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Implementation and Assessment of New Hybrid Model for Cashew Kernel Classification

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Abstract*:* Convolutional Neural Networks, represents a cutting-edge methodology for image classification. Numerous CNN models have been effectively deployed for classification of images. The training of CNN involves leveraging sophisticated deep learning algorithms, leading to significant milestones in large-scale identification methods within the realm of machine learning. Cashew nuts are widely consumed worldwide and are classified into different grades based on their size and quality. The current manual sorting and grading process for cashew kernels is labor-intensive and time-consuming. This paper proposes 9 hybrid models for cashew classification such as VGG16 + SVM, VGG16 + RF, VGG16 + KNN, Inception-V3 + SVM, Inception-V3 + RF, Inception-V3 ,VGG16 + SVM, VGG16 + RF, VGG16 + KNN, Inception-V3 + SVM, Inception-V3 + RF, Inception-V3 + KNN, ResNet50 + SVM, ResNet50 + RF, ResNet50 + KNN, Custom + SVM, were implemented. The results revealed that the ResNet-50 model combined with SVM gave highest accuracy of 97.40%. The results obtained in this paper indicate that the fusion of convolutional neural networks (CNNs) and classifiers in hybrid models yields significant improvements in automated cashew grading.

Keywords: *Convolutional Neural Network, SVM, RF, Custom, KNN, Machine Learning*

1. Introduction

Cashew nuts, scientifically known as Anacardium occidentale, originate from Brazil but have gained global cultivation. Consumption of cashews has been linked to various health advantages, including protection against cancer, heart disease, high blood pressure, and age-related degenerative diseases [1]. Cashew production extends beyond Brazil, with countries such as India, Vietnam, Nigeria, and Indonesia playing prominent roles in global supply. In fact, India emerged as the world's largest producer of Raw Cashew nuts (RCN) in 2018 [2]. The Indian cashew production industry holds a significant position in the global market, with the state of Karnataka playing a vital role. Karnataka's favorable climate and well-developed infrastructure facilitate cashew cultivation, processing, and exportation. Districts such as Dakshina Kannada, Udupi, and Uttara Kannada are acclaimed for their comprehensive coverage of cashew plantations.

The harvesting process for cashews involves several steps. After harvesting, the cashew apples are pressed to extract juice, which is used in beverages and jams. The cashew nuts are then dried either in the sun or using mechanical methods to reduce their moisture content. Once dried, the outer shell is carefully removed to reveal the edible cashew kernel. Several methods are highlighted for CNSL extraction in [3]. Precision and care are essential during this process to avoid damaging the delicate kernel. The chemical composition and Physicochemical Properties of Cashew nut Oil and Cashew nut Shell Liquid are mentioned in [4],[5]. Finally, the cashews are sorted, graded, and packed for distribution and consumption. Cashew nuts are categorised into various grades based on factors such as size, shape, colour, and quality. The grading system differs across regions, but common types include Whole Fancy (large, whole kernels), Whole Premium (slightly smaller whole kernels), Whole Standard (smaller whole kernels), Splits (halves of cashew kernels), Pieces (broken or irregularly shaped kernels), Butts (broken and irregularly shaped kernels), and Scorched Wholes (slightly darker whole kernels). Each grade has its unique applications, from gourmet products to food processing, and is used in various culinary and industrial uses such as snacking, baking, spreads, toppings, and ingredients in different food products. Whole cashews are considered supreme quality cashews and are categorized into various grades, namely W180, W210, W240, W300, W320, W400, W500, etc., where W180 refers to the grading system used for cashew kernels,W180 signifies that there are approximately 180 whole cashew kernels per pound. It is a measure of the size of the cashew nut, with higher numbers indicating larger kernels.

