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Improving Cashewnuts Production through Automated Grading Using Enhanced Convolutional Neural Networks and Advanced Image Processing

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Abstract: India produces around 15% of the world's cashew nuts, making it one of the top producers in the world. Tamil Nadu, Kerala, and Karnataka are coastal states that are the main sites used for farming. Over a million people in rural areas are employed by the cashew industry, which makes a substantial economic contribution to India through the export of cashew kernels and cashew nut shell liquid. Using cutting-edge image processing and deep learning techniques, this research attempts to create an automated cashew grading system that improves grading efficiency and accuracy. Digital cameras were used for pre-processing cashew nut photos. Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT), and Discrete Cosine Transform (DCT) were three compression techniques that were carefully coupled to guarantee efficient feature preservation under various image sizes and lighting circumstances. The CNN's capacity to discern minute visual variations between classes is enhanced by this hybrid compression technique, which eliminates duplication while maintaining crucial spatial and frequency information. The visual quality was further enhanced by applying image enhancement techniques like thresholding, contrast stretching, and homomorphic filtering.The performance of a Convolutional Neural Network (CNN) built on the ResNet-50 architecture was assessed using common accuracy metrics after it was trained on distinct databases created from every processed image set. According to the findings, the suggested hybrid compression and enhancement pipeline greatly increased classification accuracy, making it possible to create a dependable and entirely automated cashew grading system.

Keywords: Cashewnuts Grading, Convolutional Neural Network, Image Enhancement, Image Compression, Discrete Fourier Transform, Discrete Cosine Transform, Contrast Stretching, Thresholding Operations.

I. INTRODUCTION

Cashew nuts, which are edible seeds renowned for their high nutritional content and use in a variety of culinary applications, are produced by the cashew tree (Anacardium occidentale). Protein, fiber, good fats, vitamins, and vital minerals like copper and magnesium are all abundant in cashew nuts [1]. In addition to being a well-liked snack, cashews are crucial to the worldwide food and confectionary sectors. India is one of the biggest producers and exporters of cashew nuts worldwide, with the majority of cashew cultivation occurring along the country's coastline. The cashew sector is essential to maintaining rural livelihoods and making a substantial contribution to both home and foreign trade. Cashew nut sorting in India is still primarily done by hand by skilled laborers [2]. Due to weariness, human prejudice, and differences in perception, this traditional method is subjective, time-consuming, and labor-intensive, and it frequently produces inconsistent grading. Researchers have looked into automated grading systems that use machine learning and conventional image processing methods to overcome these problems. Existing systems, however, have a number of drawbacks that severely impair image quality and classification accuracy, including limited resilience to illumination changes, background noise, and erratic camera settings [3]. Furthermore, a lot of methods use little or unbalanced datasets, which leaves out important aspects of accurate grading, like cashew nut size, shape, color, and surface roughness. Furthermore, the majority of existing models concentrate on traditional feature extraction or single-stage image processing, frequently ignoring the advantages of multi-domain compression and enhancement techniques that could maintain important visual features while increasing computational efficiency. This study fills these gaps by presenting CashewGradeNet, an enhanced Convolutional Neural Network (CNN) architecture that combines cutting-edge picture enhancement and hybrid compression methods to produce fully automated, high-accuracy cashew nut grading. By providing a scalable and impartial substitute for manual grading, the suggested solution seeks to increase accuracy and productivity in the Indian cashew sector.

