Precise Cashew Classification using Machine Learning

Sowmya Nag Karnam
Department of ECE, RV College of Engineering, Bangalore, India | Visvesvaraya Technological University, Belagavi, Karnataka, India
sowmyanagk@rvce.edu.in (corresponding author)

Veenadevi Siddanahundi Vaddagallaiah
Department of ECE, RV College of Engineering, Bangalore, India | Visvesvaraya Technological University, Belagavi, Karnataka, India
veenadevi@rvce.edu.in

Pradeep Kooganahalli Rangnaik
Department of ECE, RV College of Engineering, Bangalore, India
pradeepkr.ec19@rvce.edu.in

Akshaya Kumar
Department of ECE, RV College of Engineering, Bangalore, India
akshayakumar.ec20@rvce.edu.in

Charan Kumar
Department of ECE, RV College of Engineering, Bangalore, India
charankumarmn.ec21@rvce.edu.in

Bidadi Mahesh Vishwanath
Department of ECE, RV College of Engineering, Bangalore, India
bmvishwanath.ec21@rvce.edu.in

Received: 7 June 2024 | Revised: 16 July 2024 and 31 July 2024 | Accepted: 5 August 2024

 DOI: https://doi.org/10.48084/etasr.8052

ABSTRACT

This study explores the utilization of deep learning techniques for accurate cashew classification to improve efficiency and accuracy in the cashew industry. YOLOv5, YOLOv9, and a Convolutional Neural Network (CNN) were evaluated in classifying cashews into whole, broken, split-up, split-down, and defect categories. A comprehensive labeled dataset was built to train the models, applying data augmentation to increase robustness. YOLOv5 achieved the highest accuracy of 97.65% and the fastest inference time (0.025 s per image) among the models, making it suitable for real-time applications. Although CNN offered a simpler architecture, YOLOv5's superior performance places it as the most promising candidate for large-scale cashew classification deployment.

Keywords-convolutional neural networks; YOLOv5; YOLOv9; cashew grading; data preprocessing; image augmentation

I. INTRODUCTION

Cashew nuts are increasingly sought after on a global scale, necessitating efficient and accurate grading processes to maintain high-quality standards. Traditional manual grading methods, while ensuring human oversight, are fraught with challenges such as inconsistency and labor intensiveness. This can lead to economic losses for farmers due to misclassification and inefficiencies in the overall cashew processing pipeline. Automating the grading process with machine learning offers a viable solution. Technological advancements, particularly in computer vision and pattern recognition, have paved the way for sophisticated algorithms that can analyze and classify visual data with remarkable accuracy. Implementing such automated systems allows stakeholders in the cashew industry, including farmers, processors, and exporters, to significantly enhance operational efficiency, improve market competitiveness, and meet the stringent quality demands of discerning consumers. This shift not only promises to streamline the grading process but also to increase the overall quality and reliability of cashew products in the global market.

This study studies the potential of machine learning for automated cashew classification. Three prominent models, YOLOv5, YOLOv9, and a Convolutional Neural Network (CNN), are evaluated to identify the most effective solution for classifying cashews into different quality grades based on image analysis. The focus lies on identifying a model that not only achieves high accuracy but also prioritizes efficiency and real-time applicability within the fast-paced cashew processing environment. By presenting a comprehensive evaluation of these models, this study aims to contribute valuable insights and pave the way for the greater adoption of machine learning automation in the cashew industry.

