector machine algorithm in conjunction with electrical impedance spectroscopy. Through measuring impedance modulus and impedance phase within the frequency range of 50 Hz to 1 MHz, the researchers conducted tests on 100 banana samples representing three stages of ripening. The results indicated that this method requires minimal processing time and boasts a remarkable ability to accurately identify ripeness stages, achieving a 100% accuracy rate. The implications of this approach extend to potential widespread application, presenting an opportunity to enhance the reliability and profitability of harvest automation [26].

2.3. Robotics

Robotics is a field that includes the design, creation, and operation of robots which have a variety of sensors and processes. The integration of robotics in agriculture, particularly in fruit grading, has gained popularity. These robots automate labor-intensive tasks to ensure consistent and efficient production since they are equipped with advanced sensing and learning abilities which use advanced algorithms, multi-sensor cooperation, and accurate mobile platforms. These robots are categorized according to the stages of fruit grading, from seeding to processing, and they support long-term industrialization. They are made up of a vision system, control system, mechanical actuators, and a mobile platform, and their adaptive and efficient design emphasizes their significant role in improving agriculture industry [27].

Huang P. et al. developed a banana-picking robot that uses machine vision based row-following system. Although, earlier results showed that visual perception was unreliable in headland-turning. The authors suggested a new study in which an self-navigating picking robot equipped with a smart navigation system for orchard operations is integrated to a developed headland-turning approach. The outcomes showed that the turning technique design that was implemented which enhanced the robot's capacity to rapidly converge on the path, retain less radial errors, and decrease time, space, and deviation in headland-turning [28].

Ishikawa, R., et al. develop a fracture-anticipation system for robotic system manipulation using recurrent neural networks (RNNs) and tactile sensing. The system uses peeled bananas as one of the subjects in the experiment. The implemented network achieves an 80% recall in predicting fractures while maintaining a high success rate in picking fragile objects. The system outperforms a rule-based baseline, reducing breakage and enabling fracture-free picking [29].

Lin, G., et al devised a novel robot for harvesting bananas by implementing a sophisticated learning technique known as inverse kinematics. This strategy involves guiding the robot to specific locations. To overcome the limitations of deep reinforcement learning algorithms in exploring extensive robot workspaces reliably, the researchers introduced a viable alternative termed automated target generation. Addressing the inverse kinematics challenge, they employed the twin-delayed deep deterministic approach, demonstrating an average execution time of 23.8 milliseconds and a success rate of 96.1% when using automated target generation. In contrast, without this alternative, the success rate dropped to a mere 81.2%. Validation of these results was conducted through simulation trials. Field experiments further confirmed the efficacy of the proposed approach, showcasing its ability to successfully navigate the robot to each designated goal [30].

Wu, F. et al introduced an innovative robot model derived from a customized YOLOv3 framework that integrates clustering optimization. Through the application of image segmentation and denoising techniques, the researchers extracted edge images of flower buds and inflorescence axes. Subsequently, they established a spatial geometry model, performing calculations for the middle of symmetry and centroid of the flower bud edges. Experimental outcomes highlighted the outstanding performance of the modified YOLOv3 model with clustering optimization, demonstrating a commendable equilibrium between speed and precision in both front-lighting and backlighting scenarios. The proportion of images meeting the positioning requirements reached 93% and 90%, respectively. These findings revealed that the proposed method effectively meets the real-time operational necessities of the banana bud-cutting robot, showcasing its ability to deliver reliable results in various lighting conditions [31].

Chen, M. et al. present a multi-vision technology-based assessment framework that utilize a approaches to develop the execution of multi-view-geometry-based vision modules for taking fruits in orchards. The experiment's findings proved the accuracy and consistency of the suggested adaptive stereo-matching technique at various sampling depths. Furthermore, multi-view point clouds were accurately merged using the suggested point cloud stitching technique. Theoretical and practical benchmarks for 3D sensing of banana central stocks in complex situations were developed by this study [32].

Baskaran, S. & Kumar, T. R. (2021) address issues in banana cultivation by initiating the design, structural, and computational fluid dynamics simulation of an agricultural field robot sought to assist banana cultivation through the creation of plantation holes for banana seedlings, which is then modeled in 3D using SolidWorks software with appropriate dimensions. Following this, by means of applying desired material properties to separate components, a static structural analysis is performed on the assembly. After the completion of the structural analysis, a CFD analysis is carried out using Ansys-Fluent Workbench for analyzing the wind effects on the robot [33].

Onishi, Y. et al. offer a system for recognizing fruits and automating harvesting employing a robotic arm. To detect the position of fruit, a Single Shot MultiBox Detector is utilized in conjunction with a stereo camera. After inverse kinematics determine the angles of the joints in the observed proximity, the robot arm advances to the target location of the fruit. The robot harvests the fruit by means of twisting its hand axis. The trial findings revealed that there are higher than 90% of the fruits were identified. Furthermore, the robot can pick an apple in 16 seconds [34].