II. Related Work

A sophisticated classification algorithm known as the YOLOv8–Transformer was created to divide cashew nuts into four different quality groups, according to Van-Nam Pham et al. [4]. The suggested system successfully recognizes and classifies cashew nuts by combining the benefits of the Transformer models with the YOLOv8 architecture, and it does so by using a cheap camera to capture photos. The core of this hybrid method is a new SC3T module that builds the YOLOv8 architecture by combining a Transformer block with a C3TR module. This combination enables the model to be implemented on embedded systems, primarily to enhance cashewnut classification performance in a computationally affordable way. In a study published by Sowmya Nag Karnam et al. [5], the effectiveness of three deep learning models—YOLOv5, YOLOv9, and a Convolutional Neural Network (CNN)—for the classification of cashew nuts was compared. Five types of cashew nuts were included in the researchers' extensive annotated dataset: whole, broken, split-up, split-down, and defective. To increase the model's resilience, data augmentation techniques were applied to the dataset. YOLOv5 outperformed all other models in terms of classification accuracy (97.65%) and inference time (0.025 seconds per image). Convolutional neural networks (CNN), the foundation of the entire harvesting strategy, are used by S. Charukeshi et al. [6] to automate the process of harvesting cashew fruits from the tree. This method replaces human labor with machine aid in harvesting. In order to identify and enable automated harvesting, the research study analyzes photos of cashew fruits strewn across the ground using a CNN-based model. By using this technique, workers will experience less physical strain, which will eliminate the most prevalent conditions caused by manual fruit picking, such as neck and back pain. Therefore, by automating manual labor in the process of collecting cashew fruits from trees, this suggested method will increase operational efficiency and occupational safety. The MVCNN-CASHNET model was created to categorize cashew nut grades into groups like Split, White Wholes, and Scrubbed Wholes. A. Sivaranjani and S. Senthilrani created it [7]. Images from nearby cashew processing firms were used to train the model. Each sample was taken from three different angles: top, left, and right. The MVCNN-CASHNET framework was shown to have good classification accuracy of 98.87 percent with stated error rates of 4.49 percent. This degree of automation enables consistent product quality, which is necessary to meet global market needs and customer expectations.