In [1], the YOLOv5 object detection model offered significant advancements in real-time object identification. This study evaluated its architectural improvements, training process, and transfer learning capabilities. YOLOv5-tiny achieved promising results, demonstrating its potential for various computer vision applications. In [2], YOLOv5 was used for real-time disease detection in tomato leaves, using a custom image dataset to train the model to distinguish healthy and diseased leaves, achieving high accuracy (93%) and demonstrating its potential for applications in precision agriculture. In [3], automated cashew kernel classification was investigated using supervised learning and image preprocessing. K-means clustering and feature selection techniques were employed to prepare the data. Random Forest (RF) achieved superior accuracy compared to Support Vector Machines (SVM) and Adaptive Directed Acyclic Graph (ADAG) for multi-grade cashew classification, demonstrating its potential for industrial applications. In [4], an SVM model was used for automated cashew kernel classification (whole vs. split). Feature extraction focused on the "length of the curve" for binary classification. The model achieved 93% accuracy, demonstrating its potential for efficient cashew grading in the food industry. In [5], YOLOv5l and YOLOv8l were compared in distinguishing between four categories of tomato diseases. Data augmentation significantly improved the accuracy of both models, and YOLOv8l achieved slightly higher performance. This suggests the potential of lightweight object detection models for real-time disease classification in agriculture. In [6], a CNN was used to classify potato leaf diseases, achieving high accuracy (98%) in distinguishing healthy leaves from various fungal and bacterial diseases. This demonstrates the potential of deep learning techniques for automated disease detection in agriculture. In [7], a low-cost cashew grading system was proposed, using a novel YOLOv8 transformer model for image classification. This model integrated a transformer block for improved performance and was designed for efficient implementation in embedded devices. It achieved high accuracy in classifying cashews into four quality classes, demonstrating its potential for real-world applications, particularly on small-scale farms. In [8], a computer vision system was explored for cashew nut grading, using combined features (texture, color, shape) and machine learning. This system differentiated whole from split cashews based on single-view images. Various feature extraction and classification techniques were evaluated, with SVM1-All achieving the highest accuracy (98.93%), offering a promising solution for automated cashew grading. In [9], various machine learning models were investigated, including established (SVM, CNN) and recent mobile-optimized models (MobileNet V1, EfficientNet B3) to address the limitations of traditional grading. The results showed a trade-off between accuracy and processing speed: EfficientNet B3 achieved the highest accuracy but SVM offered the fastest processing. In [10], color features were used to classify cashew kernels as white or scorched. This study used Logistic Regression (LR), Decision Tree (DT), RF, SVM, and KNN. The DT model recorded the lowest accuracy of 98.4%, while the maximum accuracy of 99.8% was obtained by the RF model with 100 trees. In [11], YOLOv5 offered high accuracy in classifying cashews. In [12-13], cashew classification was carried out using DT and CNN. In [14], the theoretical foundations of ANNs were analyzed and various studies on evaluating cashew nut quality were explored. This review provided insight into this evolving approach and guided future research directions in this domain. In [15-17], flower recognition and classification was performed using deep CNN and transfer learning. In [18], a classification algorithm used surface grayscale intensity profiles for split-up cashews and object shadows to differentiate split-down from whole cashews. Using the "length of the curve" and "shadow to the total area ratio" features achieved good accuracy in classifying split-up and whole/split-down cashews. In [19], the performance of Multi-Layer Perceptron (MLP), Naive Bayes (NB), KNN, DT, and SVM was evaluated using the WEKA toolbox. In [20], a real-time machine vision system was proposed for automated cashew kernel grading based on quality parameters such as color, texture, size, and shape. This study evaluated the performance of SVM and Backpropagation Neural Network (BPNN) classifiers for accurate cashew kernel grading. In [21-23], flower classification was performed using supervised learning and CNN. In [24], the ResNet coding in Keras was explained. In [25-27], flower harvesting techniques in urban landscapes were discussed. In [28], the early detection of weed was addressed using Efficient Net B2 and Efficient Net B4, achieving 97% and 99% accuracy, respectively. In [29], image-based fruit classification was carried out using neural networks. In [30], the classification of white wholes was discussed using ANNs.

II. MATERIALS

A. Dataset Creation

Cashew nuts were obtained with written consent from a major cashew processing industry located in Bhatkal, Karnataka, India. This industry specializes in processing cashew varieties sourced from Goa and Maharashtra. The cashews collected were raw and unprocessed. A dataset of 1,000 high-resolution cashew nut images was created. The images were captured under controlled lighting conditions with a uniform background to minimize variations, using a digital camera with a resolution of 20 megapixels. Cashews were placed manually and imaged from a fixed height to ensure a consistent top-down view. Each image was meticulously labeled using a crowd-sourcing platform to identify the cashew grade (whole, broken, defect, split-up, and split-down) according to a predefined labeling guideline document.

B. Dataset Augmentation

To enhance the size of the dataset and the robustness of the models, data augmentation techniques were implemented using OpenCV libraries. The techniques applied were random horizontal and vertical flipping, random rotation by 10°, width shift, height shift, and random cropping while maintaining at least 80% of the cashew nut in the image. Additionally, color jittering was applied to introduce slight variations in brightness, saturation, and hue. Figure 1 shows the augmentation performed on cashew images, while Figure 2 shows the zoom and shear horizontal flip operations performed on cashew images.

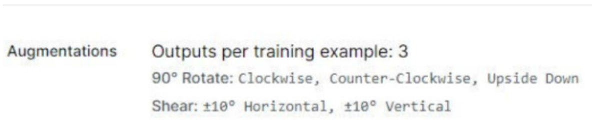

Fig. 1. Augmentations performed on cashew images.

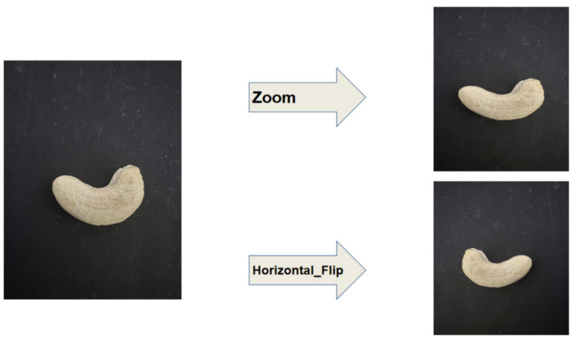

Fig. 2. Zoom and shear horizontal flip cashew images.