Zhou, H. et al. conducted a evaluation of the current state of the art in fruit harvesting robots, undertaking a survey and comparative analysis of 47 applications spanning the past two decades. This assessment not only showcased the general performance of each system but also identified prevailing research trends. Key performance metrics such as collect success rate, harvesting speed, and damage rate were selected for comparison, given their significance to the economic viability of a robotic system. The extensive research and comparison of harvesting robot performance unveiled a substantial gap between existing automated harvesting technology and commercialization. Contrary to expectations, the overall performance of these robots has not surpassed that of their human counterparts. Furthermore, the essential data required for successful commercialization remains incomplete, highlighting the considerable distance yet to be covered in bridging the existing disparities [35].

3. Challenges and Opportunities

There are challenges in implementing banana grading across the sub-domains of artificial intelligence. About computer vision, the complexity of significant quality attributes of bananas, including size, texture, color, shape, and deformity, poses challenges for accurate and reliable classification. When capturing images of bananas, only one direction is tested, but more angles are required to cover up during the image acquisition, which also entails a challenge in this direction [36]. In machine learning, issues related to computational resources for training and testing algorithms, and user-friendly predictive models for farmers and other end-users, present logistical challenges [37]. Additionally, robotics for the gentle handling of bananas presents challenges, where a requirement for advanced mechanization systems to ensure the quality of banana hands (clusters or bunches of bananas) and prolong the transportation time is needed as banana hands are susceptible to mechanical damage [38].

In spite of these challenges, numerous opportunities for artificial intelligence for banana grading have provided a way of making progress toward industry advancement. One advantage is crop cost reduction which helps by means of reducing manual labor worked by farmers and related stakeholders [39]. Another opportunity includes improved quality control which aided precision grading from various quality factors of the banana crops. Moreover, opportunities for research and innovation in the banana agricultural industry can pave the way for further development and advancement in this significant field.

Image processing and computer vision systems are scientific mechanisms in agriculture and industry due to their exceptional performance, increasing cost effectiveness, ease of use, and resilience. TCVS or Traditional computer vision systems, as of now, are widely used for fruits and vegetables grading. TCVS analyze properties such as color, texture, or even defects, to improve detecting these properties, dynamic tools are provided to TCVS so as to lessen faults in recognition. Still, many challenges are present when detecting defects such as uneven light distribution, wavelength selection, time consuming acquisition of images, and so on. While it is common to detect characteristics such as color, texture or form, other properties should also be explored. Additionally, adjusting the weight value may also be considered to increase performance. Major breakthroughs in Terahertz imaging, Raman imaging, and 3D techniques may be utilized for fruit and vegetable quality assessments [40].

4. Conclusion

The literature analysis on artificial intelligence implementations in banana grading revealed important advancements in three central areas: computer vision, machine learning, and robotics. Related studies about Computer Vision imply that approaches, involving 3D Computer Vision, image understanding, and image processing have the potential to be effective for automating labors such as ripeness recognition, illness detection, and quality assessment. This not only makes speed and precision better, but also makes less demand for manual labor. Machine learning, especially deep learning algorithms such as CNNs, supports banana farmers to make better decisions by precisely recognizing ripeness stages and identifying illnesses. For this reason, combining these algorithms into grading systems increases efficiency and lowers waste. On the one hand, Robotics brings inventive solutions in the form of autonomous picking robots, fracture-anticipation systems, and banana-harvesting robots.

Compliance with ethical standards

Acknowledgments

The researchers would also like to thank their research adviser, Dr. Edwin R. Arboleda, for his enthusiasm, patience, and vast expertise. With his guidance, the researchers were able to contribute to the completion of this research study.

Disclosure of conflict of interest

No conflict of interest to be disclosed

References

[1] Tanha Talaviya, Dhara Shah, Nivedita Patel, Hiteshri Yagnik, Manan Shah. Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, 2020, 4:58-73. https://doi.org/10.1016/j.aiia.2020.04.002

[2] Kaushal S, Kumar S, Tabrez S. Artificial Intelligence in Agriculture. *International Journal of Science and Research (IJSR)*, 2023, 11(5):1682-1688. https://doi.org/10.21275/SR22524180634

[3] Spanaki K, Sivarajah U, Fakhimi M, Despoudi S, Irani Z. Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research. *Annals of Operations Research*, 2021, 308(1–2):491–524. https://doi.org/10.1007/s10479-020-03922-z

[4] Raj M, Gupta S, Chamola V, Elhence A, Garg T, Atiquzzaman M, Niyato D. A survey on the role of Internet of Things for adopting and promoting Agriculture 4.0. *Journal of Network and Computer Applications*, 2021, 187:103107. https://doi.org/10.1016/j.jnca.2021.103107