III. Proposed Methodology

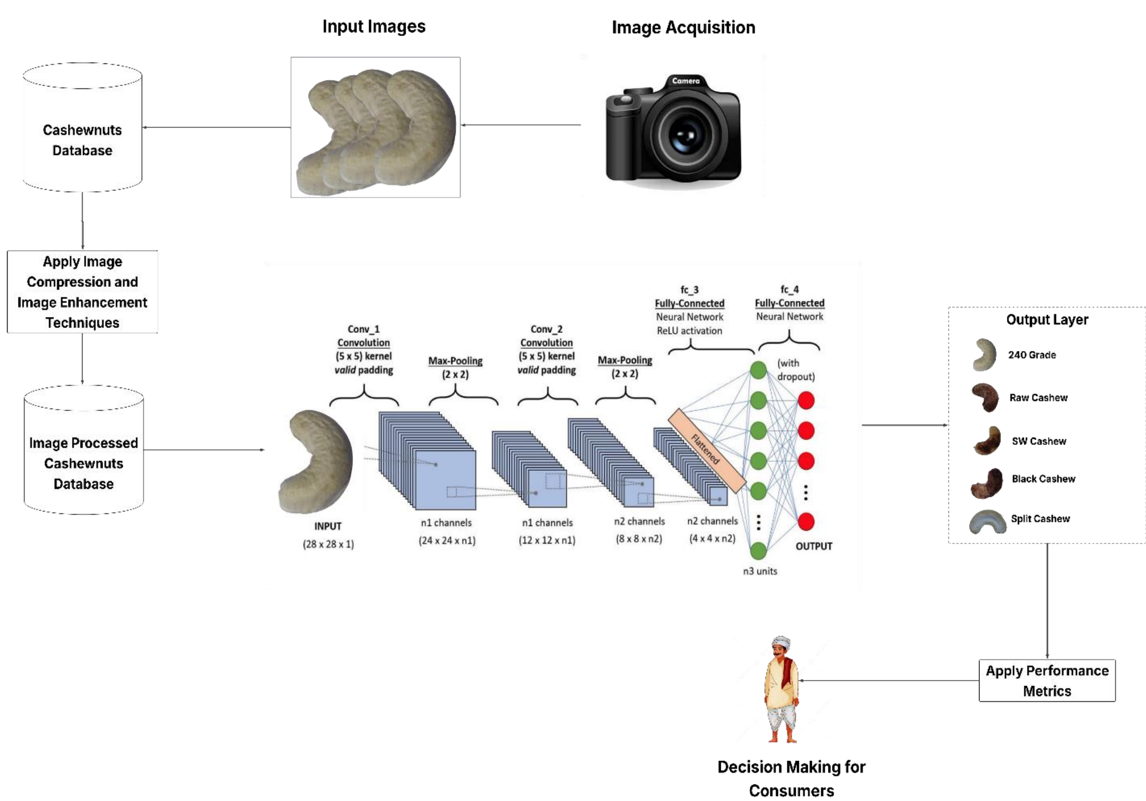


Fig. 1. Proposed CashewGradeNet Algorithm for Automatic Cashewnuts Grading

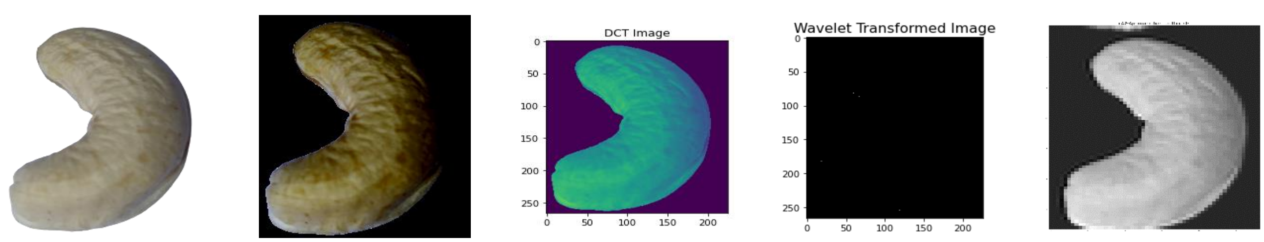
The dataset utilized in this study was collected from Krishika Cashews, a local cashew nut grading enterprise located in Nadukuppam Village, Panruti Taluk, Cuddalore District. Image acquisition was performed using a Redmi 12 5G mobile device. Prior to model training, background elements were removed from all images to ensure uniformity and reduce noise. The dataset comprised six distinct cashew nut categories: 240, Black Rotten, Raw Cashew, Split, Scorched Wholes (SW), and White Rotten. A total of 7,200 images were included, with each category containing 900 labelled samples. The CashewGradeNet algorithm proposed in this study for automatic cashew nut grading is illustrated in Figure 1. The collected image dataset was divided into a training set comprising 5400 images and a testing set of 1800 images. A Convolutional Neural Network (CNN) model was developed using this dataset to classify the cashew nuts into predefined categories. To further investigate the impact of preprocessing techniques, the original images were subjected to image compression methods, including Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), and Discrete Fourier Transform (DFT). The output from each compression technique was stored as an independent dataset. Additionally, the original dataset underwent image enhancement techniques such as contrast stretching and thresholding operations, and the resulting images were saved as a separate dataset. A CNN model was trained on each of these individual datasets to classify the cashew nuts into six categories: 240, Black Rotten, Raw Cashew, Split, Scorched Wholes (SW), and White Rotten. The classification performance of each CNN model was evaluated using standard performance metrics, and the time complexity associated with constructing each model was also analyzed.