C. Classes/Grades

- Whole: Whole cashew kernels are a premium product in the cashew nut industry, highly valued for their intact, unbroken appearance and uniform size. These kernels are classified and graded according to specific criteria including size, color, and shape. In the context of whole cashew kernels, maintaining stringent quality standards is crucial. These standards ensure that only the best kernels reach consumers, meeting expectations for both aesthetic and culinary applications.
- Defect: Cashews that are harvested before they reach full maturity may be smaller in size and have a softer texture. These immature cashews may not possess the same desirable taste and processing characteristics as fully mature kernels. Cashews may exhibit discoloration due to various factors. Although some discoloration might not affect safety, it can affect visual appeal and market value. In rare cases, cashews can be damaged by insects during storage. Such cashews should be discarded to avoid potential health risks.
- Split-up and split-down: Split cashews, unlike whole kernels, are cashew nuts that have broken into two or more pieces during processing. These splits occur naturally or as a result of mechanical handling and are classified separately from whole kernels due to their fragmented state. Despite being broken, the split cashews still maintain high nutritional value.
- Broken: These are cashew nuts that have been fractured or shattered into multiple pieces during processing or handling. Despite their fragmented state, broken cashews retain their nutritional value and are utilized in various culinary applications, including cooking, baking, and snack production.

D. Data Preprocessing

The dataset collected was meticulously divided into five distinct subsets to facilitate effective training and evaluation of models for cashew classification (grading). The training set, comprising 70% of the data, is fundamental for model training. In this phase, the model learns to recognize patterns and identify essential features that differentiate between different categories. The validation set, comprising 20% of the data, is crucial for assessing the model's performance during training. It helps in fine-tuning hyperparameters and preventing overfitting, ensuring the model generalizes effectively to new, unseen data. The test set, which comprises 10% of the data, is used for the final evaluation of the model's performance on new, unseen data. This unbiased assessment provides a reliable measure of how well the model would perform in real-world applications. Figure 3 shows the split of the dataset for training, validation, and testing.

Fig. 3. Dataset split after data augmentation.

III. IMPLEMENTATION OF MACHINE VISION ALGORITHMS FOR CASHEW CLASSIFICATION

A. Convolutional Neural Network (CNN)

CNNs are a powerful type of artificial neural network, specifically designed for image recognition and analysis tasks. They excel at extracting features from images and classifying them into different categories. Unlike traditional neural networks that process data in a single layer, CNNs leverage a unique architecture inspired by the structure of the visual cortex in the human brain. CNNs have achieved remarkable success in image classification tasks due to their inherent ability to automatically learn hierarchical representations of features directly from input data. In this case, the CNN model was trained on a dataset that contained images of cashew kernels. The CNN model used was sequential with 4 convolutional layers with filter sizes of 32, 64, 128, and 128, respectively. Four max-pooling layers were used after every convolutional layer, and two fully connected dense layers were used along with the softmax activation function for classification. The model was trained for 30 epochs.

B. YOLOv5

YOLOv5 was also used for cashew kernel classification. YOLOv5 stands out as a sophisticated object detection model, renowned for its exceptional speed and accuracy. Unlike traditional CNNs that focus solely on image classification, YOLOv5 excels at simultaneously pinpointing and identifying multiple objects within a single image. This capability makes YOLOv5 particularly well-suited for the cashew kernel classification task. A key advantage of YOLOv5 is its ability to strike a perfect balance between speed and accuracy. This is crucial for real-time applications, such as automated cashew kernel classification on a production line. The faster the model can identify and localize the kernels, the faster the subsequent classification process can be. Additionally, YOLOv5's ability to simultaneously detect multiple objects is essential for cashew-kernel classification, as images might contain numerous kernels of varying sizes scattered across the frame. The batch size was 16 and the model was trained for 20 epochs.

C. YOLOv9

An experiment with the YOLOv9 architecture was carried out, which is an evolution of the YOLO series with enhancements in accuracy and efficiency. Comparing YOLOv9 with YOLOv5 aimed to determine the optimal model for the specific classification requirements. The batch size was 8 and the model was trained for 20 epochs.

Focusing on CNN, YOLOv5, and YOLOv9 ensured a comprehensive exploration of learning techniques tailored to the precise classification of cashew kernels. These models offer varying trade-offs between speed and accuracy, allowing us to select the most suitable approach based on evaluation metrics and practical considerations. The YOLOv5 model has proven to be valuable for cashew kernel classification, but the world of object detection is constantly evolving.

IV. RESULTS

The dataset of preprocessed and augmented images was generated using Roboflow to ensure efficient model training. Google Colab was employed for its free access to powerful GPUs to accelerate the process. Training and testing were carried out using an NVIDIA T4 GPU with 12.72 GB RAM, allowing the models to be trained efficiently in about one to two hours over 30 epochs.

