AUTOMATED QUALITY GRADING AND SORTING OF EGGPLANTS USING MACHINE LEARNING

An Undergraduate Thesis

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BACHELOR OF SCIENCE IN COMPUTER ENGINEERING

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ABSTRACT

This study...

Keywords: *computer vision, grading system, eggplant classification*

This piece of work is wholeheartedly dedicated

to my parents

Papang

and

Nanay

ACKNOWLEDGMENT

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Above all, to ***Almighty God***, whose unconditional love infinitely transcends all human comprehension, for providing us with good health, divine protection and bountiful blessings.

Researchers

TABLE OF CONTENTS

Page No.

LIST OF TABLES

LIST OF FIGURES

List of Equations

CHAPTER 1

INTRODUCTION

This chapter presents an overview of the study, outlining its conceptual foundation and research direction. Section 1.1 presents the background of the study, which discusses the growing use of automation, computer vision, and machine learning in postharvest quality assessment. Section 1.2 identifies the statement of the problem, highlighting the challenges in automating the grading and sorting of eggplants. Section 1.3 states the objectives of the study, focusing on the design and development of an automated eggplant grading and sorting system. Section 1.4 discusses the significance of the study, emphasizing its benefits to farmers, traders, consumers, and future researchers. Section 1.5 defines the scope and limitations that set the boundaries of the study's application and performance. Lastly, Section 1.6 provides the definition of key terms to ensure clarity and understanding of important concepts used throughout the research.

1.1 Background of the Study

In recent years, the agricultural sector has increasingly turned to automation and artificial intelligence to enhance postharvest operations. Within this technological shift, machine learning (ML) has become pivotal for automating the quality grading and sorting of produce (Bansal and Uddin, 2023). This technology facilitates non-destructive inspection by analyzing key visual characteristics (such as color, size, shape, and surface defects) that were traditionally assessed through manual, labor-intensive methods (Khan and AlGhamdi, 2024). By integrating ML with mechatronic systems, automated graders have been developed that perform real-time classification and physical sorting, significantly boosting efficiency and accuracy for a variety of crops, including apples, citrus, and mangoes (Bu et al., 2025; Lee et al., 2023; Xu et al., 2024; Zhang et al., 2021).

Despite these advancements, a significant research gap remains for elongated and irregularly shaped produce like eggplants, as existing systems have primarily been optimized for spherical or root-type crops. For instance, studies on sweet potatoes and mandarins achieved high accuracy but relied on the produce shapes reliant on uniform rotation (Bu et al., 2025; Xu et al., 2024). Similarly, multi-camera setups for apples often struggle to achieve full-surface visibility on non-spherical items (Lee et al., 2023; Zhang et al., 2021). While deep learning has been successfully applied to classify diseases in eggplants (Haque and Sohel, 2022; Kursun and Koklu, 2025)

Addressing this technological gap is critical given the economic and agricultural importance of eggplant. A global crop with centuries of cultivation, eggplant (*Solanum melongena*), also known as aubergine or brinjal, is a major vegetable crop. Global production reaches approximately 60.8 million metric tons, cultivated on over 1.9 million hectares (Food and Agriculture Organization of the United Nations, 2025). Its significance is particularly pronounced in countries like the Philippines, where it is locally known as "*talong*" and where the production value alone amounted to ₱1.027 billion in December 2024 (Philippine Statistics Authority, 2025).

The unique morphology of eggplant poses distinct challenges for automated grading. Its elongated, curved, and irregular shape complicates the capture of a complete surface image, unlike spherical fruits that can be easily rotated. Consequently, specialized multi-angle imaging is necessary to consistently capture defects along the entire stem-end, body, and tip-end. Additionally, the vegetable's dark purple skin can obscure blemishes, and its susceptibility to specific defects like calyx browning requires highly sensitive computer vision algorithms for accurate quality assessment.