The traditional method of cashew classification involves manual sorting and grading by skilled workers. The process includes a visual inspection of each kernel, the removal of

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defective ones, sorting by size, grading based on quality factors, and packaging. While this approach permits subjective judgement and customization, it is labour-intensive, time-consuming, and susceptible to human error. Modern automated methods utilising machine vision and AI algorithms have gained increasing prominence in the industry, offering faster, more consistent, and objective classification processes. However, in smaller-scale or traditional operations, manual classification may still be practised for various reasons. Machine vision and AI algorithms have revolutionised cashew grading by automating image capture, processing, classification, defect detection, and sorting. Utilising high-resolution cameras and advanced image processing techniques, cashew nuts are analysed based on size, shape, colour, and defects. In [6], machine vision techniques are applied to grade the quality of areca nuts. Six geometric features, three colour features, and the defect area were considered for the grading procedure, and an accuracy of 90.9% was achieved. The machine learning approach in cashew nut grading involves training models on labelled cashew nut images to extract relevant features and make accurate classification decisions. This automated approach offers the advantage of objective and standardised grading based on specific criteria, leading to increased efficiency, consistency, and scalability in the grading process. According to the study's findings in [7], the accuracy of 94.28% is obtained for sorting cashews into various grades when employing a Random Forest classification model compared to SVM. In research paper [8], a system to classify five grades of cashews using shape, size, colour, and texture features and Back Propagation Neural Networks (BPNN) was proposed, which demonstrated an accuracy of 96.8%. In [9], the findings revealed that SVM outperformed BPNN in terms of accuracy rates for cashew grading applications. Deep Convolutional Neural Networks (DCNN) have noticeable advantages over conventional machine learning (ML) methods in cashew grading. DCNNs excel in extracting hierarchical features directly from raw image data, eliminating the need for manual feature engineering. DCNNs can handle variations in cashew nuts, adapt to different lighting conditions, and leverage transfer learning for efficient grading with smaller datasets. In the paper [10], four deep convolutional neural network models were implemented, which include Inception-V3, ResNet50, VGG-16, and a custom model, and it was concluded that the developed DCNN models were capable of attaining automatic, fast, and accurate cashew classification.

Combining Deep Convolutional Neural Networks (DCNN) for feature extraction and traditional machine learning (ML) algorithms for classification offers several advantages in cashew grading. DCNNs excel at learning hierarchical features directly from raw image data, capturing intricate patterns in cashew nuts. By extracting these features, ML algorithms can leverage their strengths in structured data processing and classification to make accurate grading decisions. The application of hybrid models proved highly effective in the classification of flower images. Among the various models that were implemented, the combination of ResNet-50 as a feature extractor with a support vector machine (SVM) classifier achieved an accuracy of 90.01% [11]. The combination of DCNN and machine learning has been relatively unexplored in nut classification. Thus, this study introduces a robust approach that integrates DCNN and machine learning techniques to achieve precise grading and classification of cashew kernels with exceptional accuracy. A wide variety of methods are used in the aforementioned fruit grading systems [12], [13], [14],[16], [17].In [18] digital image analysis is used to measure twelve essential kernel morphological features of wheat cultivars. These features likely included parameters such as kernel size, shape, color, and texture achieved an accuracy of 80%. Among the assortment of machine vision classification algorithms created, the Backpropagation Neural Network (BPNN) demonstrated exceptional performance, achieving an accuracy of 85% [19].In [20] a novel approach using the "shadow to total-area ratio" successfully tackled the classification challenge of distinguishing between whole and split-down cashews, achieving a remarkable accuracy. Fruit grading using spectrophotometry, machine vision approach and mobilenet V2 is carried out in [21], [22], [23].The study[24] introduced a methodology based on digital image processing techniques to identify defective grains in a sample of rice grains. A Computer Vision System was developed to detect the browning of apples using color and textural features[25].In paper[26] he fuzzy logic toolbox was utilized to grade the four major grades of cashew, demonstrating a computation time of 0.53 seconds, significantly faster than the fuzzy classifier implemented in Python. This study aims to achieve precise recognition of cashew kernels by leveraging feature extraction from various DCNN neural network models such as Inception-V3, ResNet50, VGG-16, and a custom-made model. Furthermore, the cashew kernels are classified into five distinct grades using SVM, RF, and KNN algorithms. The comparison of their classification performance is another objective of this study. The development of hybrid models, which surpass individual ML and DCNN models in terms of efficiency, is a significant outcome of this study. The insights obtained from this research not only enhance the precise classification of cashews within the cashew industry but also have the potential to attain remarkable accuracy in classifying other types of nuts

