International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 12 | Dec – 2025 DOI: 10.55041/ISJEM05304
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

A Comprehensive Review on Groundnut (*Arachis Hypogaea L.)* Decorticator, Sorter and Grader Using Image Processing

Dr .A. Lovelin Jerald
Department of Food Processing and Preservation Technology. Avinashilingam Institute for Home Science and Higher Education for Women.Coimbatore,Tamil Nadu
lovelin_fppt@avinuty.ac.in

Shri Nidhi M
Department of Food Processing and Preservation Technology Avinashilingam Institute for Home Science and Higher Education for Women Coimbatore,Tamil Nadu
22uef025@avinuty.ac.in

Sreelakshmi Anil
Department of Food Processing and Preservation Technology Avinashilingam Institute for Home Science and Higher Education for Women Coimbatore,Tamil Nadu
22uef028@avinuty.ac.in

Visalini T
Department of Food Processing and Preservation Technology Avinashilingam Institute for Home Science and Higher Education for Women Coimbatore,Tamil Nadu
22uef032@avinuty.ac.in

***Abstract*—Groundnut (Arachis hypogaea L.) is one of the most important oilseed crops grown worldwide. It plays a crucial role in food security, edible oil production, and economies based on agriculture. Post-harvest processing tasks like decortication, sorting, and grading greatly affect kernel quality, market value, and storage stability. Traditional processing methods are mostly manual or semi-mechanized. These methods often require a lot of labour, lead to inconsistent quality, and result in higher post-harvest losses.**

Recently, new technologies in agricultural engineering, machine vision, artificial intelligence (AI), and the Internet of Things (IoT) have made it possible to create automated and intelligent systems for processing groundnuts. This review looks closely at both traditional and modern methods for groundnut decortication, sorting, and grading, focusing especially on machine vision and AI techniques. It also discusses how integrating AI and IoT can help with real-time monitoring and smart control in groundnut processing. The review shows how these technologies can improve processing efficiency, enhance kernel quality, lower losses, and help with consistent quality assessment in modern agriculture systems.

Keywords—Groundnut processing, decortication, sorting, grading, machine vision, artificial intelligence, IoT

I. INTRODUCTION

Groundnut is widely grown for its oil-rich kernels and nutritional benefits. India is one of the largest producers of groundnut in the world. The country plays a vital role in edible oil production and supports many farming-related jobs. However, post-harvest losses during initial processing still pose a significant problem. According to FAO (2019), these losses mainly occur during shelling, cleaning, sorting, and grading due to poor processing methods.

Decortication, sorting, and grading are critical steps that directly affect kernel recovery, shelf life, and market price. Research by Sudini et al. (2015) and Bera et al. (2017) shows that improper decortication can cause kernel breakage, making them more prone to fungal growth and aflatoxin contamination. Likewise, ineffective sorting and grading lower uniformity and acceptance from consumers, especially in export markets.

Traditional processing depends largely on manual labour and visual checks, which can be subjective and unreliable. As the demand for high-quality, uniform agricultural products rises, there is a pressing need for automated and smarter processing systems. Recent advances in machine vision, AI, and IoT offer chances to update groundnut processing and enhance overall efficiency and traceability.

II. GROUNDNUT DECORTICATION TECHNOLOGIES

A. Conventional Groundnut Decortication Methods

Conventional groundnut decortication practices are still common in many developing regions because they are simple and require low initial investment. These methods mainly involve hand shelling, beating pods with wooden mallets, and using pedal-operated or hand-cranked shellers. According to FAO (2019), these traditional methods are widespread among smallholder farmers and rural processors where access to machines is limited. While these techniques need little infrastructure, they are very labour-intensive and time-consuming. This makes them unsuitable for large-scale or commercial processing.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 12 | Dec – 2025 DOI: 10.55041/ISJEM05304
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Several studies have shown that the efficiency of manual decortication depends on pod moisture content, shell hardness, and the skill of the operator. Kachru et al. (2016) found that differences in shell thickness and kernel size result in inconsistent shelling performance in manual processes. Kumar et al. (2018) also noted that improper moisture conditioning before shelling causes excessive kernel breakage in overly dry pods, while high-moisture pods lead to incomplete shell separation. These issues together result in lower kernel recovery and increased processing losses.

