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Deep Transfer Learning-Based Classification of Peanut Pods and Seeds using Low-Cost RGB Images

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Abstract
Assessing peanut quality is an important part of post-harvest management because poor quality can affect product value, market competitiveness, and consumer acceptance. Although traditional manual inspection methods are subjective, time-consuming, and heavily reliant on human knowledge and experience, current imaging techniques such as hyperspectral imaging provide useful spectral information but require expensive equipment and complex acquisition processes, which limits their use in real agricultural settings. This study presents a low-cost deep transfer-learning framework based on RGB images to automatically classify peanut pods and seeds. We collected 10,018 RGB images of harvested pods, dried pods, and seeds, including normal, damaged, split, and foreign-object types. We assessed the classification performance of two convolutional architectures, VGG16 and ResNet50, using stratified cross-validation. The results show that ResNet50 outperformed VGG16 at all stages of classification, achieving accuracy, precision, recall, and F1-score values of 98% for harvested pods, 99% for dried pods, and 99% for seeability. The results show that remote recognition can identify peanut surface characteristics from RGB images. The approach suggested here offers a cost-effective basis for developing automated peanut quality inspection systems in smart agriculture.

Keywords: computer vision; deep transfer learning; peanut quality assessment; rgb imaging; smart agriculture

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INTRODUCTION

Peanuts (*Arachis hypogaea* L.) are an important agricultural product with both considerable economic and nutritional value since they contain vegetable protein, oil, and essential nutrients (Yang et al., 2021). Peanut quality directly affects product price, storage stability, processing suitability, and consumer acceptance (de Freitas Floriano et al., 2020). Nevertheless, maintaining consistent quality is difficult because the crop is prone to defects during cultivation, harvesting, transportation, and storage, such as insect damage, fungal contamination, cracking, sprouting, and physical abnormalities (Yang et al., 2023). These variations can lower commercial value and cause economic losses, underscoring the importance of accurate quality assessment. Currently, peanut evaluation is still mainly done

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through manual visual inspection, a method that relies on the operator's experience and judgment (Yang et al., 2025). This method is limited by inconsistency, low efficiency, and reduced accuracy due to human fatigue during large-scale sorting (Chen et al., 2025). For these reasons, an automated inspection system is needed to achieve objective, consistent, and efficient evaluation of peanut quality.

Recent advances in artificial intelligence, especially in computer vision and deep learning, have offered promising solutions for automated crop inspection. Because they are able to automatically learn complex visual representations, methods based on deep learning in computer vision have been used more and more in crop monitoring, in the detection of plant diseases, in the classification of fruit maturity, and in the evaluation of the quality of agricultural products (Qu & Su, 2024). Unlike traditional machine learning methods, which rely on manually designed features, convolutional neural networks (CNNs) can extract hierarchical features from images, starting with edges and colors and progressing to object structures and textures (Barburiceanu et al., 2021). This ability allows CNN-based approaches to perform well in agricultural image classification tasks, especially when sufficient image datasets are available (Dai & Fan, 2022).

Recent studies have further demonstrated the effectiveness of deep learning-based image classification in various domains. Anhar et al. (2026) showed that transfer learning with EfficientNetB0 effectively classified banana ripeness levels using RGB images, while Putra et al. (2026) confirmed the capability of CNN and YOLO models for biological quality classification. Similarly, Ramdhana and Pratiwi (2023) reported the effectiveness of CNN models in image-based skin cancer classification. These findings support the applicability of CNN and transfer learning approaches for agricultural image analysis, particularly in recognizing variations in colour, texture, shape, and surface characteristics.