2. Cashew Samples and Their Grading

The primary objective of this research was to develop a grading system for whole cashews, focusing on their whiteness and shape. To accomplish this, extensive collaboration was established with cashew industries located in Karnataka to obtain a diverse collection of cashew samples. Cashews of different grades were obtained from the Mahasathi Cashew Industry in Bhatkal. The specific grades considered were W180, W210, W300, W400, and W500, which represent different sizes and qualities of cashew kernels. In the context of cashew grades, the "W" stands for "whole". The letter "W" followed by a number is used to indicate the size and quality of the cashew kernels. It represents the number of whole cashew kernels that make up one pound of cashews. W180, as shown in Fig 1(a), refers to the largest cashews, with an average of 180 kernels per pound. W210, as shown in Fig 1(b), denotes slightly smaller cashews, with approximately 210 kernels per pound. W300, as shown in Fig 1(c), represents a smaller size, with around 300 kernels per pound. Moving down the scale, W400 cashews, as shown in Fig 1(d), are even smaller, with approximately 400 kernels per pound. Finally, W500 cashews, as shown in Fig 1(e), are the smallest among the collected grades, averaging around 500 kernels per pound.

(a) (b) (c) (d) (e)

Fig 1.Cashew grades used in the implementation work

(a) W180 (b) W210 (c) W300 (d) W400 (e) W500

3. Image Acquisition and Preprocessing

The work is carried out with five categories of cashews in the dataset as follows: W180, W210,W300, W400 and W500. The Cashew datasets are carried out as W180 with 450, 300 W210, 400 with W300, W400 with 430, W500 with 420, and marigold with 856 images. The collection of all images is 2000. The image resolution is 224 x 224 pixels with each image being 24 bits. The images are in JPEG format. The cashew images for the dataset are self-capturation. 80% is allocated on training, whereas 20% is used on testing the dataset in every hybrid model.

During the image acquisition process, a systematic approach was adopted to ensure accurate representation, leveraging the advanced capabilities of the mobile camera. The cashews were photographed using iPhone 13 pro with great care and consistency, maintaining a constant distance of 6 cm between the camera and the cashew kernel, as depicted in Fig 2. A black background was employed to enhance contrast and highlight the features of the cashews. The entire process of dataset collection spanned approximately 3 to 4 weeks, during which utmost attention was given to essential factors, including lighting conditions, the distance between the cashew and the camera, background color, image brightness, and capture angle. By carefully considering these variables, comprehensive and diverse images were captured to facilitate the training of robust convolutional neural network (CNN) models. The dataset accumulated for this purpose comprised over 2000 images encompassing different grades, highlighting the thoroughness of the image collection process

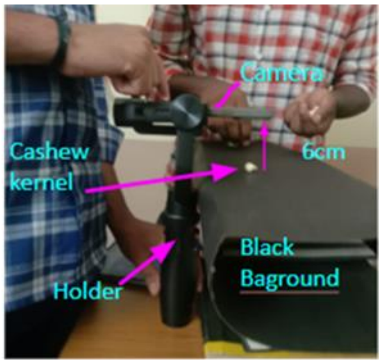

Fig. 2. Setup for image acquisition process

After the image capture process, different preprocessing steps were considered before feeding the data set to models. These preprocessing steps involved image resizing, Noise removal, and background removal. Additionally, to augment the training data set further and improve the models' generalisation capabilities, image augmentation techniques were employed. These techniques involved applying transformations like rotation, scaling, cropping, and flipping to generate a more extensive and diverse range of training examples. By incorporating these practices, the goal was to enhance the efficacy and accuracy of the DCNN models in precisely classifying cashews of various grades based on the acquired dataset. Following the acquisition of the dataset, the subsequent step involved constructing hybrid models by combining deep convolutional neural networks (DCNNs) with classifiers.