[5] Ismail N, Malik OA. Real-time visual inspection system for grading fruits using computer vision and deep learning techniques. *Information Processing in Agriculture*, 2022, 9(1):24–37. https://doi.org/10.1016/j.inpa.2021.01.005

[6] Ghadge P, Tilawat R, Sand P, Jadhav P. Applications of Computer Vision in Agriculture. *International Journal of Engineering Applied Sciences and Technology*, 2021, 5(9):166-168. https://doi.org/10.33564/IJEAST.2021.v05i09.026

[7] Tian H, Wang T, Liu Y, Qiao X, Li Y. Computer Vision Technology in Agricultural Automation — A Review. *Information Processing in Agriculture*, 2019. https://doi.org/10.1016/j.inpa.2019.09.006

[8] Mohamedon MF, Abd Rahman F, Mohamad SY, Omran Khalifa O. Banana ripeness classification using computer vision-based mobile application. *In 2021 8th International Conference on Computer and Communication Engineering (ICCCE)*. https://doi.org/10.1109/iccce50029.2021.9467225

[9] Mazen FM A, Nashat AA. Ripeness classification of bananas using an artificial neural network. *Arabian Journal for Science and Engineering,* 2019, 44(8):6901–6910. https://doi.org/10.1007/s13369-018-03695-5

[10] Athiraja A, Vijayakumar P. Banana disease diagnosis using computer vision and machine learning methods. *Journal of Ambient Intelligence and Humanized Computing,* 2020, 12(6):6537–6556. https://doi.org/10.1007/s12652-020-02273-8

[11] Kipli K, Zen H, Sawawi M, Noor MS M, Julai NH, Junaidi NH, Razali MIS M, Chin KL, Masra SM W. Image Processing Mobile Application For Banana Ripeness Evaluation. *International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA).* https://doi.org/10.1109/icassda.2018.8477600

[12] Dewi C, Mahmudy WF, Arisoesilaningsih E, Solimun S. Review of Non-Destructive Banana Ripeness Identification using Imagery Data. *Sustainable Information Engineering and Technology*. https://doi.org/10.1145/3479645.3479685

[13] Darapaneni N, Tanndalam A, Gupta M, Taneja N, Purushothaman P, Eswar S, Paduri AR, Arichandrapandian T. Banana Sub-Family Classification and Quality Prediction using Computer Vision. April 2022. CC BY-NC-ND 4.0 License.

[14] Haque ASMFA, Hakim MA, Hafiz R. CNN based automatic Computer Vision system for strain detection and quality identification of banana. *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI).* https://doi.org/10.1109/acmi53878.2021.9528269

[15] Bhargava A, Bansal A. Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University - Computer and Information Sciences*, 2021, 33(3):243–257. https://doi.org/10.1016/j.jksuci.2018.06.002

[16] Saranya N, Srinivasan K, Kumar SKP. Banana ripeness stage identification: a deep learning approach. *Journal of Ambient Intelligence and Humanized Computing*, 2022, 13:4033–4039. https://doi.org/10.1007/s12652-021-03267-w

[17] Selvaraj MG, Vergara A, Ruiz H, et al. AI-powered banana diseases and pest detection. *Plant Methods*, 2019, 15:92. https://doi.org/10.1186/s13007-019-0475-z

[18] Patel HB, Patil NJ. An Intelligent Grading System for Automated Identification and Classification of Banana Fruit Diseases Using Deep Neural Network. *International Journal of Computing and Digital Systems*. https://dx.doi.org/10.12785/ijcds/XXXXmazenXX

[19] Wang M, Wang B, Zhang R, Wu Z, Xiao X. Flexible Vis/NIR wireless sensing system for banana monitoring. *Food Quality and Safety*, 2023, 7. https://doi.org/10.1093/fqsafe/fyad025

[20] Ratha AK, Sethy PK, Barpanda NK, Behera SK. Maturity Status Estimation of Banana Using Image Deep Feature and Parallel Feature Fusion. *Lecture Notes in Networks and Systems*, 2022, 349–353. https://doi.org/10.1007/978-981-19-4863-3_33

[21] Sabilla IA, Wahyuni CS, Fatichah C, Herumurti D. Determining Banana Types and Ripeness from Image using Machine Learning Methods. *2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT)*. https://doi.org/10.1109/icaiit.2019.8834490

[22] Kosasih R, Sudaryanto S, Fahrurozi A. Classification of six banana ripeness levels based on statistical features on machine learning approach. *International Journal of Advances in Applied Sciences*, 2023, 12(4):317. https://doi.org/10.11591/ijaas.v12.i4.pp317-326

[23] Athiraja A, Vijayakumar P. Banana disease diagnosis using computer vision and machine learning methods. *Journal of Ambient Intelligence and Humanized Computing*, 2020, 12(6):6537–6556. https://doi.org/10.1007/s12652-020-02273-8

[24] Paulraj MP, Hema CR, Krishnan RP, Mohd Radzi SS. Colour Recognition Algorithm using a neural network model in determining the ripeness of a banana. *Proceeding of the International Conference on Man-Machine Systems*, 2009, pp. 2B71–2B74.