This study will look into developing an integrated computer vision and deep learning system for the real-time grading and sorting of eggplants while considering the plant's unique morphology. The core innovation is a dedicated imaging station; when an eggplant passes over this station, two synchronized cameras mounted above and below the glass simultaneously capture its top and bottom surfaces. This design eliminates the need for complex mechanical flipping (Awasthi, 2021) and overcomes the challenges of timing and inconsistent rotation posed by the vegetable's variable size and curvature. Successful validation will demonstrate a scalable system capable of reducing postharvest losses, lowering labor costs, and ensuring consistent quality standards for this high-value crop. By providing a model for grading non-spherical produce, this study will hopefully contribute to broader adoption of precision agriculture in farming. A machine learning model will then process these captured images to perform quality grading, which subsequently actuates a mechatronic sorter (eggplants will be sorted first into binary classification of "Healthy" and "Defect" or "Unhealthy". Afterwards, "Healthy" class will be sorted further into three subclasses: "Extra Class", "Class I", and "Class II," which follows the local criteria provided by the Philippine National Standards (PNS) and Bureau of Agricultural and Fisheries Product Standards (BAFPS) (PNS/BAFPS 52:2007), that is based on visual quality, size, and defect tolerances (Mandigma et al., 2021).

1.2 Statement of the Problem

The adoption of automated grading systems using ML has significantly improved postharvest efficiency for many agricultural crops. However, a critical technological gap exists for elongated and irregularly shaped produce, specifically eggplants. Existing automated systems are predominantly designed and optimized for spherical (e.g., citrus fruits, tomatoes) or root-type crops (e.g., sweet potatoes, potatoes), which allow for uniform rotation and straightforward imaging to achieve full-surface visibility.

This gap poses two main challenges – unique morphological features and automation of sorting systems for postharvest quality grading. The produce unique morphology (elongated, curved shape, dark skin) presents distinct challenges (such as darkening of skin leading to obscure defects, and susceptibility to specific blemishes like calyx browning) that current system designs cannot adequately address. These challenges include the inability to capture a complete surface image without complex handling and the need for specialized algorithms to accurately identify defects on a non-uniform, dark surface. While some research has applied deep learning to eggplant disease detection, these studies have not progressed to the development of integrated, real-time mechanical sorting systems for postharvest quality grading. This lack of a tailored automated solution is a significant limitation, given the substantial economic and agricultural importance of eggplant as a widely cultivated crop.

A primary technical obstacle is the lack of an effective imaging mechanism capable of capturing the eggplant's entire surface area in a single, synchronized pass. Conventional conveyor-based systems used for round produce are insufficient because they cannot enable a complete full surface inspection of a curved, elongated vegetable to a camera. Proposed solutions like mechanical flippers or complex multi-roller systems introduce significant drawbacks, including increased cost, mechanical complexity, and high risk of bruising or damaging the delicate skin of the produce, which defeats the purpose of non-destructive inspection.

Consequently, the absence of a suitable automated system for eggplants perpetuates a reliance on manual labor for sorting, which is inherently slow, inconsistent, and economically unsustainable. This reliance leads to significant postharvest losses due to inconsistent grading standards and the slow pace of human inspection, which can bottleneck the entire supply chain. Without a technological solution designed for its specific form, the eggplant industry cannot fully access the benefits of automation, such as enhanced throughput, objective quality control, and improved profitability for farmers. Therefore, the problem necessitates the development of a novel, integrated system that solves the fundamental challenges of imaging and handling eggplants to enable accurate, real-time, and non-destructive automated grading.

1.3 Objectives of the Study

This study aims to develop an automated eggplant sorting and grading system using ML to classify eggplants as healthy or defective, and categorize healthy ones into three quality grades ("Extra Class", "Class I", "Class II"), reducing manual labor in the sorting process.

Specifically, this study aims:

1. To design and develop a mechatronic sorting mechanism that integrates with a conveyor system to automate the physical separation of eggplants based on quality grade;
2. To develop and train a machine learning model for automatic quality grading by extracting visual features (such as color, shape, and surface defects) from images captured by the dual-camera imaging station; and
3. To evaluate the performance evaluation of the integrated system, measuring its grading accuracy, mechanical reliability, and usability for postharvest operations.