The extent to which computer vision methods can be used for assessing the quality of agricultural products is closely linked to the visual features of the objects in question, and this is also true of peanut pods and seeds: surface texture, color variation, shape features, cracks, and any visible damage are the main indicators that convolutional neural network (CNN)-based image analysis can learn to measure and classify (Jiang et al., 2025; Martinez et al., 2025; Yang et al., 2021; Yang et al., 2023). Deep learning models have shown strong abilities in extracting morphological and surface features and in relating them to quality categories or defect states when applied across a wide variety of seed types such as peanuts, corn, wheat, rice, cotton, soybeans, and others (Elfatimi et al., 2025; Erukude et al., 2025; Liu et al., 2025; Luo et al., 2023; Pranta et al., 2025; Vera et al., 2025). This evidence confirms that image-based quality evaluation is feasible for agricultural seeds in general and, in particular, for peanuts, covering complex multi-class discrimination, variety identification, and defect detection (Martinez et al., 2025). Nevertheless, agricultural image classification remains difficult because of variations in illumination, environmental conditions, sample characteristics, and defect appearance.

We have investigated various imaging techniques to assess agricultural product quality, including hyperspectral imaging (HSI), multispectral imaging, and RGB imaging. Hyperspectral imaging has shown strong ability to detect internal quality features, chemical composition, and maturity-related traits. Earlier research successfully used HSI to evaluate peanut quality, for example, to detect aflatoxin and assess maturity (Han & Gao, 2019; Zou et al., 2019). Nevertheless, HSI requires specialized sensors, expensive equipment, and complex processing methods, which hampers its practical application, especially in small-scale farm operations. On the other hand, RGB imaging offers a more accessible and cost-effective solution, as it uses commonly available data cameras and can capture external characteristics such as color, texture, and visible defects. Recent studies show that RGB-based computer

vision methods remain widely used because of their lower implementation costs, simpler acquisition processes, and compatibility with deep learning frameworks (Qu & Su, 2024).

Although deep learning-based agricultural inspection has advanced rapidly, limitations remain in assessing peanut quality. Earlier research on peanuts has mostly focused on specific goals, such as detecting aflatoxin, identifying maturity, or recognizing individual defects using hyperspectral or specialized imaging systems (Han & Gao, 2019; Zou et al., 2019). Although these studies offer useful insights, they generally address only a limited set of quality features and do not provide a comprehensive classification of peanut post-harvest categories. Moreover, RGB-based deep learning approaches for integrated classification of harvested pods, dried pods, and seeds remain scarce. Comparative evaluations of different deep learning architectures under similar experimental conditions are also insufficient, leaving it unclear which models best suit peanut characteristics.

CNN architectures based on transfer learning are now commonly used to classify agricultural images, especially when dealing with small datasets. Transfer learning enables effective feature extraction while reducing computational demands. Two CNN architectures that are widely used for image classification are VGG16 and ResNet50; VGG16 offers a dependable benchmark because of its straightforward convolutional structure, while ResNet50 employs residual learning via shortcut connections in order to achieve deeper feature extraction and enhance the stability of optimization (Shafiq & Gu, 2022; Simonyan & Zisserman, 2026). These features are important for peanut classification because quality differences often stem from slight variations in texture, surface patterns, and structural appearance. Earlier studies have shown that ResNet-based architectures achieve competitive results in agricultural classification tasks involving complex visual features. Even though more recent architectures such as EfficientNet, MobileNet, the Vision Transformer (ViT), and Swin Transformer have shown promising outcomes, CNN-based transfer learning models are still relevant because of their proven performance, the availability of pre-trained versions, and their appropriateness for use with limited datasets (Qu & Su, 2024).

Given these factors, this study aims to develop and assess a deep transfer learning framework based on low-cost RGB images to classify peanut pods and seeds. Unlike earlier studies, which mostly relied on costly imaging systems or focused on a single quality feature, this research uses locally collected RGB images to evaluate peanut quality across harvested pods, dried pods, and seeds in a multi-stage approach. The contributions of this study are as follows: (1) the creation of an RGB peanut image dataset that includes various post-harvest categories and quality classes; (2) a comparison of the VGG16 and ResNet50 transfer learning architectures under identical experimental conditions; and (3) an evaluation of the feasibility of deep learning based on RGB images as a cheap alternative for automated peanut quality inspection in the context of smart agriculture.