A. YOLOv5

Figure 4 shows the defects detected by YOLOv5, with a confidence score of 88%. Whole cashews were detected with a confidence of 74%. The texture of the cashew, being the feature that distinguishes it from other cashews, helps the model detect it with good accuracy. Split-up cashews were detected with a confidence score of 66%, while broken ones were detected with 89%. Including images with overlapping cashews in the training data improved the model's ability to handle such scenarios during real-world deployment. Figures 5 and 6 show different classes of cashews present in a single image, detected with a high confidence score.

Fig. 4. Detection of single cashews

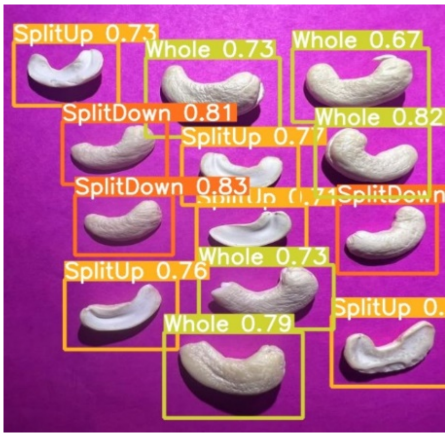

Fig. 5. Detection of mixed cashews.

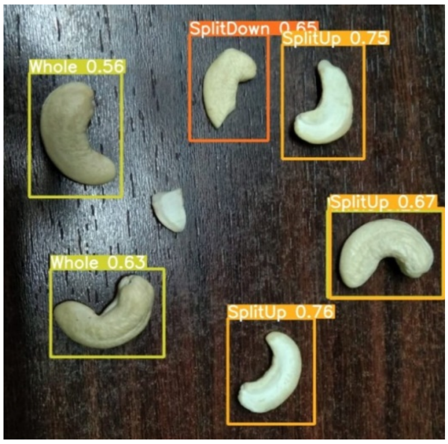

Fig. 6. Detection of mixed cashews with different backgrounds.

Figure 7 shows the confusion matrix for YOLOv5. As can be observed, YOLOv5 produced excellent classification results. The confusion matrix offers a comprehensive breakdown of the performance of a classification model. This visual tool presents key metrics, True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Figure 8 shows a precision-recall curve, a graphical representation of the trade-off between two key performance metrics. Precision defines the proportion of cashews classified as a particular class, measuring the correctness of positive detections. Recall defines the proportion of actual cashews in a particular class that the model correctly identified, measuring how well the model finds all relevant cashews.

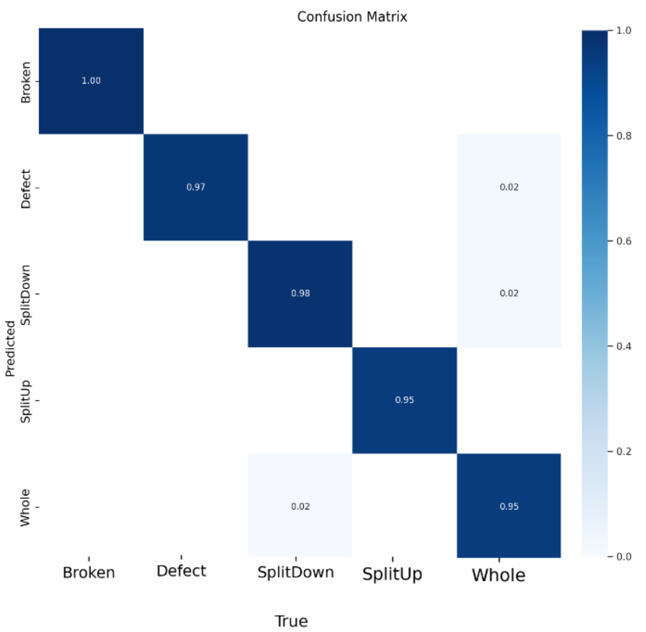

Fig. 7. Confusion matrix of YOLOv5.

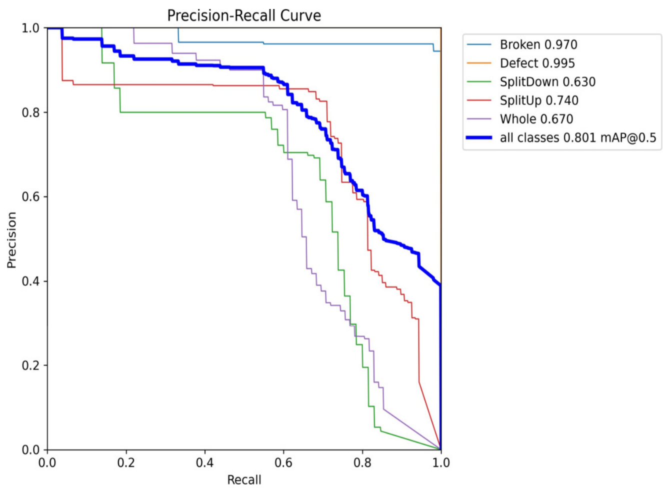

Fig. 8. Precision-recall curve of the performance of YOLOv5.