1.4 Significance of the Study

This study enhances the post-harvest process of eggplant production through automated sorting and grading using image processing and machine learning. It addresses the inefficiencies of manual sorting by ensuring accurate and consistent quality classification. The research contributes to agricultural advancement and supports SDG 2 (Zero Hunger), SDG 8 (Decent Work and Economic Growth), and SDG 12 (Responsible Consumption and Production) by promoting productivity, fair trade, and reduced post-harvest waste. Benefiting from the study are the following sectors:

Farmers. Benefit through reduced manual labor and human error in sorting and grading. The system helps them achieve consistent classification results, allowing for fairer pricing. Faster and more accurate sorting increases productivity and reduces post-harvest losses. Farmers also gain stronger market confidence by consistently meeting quality standards required by buyers and distributors.

Middlemen and Traders. Benefit from standardized grading that ensures uniform quality across distributed eggplants. Providing standardized classifications helps minimize rejection from buyers and reduces unnecessary handling and waste. This also promotes efficiency in the post-harvest process by shortening the time between sorting and distribution, ensuring that only high-quality and market-ready produce is delivered. Through improved consistency, traders can build stronger partnerships with retailers and improve the credibility of their supply chain operations.

Consumers. Receive eggplants that are clean, fresh, and free from visible defects or diseases. Consistent grading ensures that only safe and high-quality produce reaches the market, promoting good health and consumer satisfaction. The system also supports fair pricing in markets by clearly distinguishing product grades according to quality.

Future Researchers. Gain a useful reference for developing or enhancing automated grading systems in agriculture. The study offers insights into applying image processing and machine learning for post-harvest classification and quality control. It also serves as a foundation for future improvements, including system adaptation for other crops and refinement of algorithm accuracy and efficiency.

1.5 Scope and Limitations

The scope of this study focuses on the quality grading of eggplants using machine learning integrated with a mechatronic sorting system. The system is designed to first classify eggplants as either healthy or defective, and then to further classify the healthy eggplants into the quality grades of Extra Class, Class I, and Class II based on color homogeneity and shape. The system is designed to process individual eggplants as they are transported on a conveyor belt, passing through an imaging platform that enables a full surface inspection.

The focus will be on sorting long, elongated, purple eggplants only, as these are the most common type of eggplants available in Cagayan de Oro City. Uncleaned eggplants or those with significant visible foreign matter–such as thick mud–that may occlude the surface and interfere with the system's classification algorithms are excluded from the study's scope.

In this study, the conveyor belt will have a width of 400 mm, allowing for the efficient transport of individual eggplants during the sorting process. The system will be designed to handle a maximum weight capacity of 7 kg, ensuring that it can process a sufficient number of eggplants at a time without overloading the mechanism. This weight capacity ensures that the system is capable of handling typical batches of eggplants during postharvest operations, while maintaining smooth and efficient performance.

The system is restricted to detecting only external visible defects for the initial healthy/defective classification; it will not identify the specific type of disease present on defective eggplants. Furthermore, the system is fundamentally limited to detecting only external visible defects and cannot detect diseases or quality issues caused by internal fruit infestation, as these are not visible to the camera. Additionally, since the system is designed for long, elongated types of eggplants, it may struggle with or require recalibration for significantly different varieties or shapes.

1.6 Definition of Terms

Color Homogeneity The degree of uniformity in color across an object's surface.

Feature Extraction The process of identifying and quantifying important characteristics such as color, shape, and texture from images

Hyperparameter Tuning Adjusting model settings to improve its accuracy and performance.

Image Preprocessing Enhancement of raw images to reduce noise and improve analysis quality.

Image Segmentation The division of an image into regions to isolate specific objects or areas.

ImageNet A large visual dataset used for pretraining deep learning models in transfer learning applications, advancing deep learning and computer vision through massive, well-labeled datasets that enable highly accurate model training.

Quality Grading The process of evaluating and categorizing items based on visual attributes such as shape, color, and surface condition to determine the overall quality level.

Mechatronics Refers to a field of engineering that integrates mechanical, electrical, computer, and control engineering to create smarter and more efficient systems.

CHAPTER 2

REVIEW OF RELATED LITERATURE

This chapter focuses on related studies or projects that have provided additional relevant information to the proponent. Section 2.1 presents the theoretical background related to machine learning and mechatronics. Section 2.2 specifies the concept of how the system will classify the eggplants by class based on surface defects, color homogeneity, and shape. Section 2.3 presents a review of literature related to the design of employing machine learning and mechatronic integration in agricultural automation for image-based inspection and mechanical sorting applications. Collectively, these reviewed literatures support the concept presented in this study.