METHOD

This study employed an experimental research design to develop and evaluate a deep transfer learning framework for peanut quality classification using RGB images. Deep learning-based computer vision approaches have been increasingly adopted in agricultural applications because they can automatically extract discriminative visual features and support objective classification under complex image conditions (Upadhyay et al., 2025). This study compared the performance of VGG16 and ResNet50 architectures in classifying peanut pods and seeds based on visual quality characteristics. The research workflow consisted of dataset acquisition, preprocessing, labeling, dataset partitioning, model training, and performance evaluation.

The dataset was obtained from peanut farming environments in cooperation with peanut farmers and the Agriculture, Food, and Fisheries Department of Karangasem Regency. We

captured RGB images with a 64-megapixel VIVO Y53S smartphone camera using a tripod, a white Manila paper background, and natural light. We chose RGB imaging because it is more accessible and less expensive than hyperspectral imaging systems. The dataset included three categories: harvested pods, dried pods, and seeds. We divided harvested pods and dried pods into normal pods, damaged pods, and foreign objects, while classifying seeds as normal seeds, damaged seeds, split seeds, and foreign objects. Image annotation and cropping: We annotated the visual features of each sample. The final dataset comprised 10,018 RGB images: 1,939 harvested pod images, 3,123 dried pod images, and 4,956 seed images.

We labeled the images based on their visible features, such as surface appearance, structural damage, and the presence of material. We resized all images to 224 by 224 pixels to meet the input specifications of VGG16 and ResNet50. We applied data augmentation only to the training data to improve model robustness and reduce overfitting; techniques included rotation, horizontal flipping, brightness adjustment, scaling, and random cropping, while the validation and test data remained unchanged for objective evaluation.

We split the dataset using stratified random sampling into 80% training data, 10% validation data, and 10% test data. We used the training set to optimize the model, the validation set to monitor performance, and the test set for final evaluation. We performed stratified 5-fold cross-validation only on the training dataset to assess model stability while preserving the class distribution. This approach reduced bias from class imbalance and avoided data leakage. We kept images from the same physical peanut sample within the same subset to prevent overestimating the model's performance.

We evaluated the VGG16 and ResNet50 CNN architectures using transfer learning. These architectures remain widely used in agricultural image classification because pretrained CNN models can effectively extract visual features from limited agricultural datasets (Dhanya et al., 2022). We selected VGG16 as a baseline architecture, while ResNet50 was chosen for its ability to learn deeper feature representations through residual connections.

We trained the models using transfer learning with a learning rate of 0.0001, a batch size of 32, an image size of 224×224 pixels, and 30 training epochs. To address class imbalance, we used weighted cross-entropy loss, assigning higher weights to minority classes and lower weights to majority classes. This method was adopted to improve classification performance, especially for cateWe evalwith samples. We evaluated both VGG16 and ResNet50 using accuracy, precision, recall, and F1-score. We chose these measures to provide a thorough evaluation of classification ability. Accuracy assessed overall correctness, while precision and recall showed how well the models identified each class. We also analyzed the confusion matrix to examine classification errors and identify each model's limitations. This analysis helped us understand each model's limitations in distinguishing between peanut quality categories.

RESULTS AND DISCUSSION

Results

We comparatively evaluated the classification performance of VGG16 and ResNet50 in identifying harvested peanut pods using stratified 5-fold cross-validation. This validation strategy assessed each model's consistency and robustness while preserving the original class distribution across all validation folds. As shown in Table 1, ResNet50 consistently outperformed VGG16 across all five folds. ResNet50 achieved a mean accuracy of 98.77%, with fold-specific accuracy values ranging from 97.74% to 99.35%. The highest accuracy of 99.35% was attained in the first and fifth folds. In contrast, VGG16 showed lower and more variable performance, with accuracy ranging from 90.32% to 97.74%, peaking in the third fold. These results indicate that ResNet50 provides not only higher classification accuracy but also greater consistency across the evaluated data partitions.