4. Implementation of Hybrid Models

Hybrid models were implemented by combining the feature extraction capabilities of the DCNN models (VGG16, InceptionV3, ResNet50, and Custom Model) with the classification abilities of SVM, Random Forest, or KNN. The DCNN models extract informative and discriminative features from cashew nut images, capturing important visual patterns and characteristics. These features serve as high-level representations that encode essential information for accurate classification. By integrating these extracted features with the classification algorithms, the hybrid models leverage the strengths of both components to improve the classification accuracy and robustness of the system. The classifiers, such as SVM, Random Forest, and KNN, contribute to the hybrid models by performing the final classification of cashew nut images. Each classifier brings its own unique capabilities to the table. SVM excels at finding optimal decision boundaries; Random Forest benefits from ensemble learning and robustness; and KNN specialises in instance-based classification. By combining these classifiers with the extracted features, the hybrid models make more accurate and reliable predictions. Furthermore, the hybrid models enable ensemble learning, allowing for the aggregation of multiple classifiers' predictions to obtain a more confident and refined classification result. This combination of feature extraction and classification techniques in the hybrid models enhances the overall performance and adaptability of the cashew grading system, leading to more precise and efficient grading outcomes. Various DCNN models were utilized to implement the hybrid models, including VGG16, InceptionV3, ResNet50, and a custom model.

(i) VGG16: VGG16, with its deep stack of convolutional layers, is known to capture features of different scales and complexities. The early layers of VGG16 are adept at capturing low-level features such as edges, corners, and textures. As the network progresses deeper, as depicted in Figure 3(c), it learns to recognise increasingly complex shapes, patterns, and object parts. The VGG16 model exhibits the ability to effectively capture and represent essential characteristics such as texture variations, color distributions, and local structures present in images of cashew nuts. These features can include fine-grained details like spots, cracks, and surface irregularities as well as broader characteristics like overall shape and size variations.

(ii) Inception-V3: Inception V3, with its Inception modules, excels at capturing features at multiple scales. The parallel branches with different filter sizes shown in Fig 3(a) enable the model to capture local details and global. Contextual information simultaneously. InceptionV3 is capable of capturing a wide range of features, including fine textures, shapes, edges, and patterns in cashew nut images. It can discern intricate details of the cashew nut surface, detect colour variations, and learn to recognise specific visual patterns associated with different grades or characteristics.

(iii) ResNet50: ResNet50, with its residual connections, is designed to capture residual mappings and learn increasingly complex features. The skip connections in ResNet50 shown in Fig 3(b) allow for the preservation of lower-level features, enabling the model to focus on learning higher-level and more discriminative features specific to cashew grading. ResNet50 is capable of capturing features related to shape variations, surface textures, colour contrasts, and structural details of cashew nuts. It can learn to recognise both fine-grained attributes and broader characteristics that distinguish different grades or quality levels of cashew nuts