2.1 Theoretical Background

The development of an automated eggplant grading system is fundamentally grounded in the integration of theoretical paradigms of computational intelligence and mechanical control. This framework draws from the convergent disciplines of machine learning and mechatronics to create a cyber-physical system capable of perceiving, deciding, and acting. The following subsections detail the core theories that underpin the image analysis, classification, and physical sorting mechanisms of the proposed system.

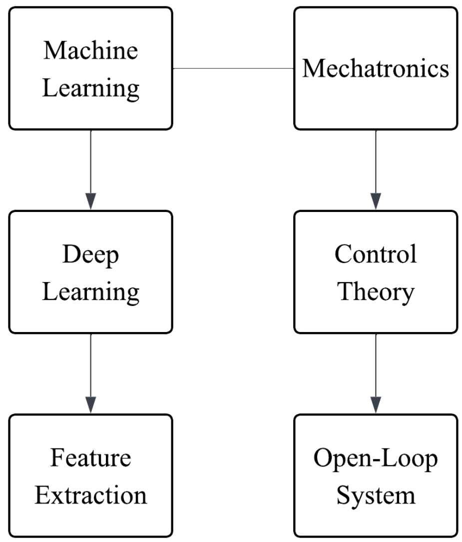

Figure 1: Theoretical Framework

The development of an automated eggplant grading system is fundamentally grounded in the integrated theoretical paradigms of computer vision, deep learning, and mechatronics. The entire process can be conceptualized through a sequential computer vision pipeline, which moves from image acquisition to physical actuation (Szeliski, 2022). This pipeline begins with the digital image formation theory, where a camera sensor captures light reflectance from objects on a conveyor belt, a common setup in food process engineering (Dougherty, 2020). The stability and quality of this initial stage are paramount, as controlled, diffuse illumination is critical to minimize specular reflections and shadows that can obscure critical features like color and surface defects, thereby ensuring consistent input for subsequent algorithmic processing.

Following acquisition, image pre-processing theories are applied to enhance data quality and standardize inputs. This involves digital signal processing techniques such as noise reduction using Gaussian or median filters (Kumar and Sodhi, 2020) and, crucially, color space transformation. Converting images from the default Red-Green-Blue (RGB) space to Hue-Saturation-Value (HSV) or *CIEL*a*b** is a well-established step in agricultural product inspection (Khan and AlGhamdi, 2024). The theoretical underpinning for this conversion lies in the decoupling of color information (chrominance) from intensity (luminance) in these spaces, making the extracted color features more robust to minor variations in lighting conditions, which is essential for accurate color-based grading.

The core of the system resides in the theoretical distinction between traditional machine learning and deep learning for feature extraction. Traditional approaches are based on manual feature engineering, drawing from image processing and pattern recognition theory to hand-craft descriptors for color (e.g., histograms, mean values), shape (e.g., aspect ratio, roundness, area), and texture (e.g., using Gray-Level Co-occurrence Matrix (GLCM) or Local Binary Patterns (LBP)) (Haralick et al., 2007; Ojala et al., 2002). In contrast, deep learning, specifically Convolutional Neural Network (CNN) theory, posits that models can automatically learn a hierarchical representation of features directly from raw pixel data (Goodfellow et al., 2016; LeCun et al., 2015). The lower layers of a CNN learn generic features like edges and corners, while deeper layers synthesize these into complex, task-specific features relevant to defect identification, thereby eliminating the need for manual feature design.

For the classification task itself, the theoretical models diverge. Machine learning classifiers operate on the principles of statistical learning theory, finding optimal hyperplanes to separate classes or constructing ensembles of decision trees, respectively, based on the handcrafted features (Breiman, 2001; Hearst et al., 1998). Conversely, an end-to-end deep learning model uses a fully connected output layer with a normalized exponential function (also known as *Softmax*) to perform classification based on the high-level features it learned itself. The theoretical advantage of CNNs is their superior ability to model complex, non-linear relationships in visual data, a capability that has been demonstrated to outperform traditional methods in numerous agricultural applications (Bharman et al., 2022).