Table 1. Comparison of 5-fold accuracy of harvested pod dataset

Fold	VGG16 Accuracy	ResNet50 Accuracy
1	94.84%	99.35%
2	96.13%	98.39%
3	97.74%	99.03%
4	96.13%	97.74%
5	90.32%	99.35%

These results show that ResNet50 delivered better and more consistent classification performance than VGG16 across different data distributions. As shown in Table 2, ResNet50 achieved accuracies, precision, recall, and F1-score rates of 98.00%, whereas VGG16 achieved 94.00% for these evaluation Measures. The better performance suggests that the residual learning mechanism was more effective in extracting visual features from images of harvested peanut pods.

Table 2. Classification results for the vgg16 and resnet50 models

Model	Accuracy	Precision	Recall	F1-score	Loss
VGG16	94,00%	94,00%	94,00%	94,00%	0.1488
ResNet50	98,00%	98,00%	98,00%	98,00%	0.0538

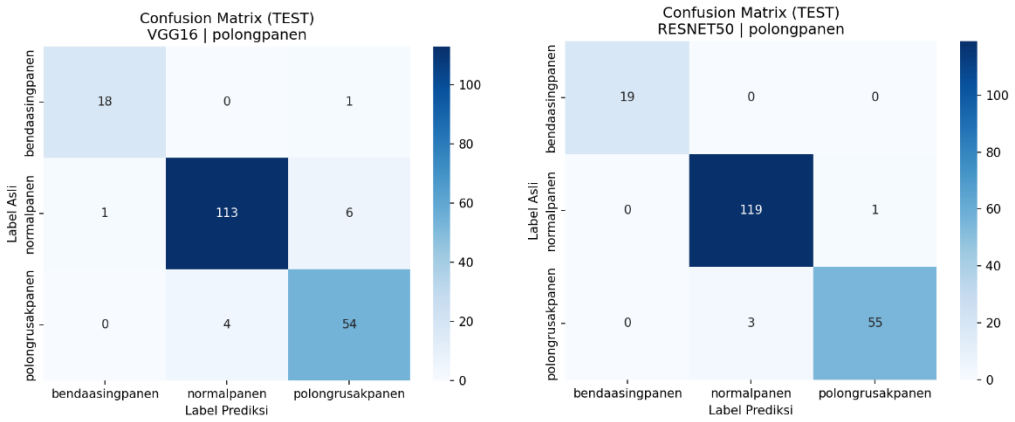

Figure 1. Confusion matrix for harvested pods

Table 3. Comparison of accuracy of 5-fold dry peanut pod dataset

Fold	VGG16 Accuracy	ResNet50 Accuracy
1	96.20%	98.60%
2	95.20%	98.00%
3	96.39%	98.60%
4	96.19%	99.20%
5	97.60%.	98.60%.

However, in the confusion matrix analysis (Figure 3), FVGG16 misclassified damaged pods as good pods, normal pods, and foreign objects. This error may occur because damaged pods and foreign objects can share similar visual features, especially their irregular surface appearance. By contrast, ResNet50 reduced these classification errors and classified foreign objects more accurately. This shows that ResNet50's ability to extract deeper features allowed it to distinguish subtle differences among the various peanut pod categories.

We also assessed the classification capabilities of VGG16 and ResNet50 on the dried peanut pod dataset using stratified 5-fold cross-validation. As shown in Table 3, ResNet50 outperformed VGG16 across all five validation folds. ResNet50 achieved a mean accuracy of 98.60%, exceeding VGG16's 96.32%. ResNet50 also showed consistent performance, with accuracy ranging from 98.00% to 99.20%, and reached its highest accuracy of 99.20% in the fourth fold. In comparison, VGG16 yielded accuracy values between 95.20% and 97.60%, with its highest performance recorded in the fifth fold. Overall, these findings indicate that ResNet50 offers higher classification accuracy and greater performance consistency than VGG16 in classifying dried peanut pods.