Another major drawback of conventional decortication methods is the lack of hygiene and quality control. Manual shelling often brings in unwanted materials like dust, shell fragments, and microbes into the kernel mass. Sudini et al. (2015) pointed out that poor post-harvest handling during manual shelling raises the risk of fungal growth and aflatoxin contamination, which significantly impacts food safety and export potential. Therefore, there is an increasing need to move from traditional practices to mechanized decortication systems that offer better efficiency, consistency, and hygiene.

Fig.1 Conventional Sorting

(Source: https://share.google/RKxeGIaQvYkeT2uFl)

B. *Mechanized Groundnut Decorticators*

Mechanized groundnut decorticators were created to address the challenges of traditional shelling methods. They improve throughput and reduce reliance on manual labour. These machines work based on mechanical principles like impact, compression, shear, or a mix of these forces. Impact-type decorticators use rotating beaters or impellers to exert force on groundnut pods, allowing shells to crack quickly. However, Lakundi et al. (2016) noted that excessive impact forces can lead to more kernel breakage, especially if operating settings are not properly adjusted.

Compression- and roller-type decorticators use controlled pressure between rotating rollers or plates. This method cracks the shells while keeping the kernels intact. Research by Lakundi et al. (2016) showed that factors like roller clearance, feed rate, and pod moisture content significantly affect shelling efficiency. The best performance was seen when pods had moisture levels around 8 to 10% (wet basis). This conditioning reduced kernel damage and improved recovery.

Recent developments in mechanized decortication include adding aspiration and cleaning units. According to ICAR (2020), using airflow to remove lighter shell pieces greatly improves shell and kernel separation while reducing the need for manual work. These power-operated systems provide higher throughput, better hygiene, and consistent performance. They are ideal for small- and medium-scale processing operations and rural agro-enterprises.

Fig.2 Mechanized Groundnut decorticator

(*Source: https://share.google/UY1lICcY58HMtmjlN)*

III. SORTING TECHNIQUES IN GROUNDNUT PROCESSING

A. *Mechanical Sorting Methods*

Sorting is an important step after decortication that separates good kernels from shells, broken pieces, immature kernels, and foreign materials. Traditional mechanical sorting systems used in groundnut processing include vibratory sieves, gravity separators, and pneumatic cleaners.

Srinivasa et al. (2017) noted that the efficiency of mechanical sorting systems depends heavily on factors like vibration frequency, sieve angle, feed rate, and airflow speed. Choosing the wrong parameters can result in lost kernels or incomplete separation. Although mechanical sorting significantly boosts output and reduces the need for manual labour, it has limitations in spotting visibly

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 12 | Dec – 2025 DOI: 10.55041/ISJEM05304
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

defective kernels, such as discoloured, shrivelled, or moldy ones (FAO, 2019).

Despite these drawbacks, mechanical sorting systems remain a key initial processing step due to their simplicity, durability, and low cost. However, the growing demand for uniform quality and export-ready kernels has pushed for better sorting technologies.

Fig 3 Mechanical Sorter

(Source: https://share.google/7ZaWzxStaT6vzSWz2)

B. Optical and Vision-Based Sorting Systems

Optical and vision-based sorting systems mark a significant step forward in groundnut processing. They allow for quick, non-contact, and objective quality checks. These systems use cameras and controlled lighting to gather visual data on kernel colour, shape, and surface texture.

Machine vision systems take pictures of kernels as they pass along conveyor belts. Image processing algorithms then separate the kernels from the background. Gonzalez and Woods (2018) discussed the use of preprocessing techniques such as thresholding, edge detection, and morphological operations to improve feature extraction. Patel et al. (2019) showed that vision-based sorting systems greatly enhance sorting accuracy and consistency compared to traditional mechanical methods

Additionally, vision-based systems cut down on human bias and allow for continuous high-speed operation. Zhao et al. (2020) noted that optical sorting technologies are increasingly used in nut and oilseed processing industries because they meet strict quality and traceability standards.