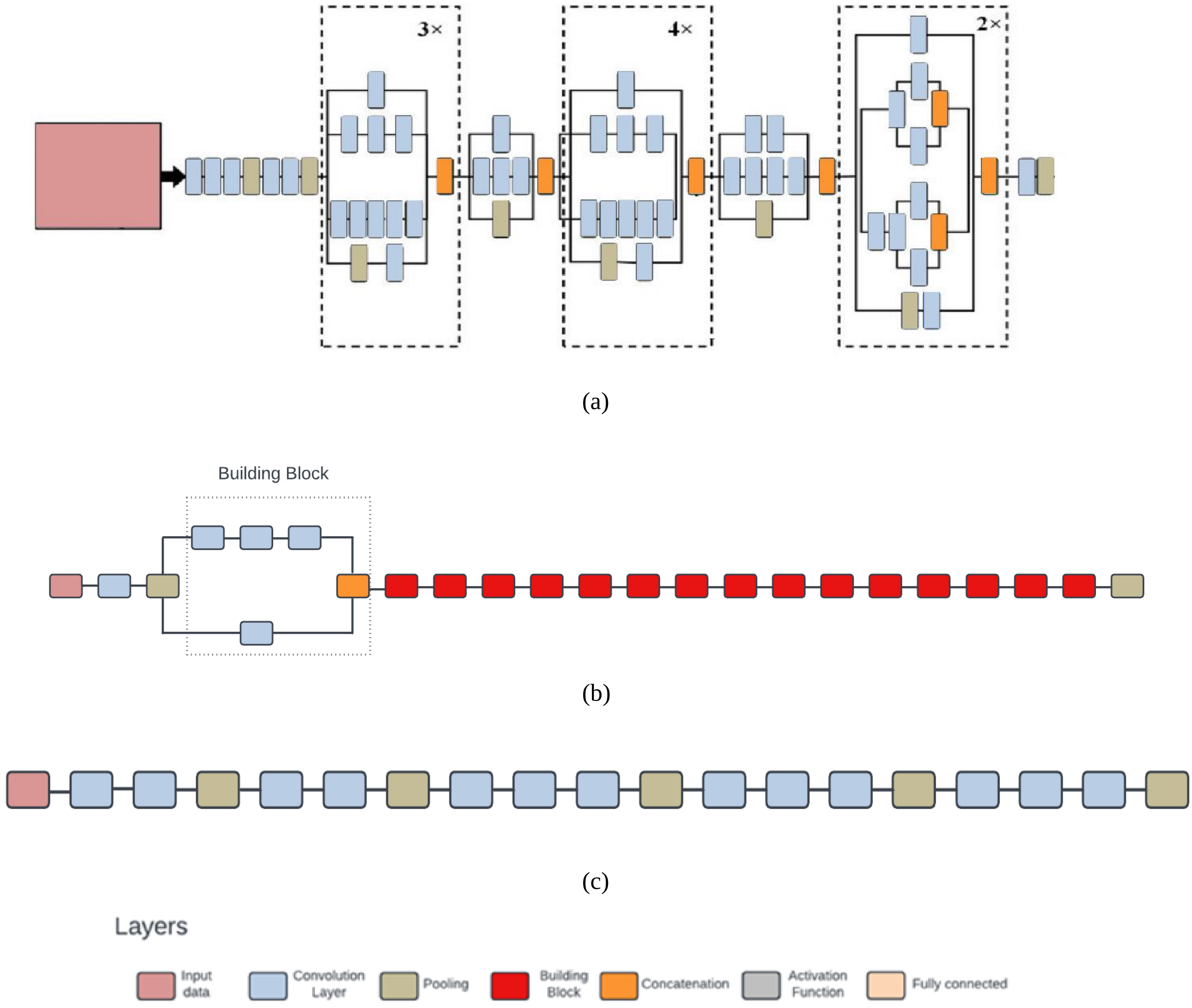

Fig. 3. Structural diagrams. (a) Inception-V3 (b) ResNet50 (c) VGG16

The features extracted by these models are abstract representations that emerge through the learning process. They are not easily interpretable in terms of specific visual attributes or patterns. The models learn to capture relevant and discriminative information from the input images, but the specific features and their interpretations are not explicitly defined or documented.

After extracting features from the DCNN models (VGG16, InceptionV3, ResNet50), Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN) classifiers were employed for the cashew grading task. Each classifier plays a distinct role as follows:

1] Support Vector Machine (SVM): SVM is a supervised machine learning algorithm that plays a crucial role in the classification phase.

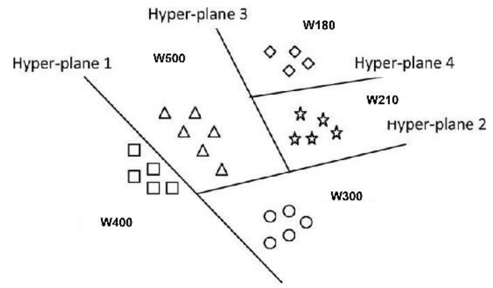

Fig. 4.Support Vector Machine Classification of five Classes

SVM aims to find an optimal hyper plane as shown in Fig 4 that best separates the extracted feature vectors of cashew nut images into different classes. By using the learned features from the DCNN models as input, SVM can create decision boundaries that maximize the margin between classes, allowing for accurate classification

SVM is particularly effective when dealing with high-dimensional feature spaces and can handle both linear and nonlinear classification tasks by employing different kernel functions. Its ability to handle complex decision boundaries and generalize well to unseen data makes SVM a valuable classifier for cashew grading.

2] Random Forest (RF): Random Forest is an ensemble learning method that combines multiple decision trees to perform classification. RF takes on the role of a classifier and operates on the feature vectors extracted from the DCNN models. RF works by creating a collection of decision trees depicted in Fig 5, where each tree is built on a random subset of the training data and a random subset of the features. The RF algorithm then aggregates the predictions of individual trees to arrive at the final classification result. RF can provide accurate classification results and is known for its ability to handle noisy or incomplete data.