Table 4 presents the classification performance of the VGG16 and ResNet50 models using accuracy, precision, recall, F1-score, and loss metrics. The results show that ResNet50 outperformed VGG16 across all assessment criteria. ResNet50 achieved 99.00% accuracy, 99.00% precision, 99.00% recall, and a 99.00% F1-score, with a loss of 0.0356. Meanwhile, VGG16 achieved 96.00% accuracy, 96.00% precision, 96.00% recall, and a 96.00% F1-score, with a loss of 0.1777. These results show that ResNet50 provided better classification performance and lower error rates than VGG16 for dried peanut pod classification.

Table 4. Classification results for the vgg16 and resnet50 models

Model	Accuracy	Precision	Recall	F1-score	Loss
VGG16	96,00%	96,00%	96,00%	96,00%	0.1777
ResNet50	99,00%	99,00%	99,00%	99,00%	0.0356

The final evaluation used the peanut seed dataset, which includes four classes: normal seeds, damaged seeds, split seeds, and foreign objects. The results show that both models achieved high classification performance; however, ResNet50 consistently outperformed VGG16. The stratified 5-fold cross-validation results presented in Table 5 show that ResNet50 achieved an average accuracy of 99.62%, while VGG16 achieved 98.61%. ResNet50 obtained the highest accuracy of 99.62% in the fourth fold, whereas VGG16 achieved the highest accuracy of 98.61% in the third fold.

Table 5. Comparison of 5-fold accuracy on the peanut seed dataset

Fold	VGG16 Accuracy	ResNet50 Accuracy
1	97,98%	99,12%
2	97,48%	98,87%
3	98,61%	99,24%
4	96,72%	99,62%
5	97,85%	98,86%

The classification results in Table 6 show that ResNet50 achieved 99.00% accuracy, precision, recall, and F1-score, compared with 96.00% for VGG16. This improvement indicates that ResNet50 better captured complex visual patterns in peanut seeds, particularly differences related to structural damage and surface characteristics. The confusion matrix analysis in Figure 2 shows that classification errors mainly occurred between split seeds, normal seeds, and damaged seeds. These categories look similar, especially when cracks or damage appear in small areas. Despite these challenges, ResNet50 produced fewer classification errors than VGG16, suggesting that deeper residual feature learning improved the model's ability to distinguish visually similar seed categories.

In all three classification scenarios, ResNet50 outperformed the other models; this better performance stems from its residual learning mechanism, which enables deeper feature extraction and produces stronger representations of complex visual patterns. Because peanut

quality classification depends on subtle differences in texture, shape, and surface defects, ResNet50 proved more effective at capturing these features than VGG16's sequential convolutional structure. Nevertheless, the results should be understood in the context of the experimental conditions, since the dataset was obtained through controlled RGB image acquisition. Further validation across different environments, lighting conditions, and peanut types is needed to assess the model's broader generalization.

Table 6. Classification Results for the VGG16 and ResNet50 Models

Model	Accuracy	Precision	Recall	F1-score	Loss
VGG16	96.00%	96.00%	96.00%	96.00%	0.1238
ResNet50	99.00%	99.00%	99.00%	99.00%	0.0340