B. Convolutional Neural Network (CNN)

The training accuracy metric represents the percentage of cashew images the model correctly classified (both defects and non-defects) during the training phase. High training accuracy suggests that the model is learning the training data well. However, it is important to avoid overfitting, where the model memorizes the training data and performs poorly on unseen data. Figure 10 shows the prediction and classification of a defective cashew and Figure 11 shows the precision-recall curve. Figure 12 shows the prediction and classification of split-down cashews. Figure 13 shows the precision-recall curve of the split-down class. Figure 14 shows the prediction and classification of whole cashews. Figure 15 shows the precision-recall curve of the whole class.

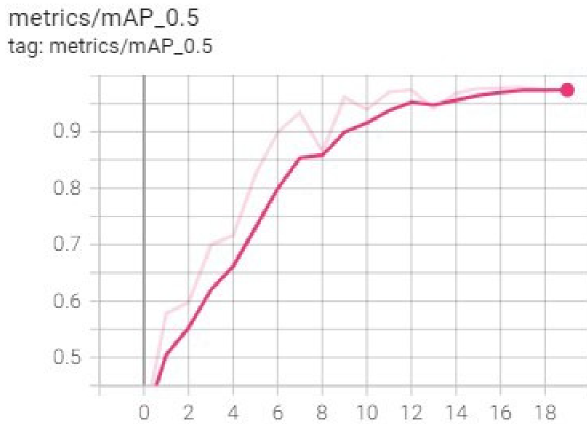

Fig. 9. Mean Average Precision (MAP) graph for YOLOv5.

```
# Display the image
plt.imshow(img_array[0])
plt.axis('off')  # Turn off axis labels
plt.show()
```

```
predicted_class_index = np.argmax(predictions[0])
predicted_class_label = class_labels[predicted_class_index]

print("Predicted Class:", predicted_class_label)
```

```
Predicted Class: Defect
```

Fig. 10. CNN model prediction on defects.

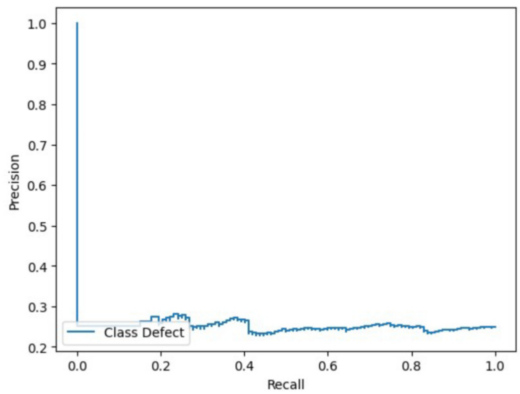

Fig. 11. Precision-recall curve of the defect class.

```
# Display the image
plt.imshow(img_array[0])
plt.axis('off')  # Turn off axis labels
plt.show()
```

```
# Get the predicted class label
predicted_class_index = np.argmax(predictions[0])
predicted_class_label = class_labels[predicted_class_index]

print("Predicted Class:", predicted_class_label)
```

```
Predicted Class: SplitDown
```

Fig. 12. CNN model prediction on split-down class.

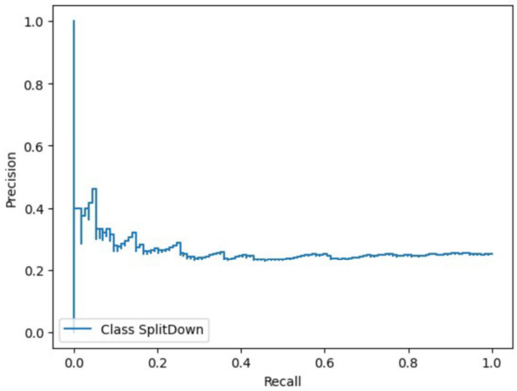

Fig. 13. Precision-recall curve of the split-down class.

```
# Display the image
plt.imshow(img_array[0])
plt.axis('off')  # Turn off axis labels
plt.show()
```

```
# Get the predicted class label
predicted_class_index = np.argmax(predictions[0])
predicted_class_label = class_labels[predicted_class_index]

print("Predicted Class:", predicted_class_label)
```

```
Predicted Class: Whole
```

Fig. 14. CNN model prediction on whole cashews.

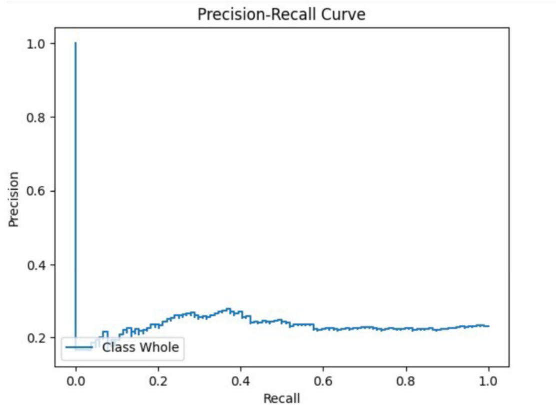

Fig. 15. Precision-recall curve of the whole class.