Fig 4 – Optical and Vision-based sorter

(Source: https://share.google/fOQl13X7LdybfZTf9)

IV. Grading Techniques for Groundnut Kernels

A. Conventional Grading Practices

Grading is the process of classifying groundnut kernels into quality categories based on attributes such as size, colour, and surface appearance. Manual grading remains widely practiced due to its simplicity and low cost. However, FAO (2019) reported that manual grading is subjective and inconsistent, as it depends heavily on human perception and operator experience.

Mechanical graders are commonly used for size-based grading using sieves or roller assemblies. Although these systems improve uniformity in kernel size, they fail to detect visual defects such as discoloration, surface damage, and mold growth. BIS (2018) emphasized that reliance on size-based grading alone does not adequately reflect kernel quality and may result in reduced market value, particularly in export-oriented markets.

B. Machine Vision –Based Grading

Machine vision-based grading systems provide an objective and repeatable approach to quality assessment by analyzing digital images of kernels. Lakundi et al. (2017) developed a vision-based grading system that extracted size, shape, and colour features from groundnut kernel images and reported significantly higher accuracy compared to manual grading methods.

Sun (2016) highlighted that vision-based grading systems enable continuous operation, digital data storage, and improved traceability. Zhao et al. (2020) further demonstrated that machine vision-based grading improves consistency and reduces labor requirements in nut and oilseed processing industries, making it a viable alternative to conventional grading practices.

V. Artificial Intelligence in Groundnut Quality Evaluation

Artificial intelligence has significantly enhanced the performance of machine vision-based grading systems by enabling automated feature learning and robust classification. Early approaches utilized artificial neural networks (ANN) and support vector machines (SVM) trained on manually extracted features. Du and Sun (2018) demonstrated that traditional machine learning algorithms can effectively classify agricultural products based on visual attributes.

Recent research has focused on deep learning models, particularly convolutional neural networks (CNN), which automatically learn hierarchical features directly from raw images. LeCun et al. (2015) established CNNs as a powerful image classification framework. Mohanty et al. (2016) and Kamilaris and Prenafeta-Boldú (2018) reported high accuracy and robustness of CNN-based models in agricultural image analysis.

Peanut-specific studies further validate the effectiveness of AI-based grading. Yang et al. (2021) demonstrated accurate peanut variety and quality classification using improved CNN architectures. Liu et al. (2024) reported high-performance peanut kernel quality detection using lightweight deep learning models. Additionally, hyperspectral imaging combined with machine learning has been explored for detecting peanut maturity and seed vigor (Zou et al., 2019; Zou et al., 2023).

VI. Integration of AI and IoT in Groundnut Processing

The combination of artificial intelligence and Internet of Things technologies allows for the creation of smart groundnut processing systems that can monitor conditions in real time and make intelligent decisions. IoT sensors keep track of operational parameters like temperature, humidity, vibration, and machine load. Wolfert et al. (2017) pointed out that collecting data through sensors helps improve decision-making in smart farming and agri-processing systems. Zhang et al. (2021) explained that AI algorithms analyze sensor data to fine-tune processing parameters, predict equipment failures, and boost operational efficiency. Navarro et al. (2020) noted that IoT-based system designs improve scalability, connectivity, and remote monitoring in agricultural processing settings. Quy (2022) further underscored the importance of IoT platforms in supporting integrated and adaptable control systems.

In groundnut processing, the integration of AI and IoT allows for real-time adjustments of decortication pressure, sorting airflow, and grading thresholds based on sensor feedback. Storing process and quality data digitally improves traceability, quality assurance, and compliance with modern food safety standards, aligning groundnut processing systems with Industry 4.0 principles.