[25] Olaniyi EO, Oyedotun OK, Khashman A. Intelligent grading system for banana fruit using neural network arbitration. *Journal of Food Process Engineering*, 2016, 40(1). https://doi.org/10.1111/jfpe.12335

[26] Bertemes-Filho P, Bertemes WL, Cavalieri R, Paré AT, Spessatto J, Savi DC. Ripening classification of bananas (Musa acuminate) using electrical impedance spectroscopy and support vector machine. *International Journal of Biosensors & Bioelectronics*, 2020, 6(4):99–101. https://doi.org/10.15406/ijbsbe.2020.06.00195

[27] Cheng C, Fu J, Su H, Ren L. Recent Advancements in Agriculture Robots: Benefits and Challenges. *MDPI - Machines*, 2023, 11:48. https://doi.org/10.3390/machines11010048

[28] Huang P, Zhu L, Zhang Z, Yang C. Row End Detection and Headland Turning Control for an Autonomous Banana-Picking Robot. *Machines*, 2021, 9(5):103. https://doi.org/10.3390/machines9050103

[29] Ishikawa R, Hamaya M, Von Drigalski F, Tanaka K, Hashimoto A. Learning by Breaking: Food Fracture Anticipation for Robotic Food Manipulation. *IEEE Access*, 2022, 10:99321-99329. https://doi.org/10.1109/ACCESS.2022.3207491

[30] Lin G, Huang P, Wang M, Xu Y, Zhang R, Zhu L. An inverse kinematics solution for a Series-Parallel hybrid Banana-Harvesting robot based on deep reinforcement learning. *Agronomy*, 2022, 12(9):2157. https://doi.org/10.3390/agronomy12092157

[31] Wu F, Duan J, Chen S, Ye Y, Ai P, Yang Z. Multi-Target recognition of bananas and automatic positioning for the inflorescence axis cutting point. *Frontiers in Plant Science*, 2021, 12. https://doi.org/10.3389/fpls.2021.705021

[32] Chen M, Tang Y, Zou X, Huang K, Huang Z, Zhou H, Wang C, Lian G. Three-dimensional perception of orchard banana central stock enhanced by adaptive multi-vision technology. *Computers and Electronics in Agriculture*, 2020, 174:105508. https://doi.org/10.1016/j.compag.2020.105508

[33] Baskaran S, Kumar TR. Modeling, structural and CFD analysis of mobile robot for banana cultivation. *Journal of Engineering Research - ICMMM Special Issue*, 2021. https://doi.org/10.36909/jer.ICMMM.12443

[34] Onishi Y, Yoshida T, Kurita H, Fukao T, Arihara H, Iwai A. An automated fruit harvesting robot by using deep learning. *ROBOMECH Journal*, 2019, 6(1). https://doi.org/10.1186/s40648-019-0141-2

[35] Zhou H, Wang X, Au W, Kang H, Chen C. Intelligent robots for fruit harvesting: recent developments and future challenges. *Precision Agriculture*, 2022, 23:1856–1907. https://doi.org/10.1007/s11119-022-09913-3

[36] Singh AP, Sahu P, Chug A, Singh D. A Systematic Literature Review of Machine Learning Techniques Deployed in Agriculture: A Case Study of Banana Crop. *IEEE Access*, 2022, PP(99):1-1. https://doi.org/10.1109/ACCESS.2022.3199926

[37] Almeyda E, Ipanaqué W. Recent Developments of Artificial Intelligence for Banana: Application Areas, Learning Algorithms, and Future Challenges. *Engenharia Agrícola*, 2022, 42(special issue):e20210144. http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v42nepe20210144/2022

[38] Guo J, Duan J, Li J, Yang Z. Mechanized Technology Research and Equipment Application of Banana Post-Harvesting: A Review. *Agronomy*, 2020, 10(3):374. https://doi.org/10.3390/agronomy10030374

[39] Das S, Ghosh I, Banerjee G, Sarkar U. Artificial Intelligence in Agriculture: A Literature Survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies*, 2018, 7(3), Volume 7, Issue 3.

[40] Bhargava A, Bansal A. Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University - Computer and Information Sciences*, 2021, 33(3):243–257. https://doi.org/10.1016/j.jksuci.2018.06.002