The integrity of any supervised learning system is dependent upon the quality of its labeled dataset. The establishment of a reliable ground truth is a theoretical problem rooted in psychometrics and expert systems. The grading labels for the eggplant images must be derived from standardized agricultural protocols, such as those provided by the United States Department of Agriculture (USDA) or equivalent bodies, which define quality classes based on size, color uniformity, and defect tolerances (USDA, 2013). Locally, the project will utilize the criteria defined by the Philippine National Standard (PNS), and Bureau of Agricultural and Fisheries Product Standards (BAFPS) (specifically the PNS/BAFPS 52:2007), which classifies eggplants into Extra Class, Class I, and Class II based on visual quality, size, and defect tolerances (BAFPS, 2007; PNS, 2019). To ensure scientific rigor, the concept of inter-rater reliability, often measured by Cohen's Kappa statistic (κ), must be applied to quantify the agreement between human experts who label the dataset, thereby validating the consistency of the training labels (He et al., 2022; McHugh, 2012).

The closed-loop system theory integrates the digital classification with physical actuation. The decision output from the classification model (e.g., a specific grade) is transmitted via a software-to-hardware interface to a Programmable Logic Controller (PLC) or microcontroller (Bolton, 2015). This triggers a mechatronic actuator, such as a pneumatic pusher or a servo-controlled diverter, which physically sorts the eggplant into its designated bin on the conveyor line. This final stage embodies the principle of cyber-physical systems, where computational intelligence directly controls a physical process to achieve full automation, replicating and potentially surpassing human grading efficiency (Lee, 2008; Zhang et al., 2022).

CHAPTER 3

METHODOLOGY

In this chapter, we detail the methodology employed to conduct the study, providing a comprehensive overview of the research design, data collection, and analytical procedures.

3.1 Research Design

Your research design.

3.2 Formula

3.3 Tables

Table 1: A sample long table.

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Table 2: Sample Data Table

Item	Quantity	Price ($)
Apples	10	0.50
Bananas	5	0.30
Cherries	20	1.20
Dates	50	2.50

3.4 Images

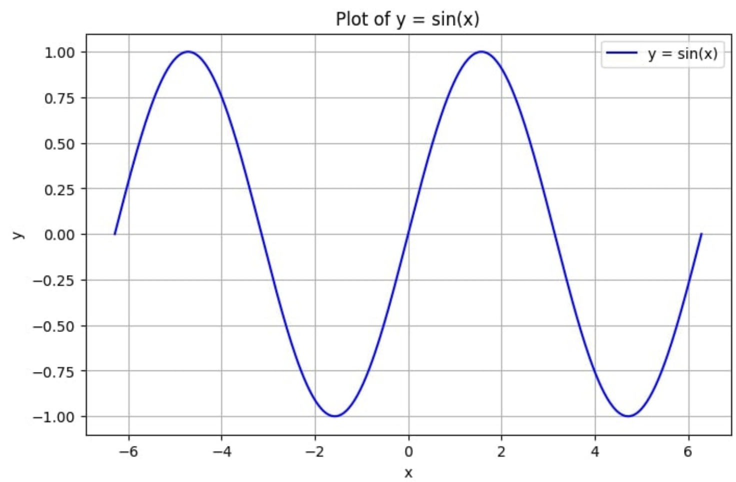

Figure 2

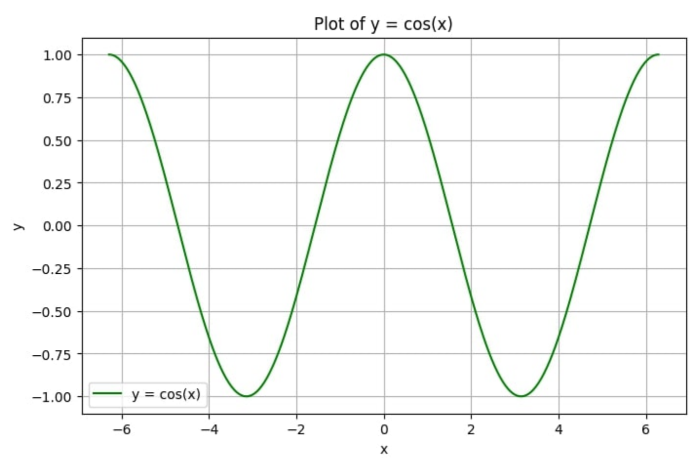

Figure 3: Cosine Graph

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the findings from the research conducted and provides a thorough analysis and interpretation of these results.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This chapter provides the summary of the results obtained in this study and gives some recommendations for further investigation.