VII. PROPOSED METHODOLOGY

The proposed system combines a mechanical groundnut decorticator with a sorting and grading unit and an image-based quality assessment module. Groundnut pods are placed in a stainless-steel hopper and moved to the shelling chamber. Here, a rotating disc mechanism driven by an electric motor and a belt and pulley system achieves decortication. Controlled friction and impact forces crack the shells while reducing kernel breakage.

Next, the shelled mixture goes to a vibratory sorting unit with three stainless steel trays of different slot sizes. A rotary disc and connecting rod mechanism create vibratory motion, allowing size-based separation of kernels into large, medium, and small or broken categories. There are separate outlets for the hygienic collection of graded kernels.

To improve quality evaluation, the system includes an image-based grading feature. Images of sorted kernels are taken under controlled lighting and analyzed with a convolutional neural network (CNN) through a web-based interface. The model classifies kernels based on visual features like colour and surface condition, providing an objective quality assessment. This combined mechanical and AI-based approach increases accuracy, efficiency, and consistency in groundnut processing.

VIII. CONCLUSION

The groundnut decorticator, sorter, and grader combines efficient mechanical processing with quality assessment using artificial intelligence. This design addresses key issues in small and medium-scale groundnut processing. The rotating disc decortication mechanism is carefully designed to shell groundnuts effectively while reducing kernel breakage and mechanical damage. This leads to a higher recovery of whole kernels, which improves product quality and market value.

After decortication, the system uses a vibratory tray-based sorting mechanism that efficiently separates groundnuts by size. This classification enhances uniformity in further processing and packaging, while also decreasing reliance on manual labor. The vibratory system promotes smooth material flow, consistent separation, and better throughput.

For quality evaluation, the system uses image-based grading with a Convolutional Neural Network (CNN). High-resolution images of the kernels are analyzed to identify defects such as discoloration, shriveling, and broken kernels. This automated grading method gives consistent, objective, and repeatable results, removing the subjectivity and fatigue-related mistakes common in manual inspection. Consequently, the overall grading accuracy and reliability are greatly improved.

The entire system is compact, hygienic, and energy-efficient, making it ideal for decentralized processing units, farmer producer organizations (FPOs), self-help groups (SHGs), and small agro-processing businesses. Its user-friendly design and low operating costs make it accessible in rural and semi-urban areas. Overall, the project offers a cost-effective, scalable, and reliable solution that boosts processing efficiency, improves kernel quality, reduces post-harvest losses, and adds value in groundnut processing operations.

REFERENCES

[1] Z. Liu, C. Wang, X. Zhong, G. Shi, H. Zhang, D. Yang, and J. Wang, “A lightweight method for peanut kernel quality detection based on SEA-YOLOv5,” *Agriculture (MDPI)*, vol. 14, no. 12, Art. 2273, 2024.

[2] V. N. Pham, “A low-cost deep-learning-based system for grading cashew nuts,” *Computers (MDPI)*, vol. 13, no. 3, Art. 71, 2024.

[3] P. Ni, Z. Wang, and H. Chen, “Design and optimization of key parameters for a machine vision-based walnut shell–kernel sorting device,” *Agriculture (MDPI)*, vol. 14, no. 9, Art. 1632, 2024.

[4] A. Soussi, S. A. Al-Ghamdi, and P. Y. T. Ong, “Smart sensors and smart data for precision agriculture — A review,” *Sensors (MDPI)*, vol. 24, no. 8, Art. 2647, 2024.

[5] Z. Liu, C. Wang, X. Zhong, G. Shi, H. Zhang, D. Yang, and J. Wang, “A lightweight method for peanut kernel quality detection based on SEA-YOLOv5,” *Agriculture (MDPI)*, vol. 14, no. 12, Art. 2273, 2024.

[6] V. N. Pham, “A low-cost deep-learning-based system for grading cashew nuts,” *Computers (MDPI)*, vol. 13, no. 3, Art. 71, 2024.