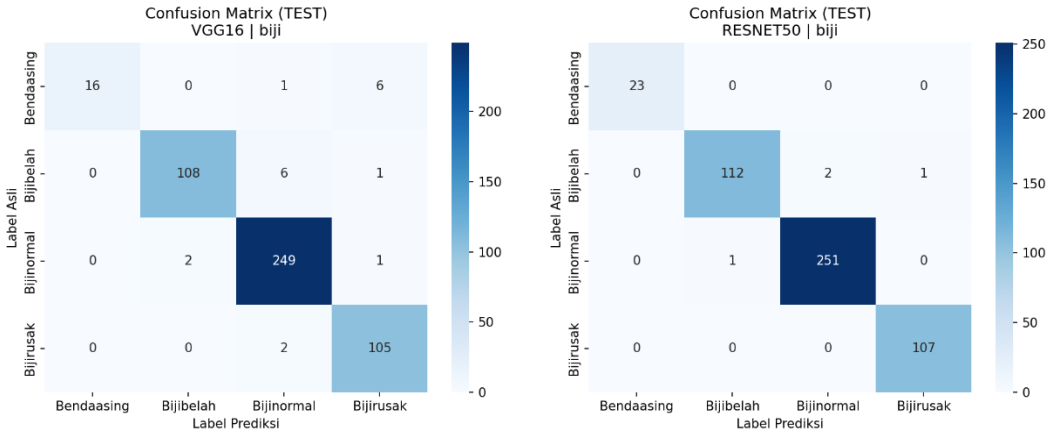

Figure 2. Confusion matrix peanut seeds

Discussion

The findings show that deep transfer learning using RGB images effectively classifies peanut pods and seeds across various post-harvest types. ResNet50 outperforms VGG16 when classifying harvested pods, dried pods, and seeds, indicating that deeper feature representation is important for identifying variations in peanut quality. Assessing peanut quality depends on subtle visual differences such as surface texture, color variation, shape irregularities, and structural defects, which in turn requires effective extraction of hierarchical image features. As has been shown in previous studies, deep learning models are able to automatically learn morphological and surface features from agricultural images, allowing for accurate seed classification and the evaluation of quality-related traits (Luo et al., 2023).

ResNet50 performs better than VGG16 due to its residual learning approach. Unlike VGG16, which has a sequential convolutional structure, ResNet50 includes shortcut connections that help gradients propagate and enable deeper feature extraction without suffering severe degradation. This architectural advantage matters for peanut classification, since the quality categories often look visually similar. For instance, damaged pods and foreign objects may have similar irregular surface patterns, and split seeds and damaged seeds may show overlapping structural features. ResNet50's ability to learn deeper representations likely explains its improved discriminative power. Similarly, studies on agricultural classification show that ResNet-based architectures perform well in capturing complex visual variations in crop and seed images (Yang et al., 2023).

The results also show the potential of using low-cost RGB-based deep learning for crop inspection. Earlier studies have generally used hyperspectral imaging to assess peanut quality because it records spectral data related to chemical composition and internal features (Han & Gao, 2019; Zou et al., 2019). However, its high cost, need for specialized equipment, and

complex data processing limit practical implementation, especially in small-scale agricultural settings. The present study shows that RGB images, despite having less spectral information, can provide enough visual information for classification when used with suitable deep learning models. This result supports earlier research showing that RGB-based computer vision methods provide accessible and efficient alternatives for agricultural monitoring and quality evaluation (Dai & Fan, 2022; Qu & Su, 2024).

The study also goes beyond earlier peanut research by showing that a single RGB-based system can perform multi-stage peanut classification, including harvested pods, dried pods, and seeds. Earlier work has mainly focused on specific aspects of peanut quality, such as identifying variety, assessing maturity, or detecting defects, using specialized imaging techniques (Yang et al., 2021; Yang et al., 2023). By contrast, this study includes several post-harvest categories and examines two typical CNN architectures under similar experimental conditions. This method offers further insight into which transfer learning models are suitable for real-world peanut quality inspection.

From an application perspective, the framework provides a basis for creating affordable automated peanut inspection systems. Using smartphones for RGB imaging reduces the need for costly imaging equipment and makes it easier to adapt the system to agricultural settings. However, the present evaluation was carried out under controlled image-acquisition conditions, such as a consistent background and lighting. Therefore, further studies should assess the model's robustness in more varied field conditions, such as different illumination levels, camera positions, peanut varieties, and environmental backgrounds. Moreover, future research could explore lightweight architectures and explainable artificial intelligence approaches to improve deployment feasibility and increase transparency in agricultural decision-making.

In summary, this study shows that transfer learning with ResNet50 effectively classifies peanut quality from RGB images. Its low-cost image acquisition and deep feature extraction offer a practical pathway for smart agriculture, especially where advanced imaging technologies are not economically viable. However, broader validation with external datasets and under real-world acquisition conditions is still needed before large-scale implementation.