IV. Results and Discussion

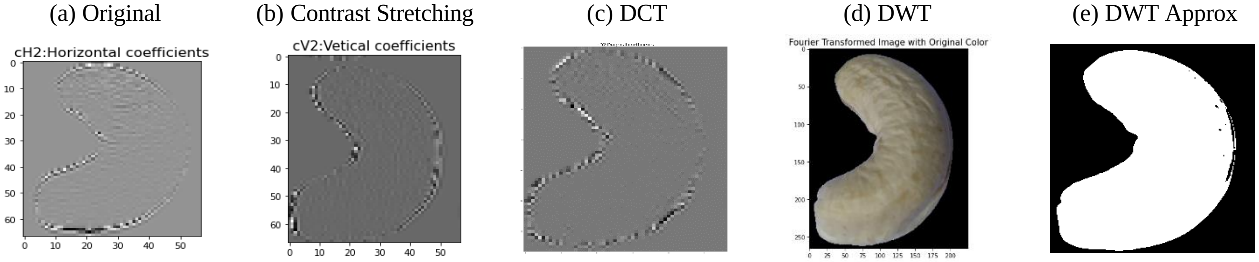
To automate cashew nut grading, Python 3.8 was used to construct the CashewGradeNet algorithm. Preprocessing was applied to the gathered photos, standardizing the backgrounds for uniformity. To create different datasets, picture compression methods including Discrete Wavelet Transform (DWT) using skimage.color, Discrete Fourier Transform (DFT) using cv2 (with high-pass filtering), and Discrete Cosine Transform (DCT) using scipy.fftpack were used. CV2 was used for thresholding, combining Otsu's binarization method with median blur filtering. Additionally, homomorphic filtering was used to highlight changes in illumination and improve contrast. Images were scaled to 180x180 pixels, normalized to [0, 1], and loaded in batches of 30 to create a CNN model based on Keras and TensorFlow. Convolution, pooling, and a dense output layer with six neurons for classification were all part of the design. Confusion matrices for every dataset were used to assess performance. The performance of the CNN was measured using the confusion matrix obtained for the individual dataset shown in Figure 4 and Figure 5 and the results were given in Table 1.

(a) 240 (b) Black Rotten (c) Raw (d) Split (e) SW (f) White Rotten

Fig. 2. Samples of Cashewnuts taken for Classification



(a) Original (b) Contrast Stretching (c) DCT (d) DWT (e) DWT Approx



(f) DWT Horizontal (g)DWT Vertical (h)DWT Diagonal (i) DFT (j) Threshold

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Fig. 3. Output of the Various Image Processing Techniques if 240 Cashewnut Image

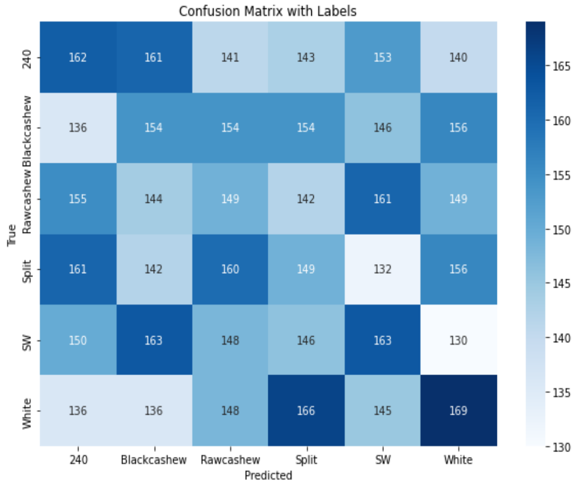

Fig. 4. Confusion Matrix for the Original Cashewnuts dataset containing 7200 images

Several feature extraction methods, such as Contrast, DCT, DFT, DWT, and its sub-bands (Approximation, Diagonal, Vertical, and Horizon), in addition to threshold-based features, were used to assess the CNN model on the PNG dataset. Overall, the findings demonstrate that all approaches produced consistent model performance across various feature transformations, with accuracy values ranging from 0.718 to 0.725 and recall values between 0.68 and 0.72. The Contrast-based dataset outperformed the others in terms of accuracy (0.725) and precision (0.75), exhibiting a high degree of classification dependability and few false positives. Despite requiring the most training time (more than five hours), the DWT Diagonal technique yielded the highest recall (0.72), indicating its efficacy in identifying affirmative situations. The DWT Approximation approach, on the other hand, provided a nearly ideal balance, with the fastest training time (about 1 hour 58 minutes), good accuracy (0.722), and reasonable recall (0.69), making it the most effective choice. With balanced accuracy and recall (both around 0.70), the threshold-based dataset likewise demonstrated strong performance. With contrast enhancement and DWT Approximation appearing as the most successful methods—contrast for maximum accuracy and precision, and DWT Approximation for computational efficiency with good generalization—the CNN performed consistently across all modifications