3] k-Nearest Neighbors (KNN): KNN is a non-parametric and instance-based classification algorithm that assigns a class label to a test sample based on the majority vote of its k nearest neighbors in the feature space. In this work, KNN operates on the feature vectors extracted from the DCNN models and uses them to measure the similarity or distance between cashew nut samples.

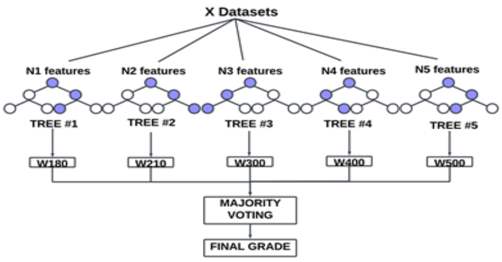

Fig. 5. Random Forest Classification of Five Classes

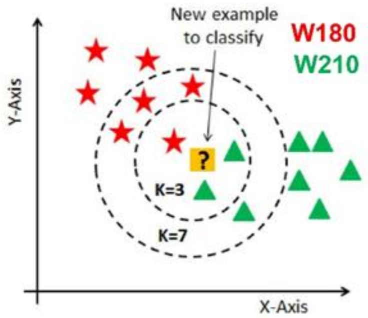

Fig. 6. KNN Classification of Two Classes

KNN is a simple yet effective algorithm, as it does not assume any underlying distribution of the data and can handle both linear and nonlinear classification tasks. The choice of the value k as shown in Fig 6, the number of nearest neighbors to consider, can impact the performance of KNN. KNN is particularly useful when there are local patterns or when the decision boundaries between classes are not well-defined.

Overall, the SVM, Random Forest, and k-Nearest Neighbours classifiers play important roles in our cashew grading process. They take the extracted feature vectors from the DCNN models and use them to perform the final classification of cashew nut images. Each classifier has its strengths and characteristics, such as SVM's ability to find optimal decision boundaries, Random Forest's ensemble learning and robustness, and KNN's instance-based classification. By employing these classifiers, one can leverage their respective advantages and select the best-performing classifier for accurate cashew grading based on specific requirements and the characteristics of dataset.

Different DCNN models were combined with Support vector machine classifier as shown in Fig 7(a) , with KNN classifier as shown in Fig 7(b) for the classification of cashews into different categories. Different hybrid models were implemented, which are outlined below:

1] VGG16 + SVM:

VGG16 is a powerful CNN architecture that can extract rich and discriminative features from images, making it suitable for various computer vision tasks. SVM is a robust and well-established classification algorithm that works well with high-dimensional feature spaces, making it a good choice for classification based on the extracted features. The combination of VGG16 and SVM allows for leveraging the strengths of both methods, where VGG16 extracts informative features and SVM performs accurate classification. 2] VGG16 + RF:

Random Forest (RF) is an ensemble method that can handle high-dimensional feature spaces efficiently and can provide robust classification results. VGG16 is capable of extracting detailed and discriminative features from images, which can be used as input to the random forest classifier. RF is less prone to over fitting and can handle noisy data well, making it a suitable choice for classification tasks.

3] VGG16 + KNN:

KNN is a simple yet effective algorithm for classification, particularly in scenarios where the decision boundaries are non-linear or complex. VGG16 can extract up to 512 high-level features that capture intricate patterns, which can be used as inputs for the KNN algorithm. KNN does not require training and can make predictions quickly once the feature vectors are computed.

4] InceptionV3 + SVM:

InceptionV3 is a powerful CNN architecture that excels in object recognition tasks, thanks to its ability to capture classifier that can work well with the extracted features from InceptionV3. The combination of InceptionV3 and SVM can lead to accurate classification results for various visual recognition problems.

5] InceptionV3 + RF:

The InceptionV3 model has the capability to extract intricate and valuable features from images, which can serve as input for the random forest classifier, enabling enhanced classification performance. Random Forest can handle high-dimensional feature spaces and provide robust classification results. The combination of InceptionV3 and RF leverages the strengths of both methods, leading to improved classification accuracy and the ability to handle complex image data.