CONCLUSION

The study showed that a low-cost deep transfer learning method using RGB images effectively classifies peanut pods and seeds. When VGG16 and ResNet50 were compared, ResNet50 performed better than VGG16 in all cases, whether the pods were harvested or dried, and it also outperformed VGG16 in classifying seeds, demonstrating its greater ability to extract complex visual features such as texture, shape, and surface defects. The results prove that combining RGB imaging with deep learning offers a practical solution for automated peanut quality assessment, especially in agricultural settings where more advanced imaging techniques like hyperspectral systems are not readily available. This research contributes by creating a locally collected, multi-category peanut image dataset and by assessing CNN-based transfer learning methods under the same experimental conditions. Nevertheless, the present evaluation used controlled image acquisition conditions; future work should assess the model's robustness under a variety of field conditions, with different peanut varieties, and in real-world deployment situations. In summary, the approach suggested here provides a promising basis for developing inexpensive and scalable computer vision inspection systems to support smart agriculture applications.

REFERENCES

Anhar, A., Wajidi, F., & Nur Insani, C. (2026). Two-Stage Transfer Learning with EfficientNetB0 for Four-Class Banana Ripeness Classification. *Edumatic: Jurnal Pendidikan Informatika*, *10*(2), 300–309.

https://doi.org/10.29408/edumatic.v10i2.34588
Barburiceanu, S., Meza, S., Orza, B., Malutan, R., & Terebes, R. (2021). Convolutional neural networks for texture feature extraction. Applications to leaf disease classification in precision agriculture. *Ieee Access*, *9*, 160085-160103. https://doi.org/10.1109/ACCESS.2021.3131002
Chen, S., Zhang, Y., Wang, J., Li, X., & Liu, Y. (2025). Deep learning-based visual inspection for agricultural product quality evaluation: Current advances and future perspectives. *Computers and Electronics in Agriculture, 225*, 109256.
Dai, G., & Fan, J. (2022). An industrial-grade solution for crop disease image detection tasks. *Frontiers in Plant Science*, *13*, 921057. https://doi.org/10.3389/fpls.2022.921057
de Freitas Floriano, R., Gräbin, K., Rossi, R. C., Ferreira, C. D., & Ziegler, V. (2020). Impact of roasting conditions on the quality and acceptance of the peanut paste. *Journal of texture studies*, *51*(5), 841-848. https://doi.org/10.1111/jtxs.12541
Dhanya, V. G., Subeesh, A., Kushwaha, N. L., Vishwakarma, D. K., Kumar, T. N., Ritika, G., & Singh, A. N. (2022). Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*, *6*, 211-229. https://doi.org/10.1016/j.aiia.2022.09.007
Elfatimi, E., Eryiğit, R., & Elfatimi, L. (2025). Automated End-to-End Deep Learning Framework for Complex Multiclass Brassica Seed Classification. *Seeds*, *4*(4), 67. https://doi.org/10.3390/seeds4040067
Erukude, S. T., Mascarenhas, J. N., & Shamir, L. (2025). CornViT: A Multi-Stage Convolutional Vision Transformer Framework for Hierarchical Corn Kernel Analysis. *Computers*, *15*(1), 2. https://doi.org/10.3390/computers15010002
Han, Z., & Gao, X. (2019). A novel method for peanut aflatoxin detection based on hyperspectral imaging and deep learning. *Computers and Electronics in Agriculture, 165*, 104947. https://doi.org/10.1016/j.compag.2019.104888
Hassan, E. (2024). Enhancing coffee bean classification: a comparative analysis of pre-trained deep learning models. *Neural Computing and Applications*, *36*(16), 9023-9052. https://doi.org/10.1007/s00521-024-09623-z
Jiang, C., Miao, K., Hu, Z., Gu, F., & Yi, K. (2025). Image Recognition Technology in Smart Agriculture: A Review of Current Applications Challenges and Future Prospects. *Processes*, *13*(5), 1402. https://doi.org/10.3390/pr13051402
Liu, C.-M., Shen, Y., Mu, F., Long, H., Bilal, A., Xia, Y., & Dai, Q. (2025). Detection of surface defects in soybean seeds based on improved Yolov9. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-92429-3
Luo, T., Zhao, J., Gu, Y., Zhang, S., Qiao, X., Tian, W., & Han, Y. (2023). Classification of weed seeds based on visual images and deep learning. *Information Processing in Agriculture*, *10*(1), 40-51. https://doi.org/10.1016/j.inpa.2021.10.002
Martinez, E. E. P., Kudenov, M. W., Dunne, J. C., & Garrity, N. (2025). Enhancing peanut pre-sizing with PodTracker: A multiple pod tracking algorithm. *The Plant Phenome Journal*, *8*(1). https://doi.org/10.1002/ppj2.70035
Pranta, A. S. U. K., Fardin, H., Hossain, A., Sakib, A. H., Ahmed, Md. R., Haque, R., Reza, A. W., & Dewan, M. A. A. (2025). A Novel MaxViT Model for Accelerated and Precise Soybean Leaf and Seed Disease Identification. *Computers*, *14*(5), 197. https://doi.org/10.3390/computers14050197
Putra, I. G. A. D., Gunadi, I. G. A., & Sunarya, I. M. G. (2026). Benchmarking CNN and YOLO Models for Automated Classification of Fish Freshness. *Edumatic: Jurnal Pendidikan Informatika*, *10*(2), 340–349. https://doi.org/10.29408/edumatic.v10i2.35019
Qu, H. R., & Su, W. H. (2024). Deep learning-based weed–crop recognition for smart agricultural equipment: A review. *Agronomy*, *14*(2), 363.