C. YOLOv9 Model

Figure 16 shows the detection of mixed cashews along with the confidence scores using YOLOv9. Figure 17 shows the confusion matrix for YOLOv9. It can be observed that YOLOv9 produces excellent classification results for some classes but is unable to produce better results when it comes to split-up and split-down classes.

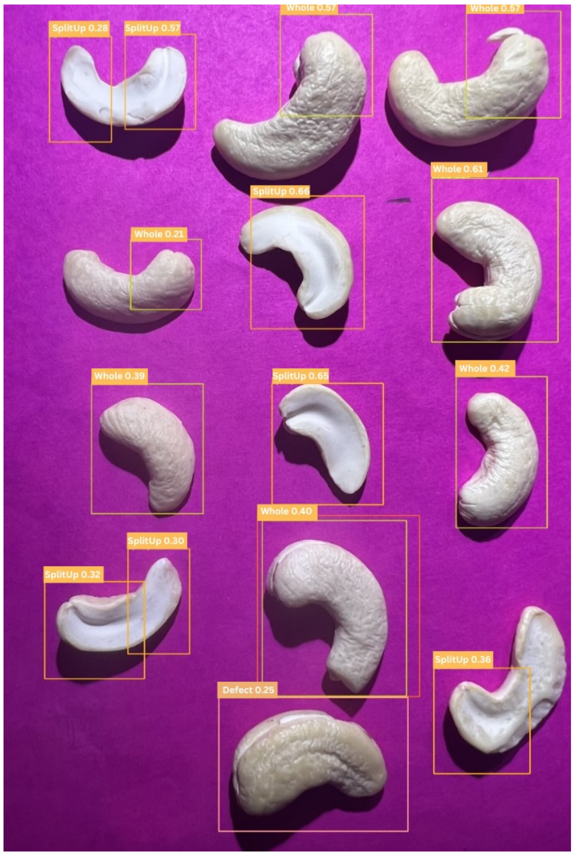

Fig. 16. Detection of mixed cashews.

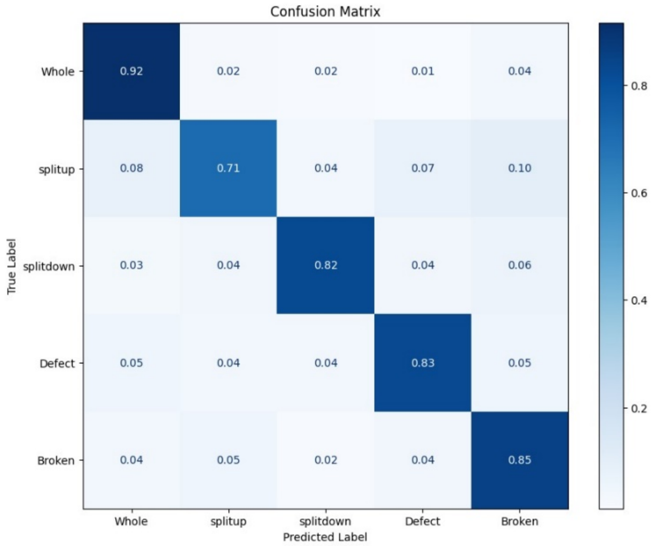

Fig. 17. Confusion matrix of YOLOv9.

Figure 18 shows the precision-recall curve of YOLOv9, which fell between 0.84-0.88 for all classes.

The classification accuracy of YOLOv5 was higher than that obtained in [4]. YOLOv5 was able to classify whole and split-down classes successfully. This model achieved promising results compared to traditional methods.

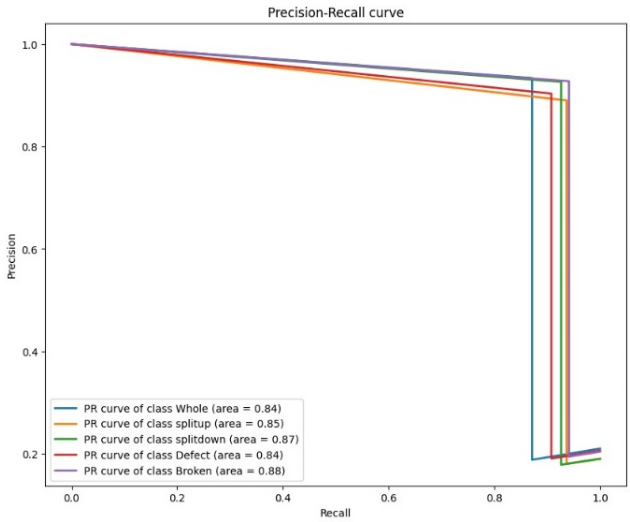

Fig. 18. Precision-recall curve of YOLOv9.