6] InceptionV3 + KNN:

InceptionV3 captures 2048 features effectively, which include both local and global image features, providing valuable input to the KNN algorithm. KNN can utilize the extracted features from InceptionV3 for classification, particularly when the decision boundaries are non-linear or complex.

7] ResNet50 + SVM:

ResNet50 is known for its ability to handle very deep networks and capture intricate visual patterns effectively. SVM can make use of the features extracted by ResNet50 and perform accurate classification based on the learned decision boundaries.

8] ResNet50 + RF:

ResNet50's feature extraction capabilities can capture deep and meaningful features from images and the extracted features serves as input to the random forest classifier. Random Forest can handle high-dimensional feature spaces and provide robust classification results. The combination of ResNet50 and RF benefits from the powerful feature extraction capabilities of ResNet50 and the robustness of RF, resulting in improved classification accuracy and robustness.

9] ResNet50 + KNN:

ResNet50 captures deep and intricate visual patterns effectively, providing valuable input to the KNN algorithm. It has the ability to capture 2048 features from the image. KNN can utilize the extracted features from ResNet50 for classification, particularly when dealing with non-linear or complex decision boundaries. The combination of ResNet50 and KNN leverages the strengths of both methods, resulting in accurate classification and the ability to handle complex visual data.

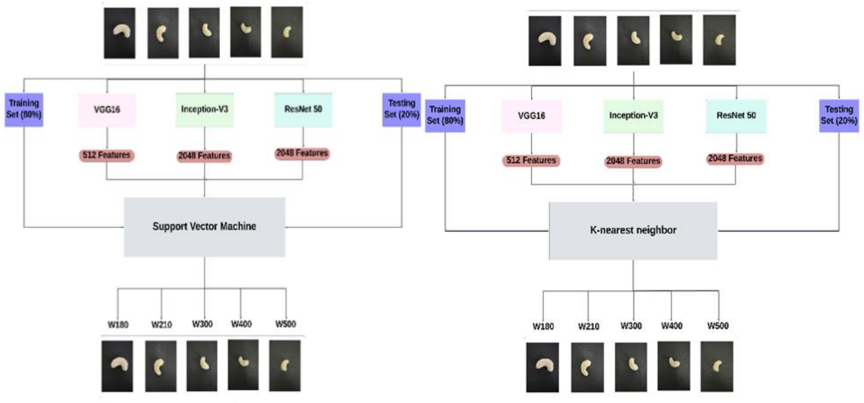

Fig 7. (a) CNN models combined with Support Vector Machine classifier. (b) CNN models combined with k-Nearest Neighbors classifier

5. Evaluation of Model Performance

The implementation work was performed on the Python of Google Colab with the 64bit Windows 10 is used for working methodology. The system has a graphic card of 2 GB with an Intel i5-Core with processor of @ 2.5 GHz and RAM of 8 GB. The Nine models are each performed with the combination of SVM, KNN and RF. The complete dataset was divided into training and test datasets in an 80:20 ratio. The models were trained and evaluated on their respective datasets.

Classification report comprises precision, Recall, individual accuracy of grades, and overall accuracy of the model. Recall is the ratio of true positives to the sum of true positives and false negatives (incorrectly classified positive instances), and Precision is a metric commonly used to evaluate the performance of a classification model. It is the ratio of true positives (correctly classified positive instances) to the sum of true positives and false positives (incorrectly classified negative instances). The F1 score is the harmonic mean of precision and recall and provides a balanced measure of the model's accuracy.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)}$$

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)}$$

$$F1\ Score = \frac{2*(Precision*Recall)}{(Precision+Recall)}$$

Model evaluators: In general, TP (true positives) represents the number of samples correctly classified as a specific grade; TN (true negatives) represents the number of samples correctly classified as not belonging to that grade; FP (false positives) represents the number of samples incorrectly classified as a specific grade; and FN (false negatives) represents the number of samples incorrectly classified as not belonging to that grade. These metrics are important for evaluating the performance of classification models, providing insights into the accuracy and effectiveness of the models in differentiating between grades.