[7] P. Ni, Z. Wang, and H. Chen, “Design and optimization of key parameters for a machine vision-based walnut shell–kernel sorting device,” *Agriculture (MDPI)*, vol. 14, no. 9, Art. 1632, 2024.

[8] A. Soussi, S. A. Al-Ghamdi, and P. Y. T. Ong, “Smart sensors and smart data for precision agriculture — A review,” *Sensors (MDPI)*, vol. 24, no. 8, Art. 2647, 2024.

[9] V. K. Quy, “IoT-enabled smart agriculture: Architecture, applications, and future directions,” *Applied Sciences (MDPI)*, vol. 12, no. 7, Art. 3396, 2022.

[10] M. Balasubramaniyan, S. S. Suresh, and R. Manikandan, “Color-contour-texture based peanut classification using deep spectral feature learning,” *Journal of Food Engineering*, vol. 315, 2022.

[11] X. Zou, Y. Ma, and M. Chen, “Hyperspectral imaging and machine learning for peanut variety classification,” *Journal of Food Processing and Preservation*, 2022.

[12] J. Xu, Q. He, and H. Li, “Review of agricultural IoT technology and applications,” *Computers and Electronics in Agriculture*, vol. 192, 2022.

[13] Z. Liu, J. Wang, and X. Zhong, “Classification of peanut quality based on coordinated attention convolutional network,” *Journal of Food Measurement and Characterization*, vol. 38, no. 9, pp. 1–14, 2022.

[14] H. Yang, Y. Zhang, L. Bai et al., "A novel method for peanut variety identification and classification by improved VGG16," *Scientific Reports*, vol. 11, Art. 95240, 2021.

[15] Y. Zhang, S. Wang, and D. Ji, "Smart agriculture based on Internet of Things and AI — A review," *IEEE Access*, vol. 9, pp. 115–128, 2021.

[16] E. Navarro, R. Nouvel, L. H. Taylor et al., "A systematic review of IoT solutions for smart farming," *Sensors (Basel)*, vol. 20, no. 3, Art. 771, 2020.

[17] X. Zhao, M. K. Jones, and L. Wang, "Vision-based grading of agricultural products: Methods and recent advances," *Biosystems Engineering*, vol. 189, pp. 12–24, 2020.

[18] E. Navarro, A. R. Ruiz-García, and S. L. Smith, "A systematic review of IoT solutions for smart farming," *Sensors*, vol. 20, no. 3, Art. 771, 2020.

[19] S. Wolfert, C. Verdouw, and M. van der Vorst, "Digital twins and big data for the agrifood sector," *Frontiers in Sustainable Food Systems*, vol. 4, Art. 100, 2020.

[20] E. Navarro, R. Nouvel, L. H. Taylor et al., "A systematic review of IoT solutions for smart farming," *Sensors (Basel)*, vol. 20, no. 3, Art. 771, 2020.

[21] X. Zhao, M. K. Jones, and L. Wang, "Vision-based grading of agricultural products: Methods and recent advances," *Biosystems Engineering*, vol. 189, pp. 12–24, 2020.

[22] E. Navarro, A. R. Ruiz-García, and S. L. Smith, "A systematic review of IoT solutions for smart farming," *Sensors*, vol. 20, no. 3, Art. 771, 2020.

[23] S. Wolfert, C. Verdouw, and M. van der Vorst, "Digital twins and big data for the agrifood sector," *Frontiers in Sustainable Food Systems*, vol. 4, Art. 100, 2020.

[24] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.

[25] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed., Pearson, 2018.

[26] S. Du and D.-W. Sun, "Defect detection methods for food materials using computer vision and hyperspectral imaging — recent progress and future trends," *Critical Reviews in Food Science and Nutrition*, vol. 58, no. 1, pp. 1–23, 2018.

[27] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming — A review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017.

[28] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, Art. 1419, 2016.

[29] D.-W. Sun, *Computer Vision Technology for Food Quality Evaluation*, 2nd ed., Academic Press, 2016.

[30] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.