TABLE I. COMPARATIVE ANALYSIS

	[4]	**This study**		
Model	Shadow analysis	CNN	YOLOv5	YOLOv9
Accuracy	93%	97.62%	97.65%	82%

V. CONCLUSION

This study compared the performance of three CNN architectures for cashew classification: CNN, YOLOv5, and YOLOv9. A dataset of cashew images was created to train and evaluate each model. The results showed that YOLOv5 was the most effective model, achieving a remarkable accuracy of 97.65%, surpassing the CNN model (97.62%) and YOLOv9 (82%). These findings highlight YOLOv5's potential as the most suitable model for cashew classification within the constraints of this study. Future work should address the classification of other grades of cashews, such as scorched whole grades. Additionally, a hardware implementation of cashew grading should be explored. In contrast to existing methods that rely on shadow analysis for the classification of split-up and split-down cashews, varying lighting conditions are challenging, This study introduced a novel method that does not rely on shadow analysis. Despite this departure from traditional techniques, the proposed model achieves high accuracy in distinguishing between split-up and split-down cashews. This approach not only simplifies the classification process but also demonstrates robust performance under diverse lighting conditions, highlighting its potential for practical applications in the industry.

REFERENCES

[1] A. A. Alsuwaylimi, R. Alanazi, S. M. Alanazi, S. M. Alenezi, T. Saidani, and R. Ghodhbani, "Improved and Efficient Object Detection Algorithm based on YOLOv5," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14380–14386, Jun. 2024, https://doi.org/10.48084/etasr.7386.

[2] R. Rajamohanan and B. C. Latha, "An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12033–12038, Dec. 2023, https://doi.org/10.48084/etasr.6377.

[3] M. Arora and D. V. Devi, "A machine vision based approach to Cashew Kernel grading for efficient industry grade application," *International Journal of Advance Research, Ideas and Innovations in Technology*, vol. 4, no. 6, pp. 865–871, 2018.

[4] K. Sowmya Nag and S. V. Veena Devi, "Classification of Cashew kernels into Wholes and Splits using Machine Vision Approach," *Tuijin Jishu/Journal of Propulsion Technology*, vol. 44, no. 5, pp. 2668–2680, Dec. 2023, https://doi.org/10.52783/tjjpt.v44.i5.3013.

[5] R. Ahmed and E. H. Abd-Elkawy, "Improved Tomato Disease Detection with YOLOv5 and YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 13922–13928, Jun. 2024, https://doi.org/10.48084/etasr.7262.

[6] A. Abbas, U. Maqsood, S. U. Rehman, K. Mahmood, T. AlSaedi, and M. Kundi, "An Artificial Intelligence Framework for Disease Detection in Potato Plants," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12628–12635, Feb. 2024, https://doi.org/10.48084/etasr.6456.

[7] V. N. Pham, Q. H. Do Ba, D. A. Tran Le, Q. M. Nguyen, D. Do Van, and L. Nguyen, "A Low-Cost Deep-Learning-Based System for Grading Cashew Nuts," *Computers*, vol. 13, no. 3, Mar. 2024, Art. no. 71, https://doi.org/10.3390/computers13030071.

[8] A. Sivaranjani and S. Senthilrani, "Computer Vision-Based Cashew Nuts Grading System Using Machine Learning Methods," *Journal of Circuits, Systems and Computers*, vol. 32, no. 03, Feb. 2023, Art. no. 2350049, https://doi.org/10.1142/S0218126623500494.

[9] D. Pandit, N. Prakash, S. Shree M, S. H. Dahale, and S. Tripathi, "Computer Vision-based Automated Cashew Kernel Grading," in *Proceedings of the 2023 5th International Conference on Image, Video and Signal Processing*, Singapore, Mar. 2023, pp. 89–94, https://doi.org/10.1145/3591156.3591169.

[10] G. P. Baitu, O. A. A. Gadalla, and Y. B. Öztekin, "Traditional Machine Learning-Based Classification of Cashew Kernels Using Colour Features," *Tekirdağ Ziraat Fakültesi Dergisi*, vol. 20, no. 1, pp. 115–124, Jan. 2023, https://doi.org/10.33462/jotaf.1100782.

[11] V. H. Pham, N. K. Nguyen, and V. M. Pham, "A Novel Approach to Cashew Nut Detection in Packaging and Quality Inspection Lines," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 12, 2022, https://doi.org/10.14569/IJACSA.2022.0131243.

[12] V. G. Narendra, M. Krishanamoorthi, G. Shivaprasad, V. G. Amitkumar, and P. Kamath, "Almond kernel variety identification and classification using decision tree," *Journal of Engineering Science and Technology*, vol. 16, no. 5, pp. 3923–3942, 2021.

[13] S. K. Vidyarthi, S. K. Singh, R. Tiwari, H. W. Xiao, and R. Rai, "Classification of first quality fancy cashew kernels using four deep convolutional neural network models," *Journal of Food Process Engineering*, vol. 43, no. 12, 2020, Art. no. e13552, https://doi.org/10.1111/jfpe.13552.