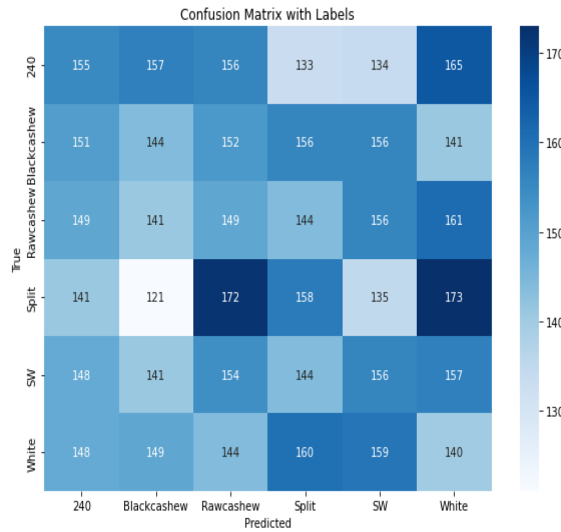

Fig 4. Confusion Matrix for the DWT Cashewnuts dataset containing 7200 images

TABLE I

PERFORMANCE METRICS OF CNN FOR VARIOUS IMAGE PROCESSING TECHNIQUES FOR 7200 IMAGES

	PNG Dataset	Contrast	DCT	DFT	DWT	DWT Approx	DWT Diagonal	DWT Vertical	DWT Horizon
Time	2h: 09m: 19s: 22ms	2h: 6m: 22s: 67ms	2h: 57m: 37s: 20ms	2h: 5m: 33s: 54s	1h: 58m: 55s	5h: 19m: 30s: 61ms	2h: 00m: 18s:	2h: 19m: 27s: 01ms	2h: 11m: 09s: 4ms
Accuracy	0.725	0.721	0.719	0.720	0.722	0.722	0.721	0.721	0.718
Error Rate	0.275	0.28	0.281	0.28	0.278	0.278	0.279	0.279	0.282
Recall	0.715	0.69	0.68	0.68	0.69	0.72	0.70	0.69	0.68
Specificity	0.835	0.833	0.831	0.832	0.833	0.833	0.832	0.833	0.831
Precision	0.75	0.65	0.69	0.63	0.67	0.66	0.62	0.64	0.64
Negative Predicted Value	0.835	0.833	0.831	0.832	0.833	0.833	0.832	0.833	0.831

VI. Conclusion

The present research introduces CashewGradeNet, an automated cashew nut grading system that combines a Convolutional Neural Network built on the ResNet-50 architecture with sophisticated picture preprocessing methods. The system showed encouraging results in cashew nut quality classification by using a variety of image improvement and compression techniques, including DWT, DCT, DFT, thresholding, and contrast stretching. With the greatest classification accuracy of 72.6% among all preprocessing methods, DWT-Horizontal was closely followed by thresholding and contrast enhancement. The model's poor recall values show that there is room for improvement in identifying positive instances, even if it obtained high specificity and low false positive rates across all datasets. This suggests that the model tends to favor negative class predictions, which might not be the best option for situations where it's crucial to accurately identify all quality grades. Despite this drawback, the suggested approach is scalable and computationally efficient; the majority of preprocessing techniques take less than 22 minutes each run. With its potential to improve quality control and operational efficiency in India's cashew processing sector, CashewGradeNet presents a feasible route to completely automated and precise cashew grading. To guarantee more reliable detection of all cashew quality categories, future research should concentrate on enhancing recall through data balancing techniques, architectural optimization, or the addition of attention mechanisms.

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