5.1 Summary of Findings

The study's findings address the initial research questions by confirming the effectiveness, reliability, and diverse applications of telemetry systems. The ”Summary of Findings” section provides a concise overview of the key results from your research. This section should be factual and focus on presenting the data without interpretation. It should include:

Key Results:

Briefly summarize the most significant findings. Use bullet points or numbered lists for clarity if appropriate. Present the data as it was found, highlighting major patterns, relationships, or trends. Data Presentation:

Include tables, graphs, or charts that succinctly summarize the data. Make sure each visual aid is clearly labeled and includes a brief description. Coverage of Research Questions:

Address each of the research questions or hypotheses posed at the beginning of the study. Summarize the results relevant to each question.

5.2 Conclusion

The ”Conclusions” section interprets the findings and discusses their implications. This section should:

Interpret Findings:

Provide an interpretation of the data summarized in the previous section. Discuss what the results mean in the context of the research questions or hypotheses. Implications:

Explain the significance of the findings. Discuss how the results contribute to the field of study or practical applications. Limitations:

Acknowledge any limitations in the study that may affect the results or their interpretation.

5.3 Recommendations

The ”Recommendations” section provides actionable suggestions based on the study’s findings and conclusions. This section should:

Practical Applications:

Offer specific recommendations for practitioners, policymakers, or other stakeholders based on the findings. Future Research:

Suggest areas for further investigation that could address the study’s limitations or build on its findings. Implementation:

Provide guidance on how the recommendations can be implemented effectively.

APPENDICES

Type your appendix here.

References

Awasthi, A. (2021). *Development and Fabrication of a Power Operated Low-Cost Small-Scale Fruit and Vegetable Grading Machine*. PhD thesis, Punjab Agricultureal University Ludhiana.

BAFPS (2007). *PNS/BAFPS 52:2007 Fresh vegetables - Eggplant - Grading and Classification*. Quezon City, Philippines. As cited in Pinakbet Adventures ni Pina: Komik Serye.

Bansal, J. C. and Uddin, M. S. (2023). Computer vision and machine learning in agriculture: An introduction. In *Computer Vision and Machine Learning in Agriculture, Volume 3*, pages 1–18. Springer.

Bharman, P., Saad, S. A., Khan, S., Jahan, I., Ray, M., and Biswas, M. (2022). Deep learning in agriculture: a review. *Asian Journal of Research in Computer Science*, 13(2):28–47.

Bolton, W. (2015). *Programmable logic controllers*. Newnes.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Bu, Y., Liu, H., Li, H., Murengami, B. G., Wang, X., and Chen, X. (2025). Grading algorithm for orah sorting line based on improved shufflenet v2. *Applied Sciences*, 15(8):4483.

Dougherty, E. R. (2020). *Digital image processing methods*. CRC Press.

Food and Agriculture Organization of the United Nations (2025). *FAOSTAT: Production (Crops and livestock products) - Eggplants (aubergines)*. FAO. Data retrieved for item 'Eggplants (aubergines)'.

Goodfellow, I., Bengio, Y., Courville, A., and Bengio, Y. (2016). *Deep learning*, volume 1. MIT press Cambridge.

Haque, M. R. and Sohel, F. (2022). Deep network with score level fusion and inference-based transfer learning to recognize leaf blight and fruit rot diseases of eggplant. *Agriculture*, 12(8).

Haralick, R. M., Shanmugam, K., and Dinstein, I. H. (2007). Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6):610–621.

He, M., Baker, R., Hutt, S., and Zhang, J. (2022). A less overconservative method for reliability estimation for cohen's kappa.

Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J., and Scholkopf, B. (1998). Support vector machines. *IEEE Intelligent Systems and their applications*, 13(4):18–28.

Khan, A. and AlGhamdi, M. (2024). An intelligent and fast system for detection of grape diseases in rgb, grayscale, ycbcr, hsv and l* a* b* color spaces. *Multimedia Tools and Applications*, 83(17):50381–50399.