[14] V. Nagpure, "Review on Back Propagation Neural Network Application for Grading of Cashew Nuts," *International Journal of Science and Research*, vol. 4, no. 10, pp. 1958–1962, 2013.

[15] R. Kaur, A. Jain, and S. Kumar, "Optimization classification of sunflower recognition through machine learning," *Materials Today: Proceedings*, vol. 51, pp. 207–211, Jan. 2022, https://doi.org/10.1016/j.matpr.2021.05.182.

[16] N. Alipour, O. Tarkhaneh, M. Awrangjeb, and H. Tian, "Flower Image Classification Using Deep Convolutional Neural Network," in *2021 7th International Conference on Web Research (ICWR)*, Tehran, Iran, May 2021, pp. 1–4, https://doi.org/10.1109/ICWR51868.2021.9443129.

[17] R. Lv, Z. Li, J. Zuo, and J. Liu, "Flower Classification and Recognition Based on Significance Test and Transfer Learning," in *2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE)*, Jan. 2021, pp. 649–652, https://doi.org/10.1109/ICCECE51280.2021.9342468.

[18] S. Sunoj, C. Igathinathane, and S. Jenicka, "Cashews whole and splits classification using a novel machine vision approach," *Postharvest Biology and Technology*, vol. 138, pp. 19–30, Apr. 2018, https://doi.org/10.1016/j.postharvbio.2017.12.006.

[19] M. Thakkar, M. Bhatt, and C. K. Bhensdadia, "Performance Evaluation of Classification Techniques for Computer Vision based Cashew Grading System," *International Journal of Computer Applications*, vol. 18, no. 6, pp. 9–12, Mar. 2011, https://doi.org/10.5120/2291-2975.

[20] A. Shyna and R. M. George, "Machine vision based real time cashew grading and sorting system using SVM and back propagation neural network," in *2017 International Conference on Circuit ,Power and Computing Technologies (ICCPCT)*, Kollam, India, Apr. 2017, pp. 1–5, https://doi.org/10.1109/ICCPCT.2017.8074385.

[21] A. Shukla, A. Agarwal, H. Pant, and P. Mishra, "Flower Classification using Supervised Learning," *International Journal of Engineering Research and*, vol. 9, no. 05, May 2020, https://doi.org/10.17577/IJERTV9IS050582.

[22] M. Toğaçar, B. Ergen, and Z. Cömert, "Classification of flower species by using features extracted from the intersection of feature selection methods in convolutional neural network models," *Measurement*, vol. 158, Jul. 2020, Art. no. 107703, https://doi.org/10.1016/j.measurement.2020.107703.

[23] Z. Wang, K. Wang, X. Wang, and S. Pan, "A Convolutional Neural Network Ensemble for Flower Image Classification," in *Proceedings of the 2020 9th International Conference on Computing and Pattern Recognition*, Xiamen, China, Jan. 2021, pp. 225–230, https://doi.org/10.1145/3436369.3437427.

[24] P. Dwivedi, "Understanding and coding a ResNet in Keras," *Towards Data Science*, 2019.

[25] C. Shree, R. Kaur, S. Upadhyay, and J. Joshi, "Multi-feature Based Automated Flower Harvesting Techniques in Deep Convolutional Neural Networking," in *2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)*, Ghaziabad, India, Apr. 2019, pp. 1–6, https://doi.org/10.1109/IoT-SIU.2019.8777338.

[26] H. Hoyle, B. Norton, N. Dunnett, J. P. Richards, J. M. Russell, and P. Warren, "Plant species or flower colour diversity? Identifying the drivers of public and invertebrate response to designed annual meadows," *Landscape and Urban Planning*, vol. 180, pp. 103–113, Dec. 2018, https://doi.org/10.1016/j.landurbplan.2018.08.017.

[27] H. Hiary, H. Saadeh, M. Saadeh, and M. Yaqub, "Flower classification using deep convolutional neural networks," *IET Computer Vision*, vol. 12, no. 6, pp. 855–862, 2018, https://doi.org/10.1049/iet-cvi.2017.0155.

[28] N. C. Kundur and P. B. Mallikarjuna, "Deep Convolutional Neural Network Architecture for Plant Seedling Classification," *Engineering, Technology & Applied Science Research*, vol. 12, no. 6, pp. 9464–9470, Dec. 2022, https://doi.org/10.48084/etasr.5282.

[29] Y. D. Zhang *et al.*, "Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation," *Multimedia Tools and Applications*, vol. 78, no. 3, pp. 3613–3632, Feb. 2019, https://doi.org/10.1007/s11042-017-5243-3.

[30] N. V. Ganganagowdar and H. K. Siddaramappa, "Recognition and classification of White Wholes (WW) grade cashew kernel using artificial neural networks," *Acta Scientiarum. Agronomy*, vol. 38, pp. 145–155, Jun. 2016, https://doi.org/10.4025/actasciagron.v38i2.27861.