Ramdhana, A. C., & Pratiwi, N. (2023). Perbandingan Kinerja Model Convolutional Neural Network pada Klasifikasi Kanker Kulit. *Edumatic: Jurnal Pendidikan Informatika*, *7*(2), 197–206. https://doi.org/10.29408/edumatic.v7i2.19823

Shafiq, M., & Gu, Z. (2022). Deep residual learning for image recognition: A survey. *Applied sciences*, *12*(18), 8972. https://doi.org/10.3390/app12188972

Simonyan, K., & Zisserman, A. (2026). Very deep convolutional networks for large-scale image recognition. arXiv. 2014 doi: 10.48550. *arXiv preprint arXiv.1409.1556*, *1409*.

Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Nandede, B. M., Kumar, M., ... & Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artificial Intelligence Review*, *58*(3), 92. https://doi.org/10.1007/s10462-024-11100-x

Vera, Y. P., Flores, M. K. C. C., Córdova, S. A. A. A., Macedo, I. E. C. C., Biamonte, P. A. L. L., & Callohuanca, E. A. R. R. (2026). Deep Learning Models for Defect Identification in Oryza sativa Rice Grains: A Comparative Study. *Agriengineering*, *8*(6), 252. https://doi.org/10.3390/agriengineering8060252

Yang, H., Ni, J., Gao, J., Han, Z., & Luan, T. (2021). A novel method for peanut variety identification and classification by Improved VGG16. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-95240-y

Yang, L., Wang, C., Yu, J., Xu, N., & Wang, D. (2023). Method of Peanut Pod Quality Detection Based on Improved ResNet. *Agriculture*, *13*(7), 1352. https://doi.org/10.3390/agriculture13071352

Yang, Y., Chen, J., & Chen, L. (2025). A comprehensive insight into peanut storage: Patterns of quality changes, pathways of quality deterioration, and storage strategies. *Food Chemistry: X*, 102973. https://doi.org/10.1016/j.fochx.2025.102973

Zou, X., Zhao, J., Povey, M., & Holmes, M. (2019). Nondestructive maturity detection of peanut pods using hyperspectral imaging and machine learning methods. *Computers and Electronics in Agriculture, 162*, 663–670.