Khan, Z., Rawat, S., Kumar, S., and Sharma, A. (2025). Using computer vision for automated grading and sorting of fruits and vegetables. *International Journal of Agriculture and Food Science*, 7:1056–1065.

Kumar, A. and Sodhi, S. S. (2020). Comparative analysis of gaussian filter, median filter and denoise autoenocoder. In *2020 7th international conference on computing for sustainable global development (INDIACom)*, pages 45–51. IEEE.

Kursun, R. and Koklu, M. (2025). Effectiveness of sift features in enhancing watermelon leaf disease classification accuracy. In *2025 International Conference on Computer Systems and Technologies (CompSysTech)*, pages 1–6.

Lalam, R., Lavanya, K., Nadella, V., and Kiran, B. R. (2025). Automatic sorting and grading of fruits based on maturity and size using machine vision and artificial intelligence. *Journal of Scientific Research and Reports*, 31(1):153–163.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

Lee, E. A. (2008). Cyber physical systems: Design challenges. In *2008 11th IEEE international symposium on object and component-oriented real-time distributed computing (ISORC)*, pages 363–369. IEEE.

Lee, J.-H., Vo, H.-T., Kwon, G.-J., Kim, H.-G., and Kim, J.-Y. (2023). Multi-camera-based sorting system for surface defects of apples. *Sensors*, 23(8).

Lyu, J., Jin, L., Ma, X., Li, Y., Sun, M., Jin, N., Wang, S., Hu, L., and Yu, J. (2025). Agronomic and quality traits of 30 eggplant germplasm resources from china. *Plants*, 14(12):1838.

Mandigma, M. G. R., Reyes, A. V., and Tecson, J. V. D. (2021). *Pinakbet Adventures ni Pina: Komik Serye tungkol sa mga sumusunod na Philippine National Standards (PNS)*. Bureau of Agriculture and Fisheries Standards (BAFS), Diliman, Quezon City. ISBN 978-621-455-226-9 (PDF).

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia medica*, 22(3):276–282.

Ojala, T., Pietikainen, M., and Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on pattern analysis and machine intelligence*, 24(7):971–987.

Philippine Statistics Authority (2025). *Philippines Production: Value: Crops: Eggplant*. Philippine Statistics Authority. As reported by CEIC.

PNS (2019). Philippine National Standard on Good Agricultural Practices (PNS-GAP): ”Gabay para sa ligtas na pagkain”. Diliman, Quezon City, Philippines. Story by Mandigma, M. G. R., and Tecson, J. V. D. R.; Arts and Graphics by Reyes, A. V.

Sun, H., Fu, R., and Kang, D.-K. (2025). A novel efficient eggplant disease detection method with multi-scale learning and edge feature enhancement. *Frontiers in Plant Science*, 16:1666955.

Szeliski, R. (2022). *Computer vision: algorithms and applications*. Springer Nature.

USDA (2013). *United States Standards for Grades of Eggplant,* §51.2190 *to* §51.2207. Washington, D.C., effective february 4, 2013 edition. Supersedes third issue effective October 29, 1953.

Waghmare, D., Mulani, A., Takale, S. R., Godase, V., and Mulani, A. (2025). A Comprehensive Review on Automatic Fruit Sorting and Grading Techniques with Emphasis on Weight-based Classification. *Research & Review: Electronics and Communication Engineering*, 2:1–10.

Xu, J., Lu, Y., and Deng, B. (2024). Design, prototyping, and evaluation of a new machine vision-based automated sweetpotato grading and sorting system. *Journal of the ASABE*, 67(5):1369–1380.

Zhang, K., Shi, Y., Karnouskos, S., Sauter, T., Fang, H., and Colombo, A. W. (2022). Advancements in industrial cyber-physical systems: An overview and perspectives. *IEEE Transactions on Industrial Informatics*, 19(1):716–729.

Zhang, Z., Lu, Y., and Lu, R. (2021). Development and evaluation of an apple infield grading and sorting system. *Postharvest Biology and Technology*, 180:111588.

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I also declare that the intellectual content of this manuscript is the product of my own work, except to the extent that assistance from others in the project design and conception or in style, presentation and linguistic expression is acknowledged.

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