6. Results

Various combinations of deep learning models and machine learning algorithms were employed to classify cashews into different grades. The VGG16 model, when combined with SVM, exhibited a commendable accuracy of 91%, showcasing its effectiveness in accurate classification. Similarly, the InceptionV3 model combined with SVM achieved an accuracy of 83%, demonstrating reasonably accurate classification despite being slightly lower than the VGG16 + SVM combination. Surpassing all other combinations, the ResNet50 model combined with SVM achieved an outstanding accuracy of 97.4%, signifying its exceptional performance in accurately classifying cashews.

Table 1: The Hybrid Model of classification using the five grades of the dataset

	Cashew Grade	Features	Precision	Recall	F-Score	Accuracy (%)	Overall Accuracy
VGG16 + SVM	W180	500	1	0.95	0.97	99.00%	91%
	W210		0.88	0.9	0.89	95.52%	
	W300		0.86	0.91	0.89	96.01%	
	W400		0.88	0.91	0.9	95.02%	
	W500		0.92	0.85	0.89	95.52%	
InceptionV3 +SVM	W180	500	0.87	1	0.93	95.55%	83%
	W210		0.76	0.76	0.76	93.10%	
	W300		0.82	0.78	0.8	92.24%	
	W400		0.86	0.73	0.79	91.37%	
	W500		0.8	0.82	0.82	92.24%	
ResNet50+ SVM	W180	500	1	1	1	100%	97.40%
	W210		1	0.94	0.97	99.13%	
	W300		0.96	1	0.98	99.13%	
	W400		0.96	0.96	0.96	92.17%	
	W500		0.96	0.96	0.96	92.17%	
VGG16+RF	W180	500	0.93	1	0.97	98.27%	95%
	W210		1	0.86	0.92	98.27%	
	W300		0.92	0.92	0.92	96.55%	
	W400		1	0.93	0.96	98.27%	
	W500		0.92	1	0.96	98.27%	
	W180	500	0.71	0.96	0.82	90.51%	71%

Inception V3 + RF	W210		1	0.24	0.38	88.79%	
	W300		0.79	0.65	0.71	89.65%	
	W400		0.59	0.77	0.67	82.75%	
	W500		0.75	0.75	0.75	89.65%	
ResNet50+ RF	W180	500	1	1	1	100%	90%
	W210		1	0.88	0.94	98.27%	
	W300		0.74	0.87	0.8	91.37%	
	W400		0.91	0.81	0.86	93.96%	
	W500		0.88	0.92	0.9	95.68%	
VGG16+ KNN	W180	500	0.88	1	0.93	96.55%	83%
	W210		0.83	0.71	0.77	94.82%	
	W300		1	0.58	0.74	91.37%	
	W400		1	0.79	0.88	94.82%	
	W500		0.61	1	0.76	87.93%	
Inception V3 + KNN	W180	500	0.57	0.96	0.71	82.75%	64%
	W210		0.83	0.29	0.43	88.79%	
	W300		0.65	0.48	0.55	84.48%	
	W400		0.57	0.62	0.59	81.03%	
	W500		0.81	0.71	0.76	90.51%	
ResNet50+ KNN	W180	500	0.9	1	0.95	97.41%	84.48%
	W210		1	0.76	0.87	96.55%	
	W300		0.69	0.78	0.73	88.75%	
	W400		0.91	0.77	0.83	93.10%	
	W500		0.81	0.88	0.84	93.10%	

Furthermore, the VGG16 model combined with Random Forest (RF) yielded comparable results to the ResNet50 + SVM combination, achieving an accuracy of 97.40%. Conversely, the InceptionV3 model combined with RF exhibited lower performance with an accuracy of 71%. The ResNet50 model combined with RF achieved a good accuracy of 90%, albeit slightly lower than the ResNet50 + SVM combination. In terms of the VGG16 model combined with k-Nearest Neighbors (KNN), it achieved an accuracy of 83%, similar to the VGG16 + RF combination. On the other hand, the InceptionV3 model combined with KNN displayed lower performance with an accuracy of 64%. Lastly, the ResNet50 model combined with KNN achieved an accuracy of 84%, which was similar to the VGG16 + KNN combination.

A confusion matrix provides a tabular representation of the performance of a classification model. It shows the predicted labels (grades) by the model compared to the actual labels (ground truth grades)

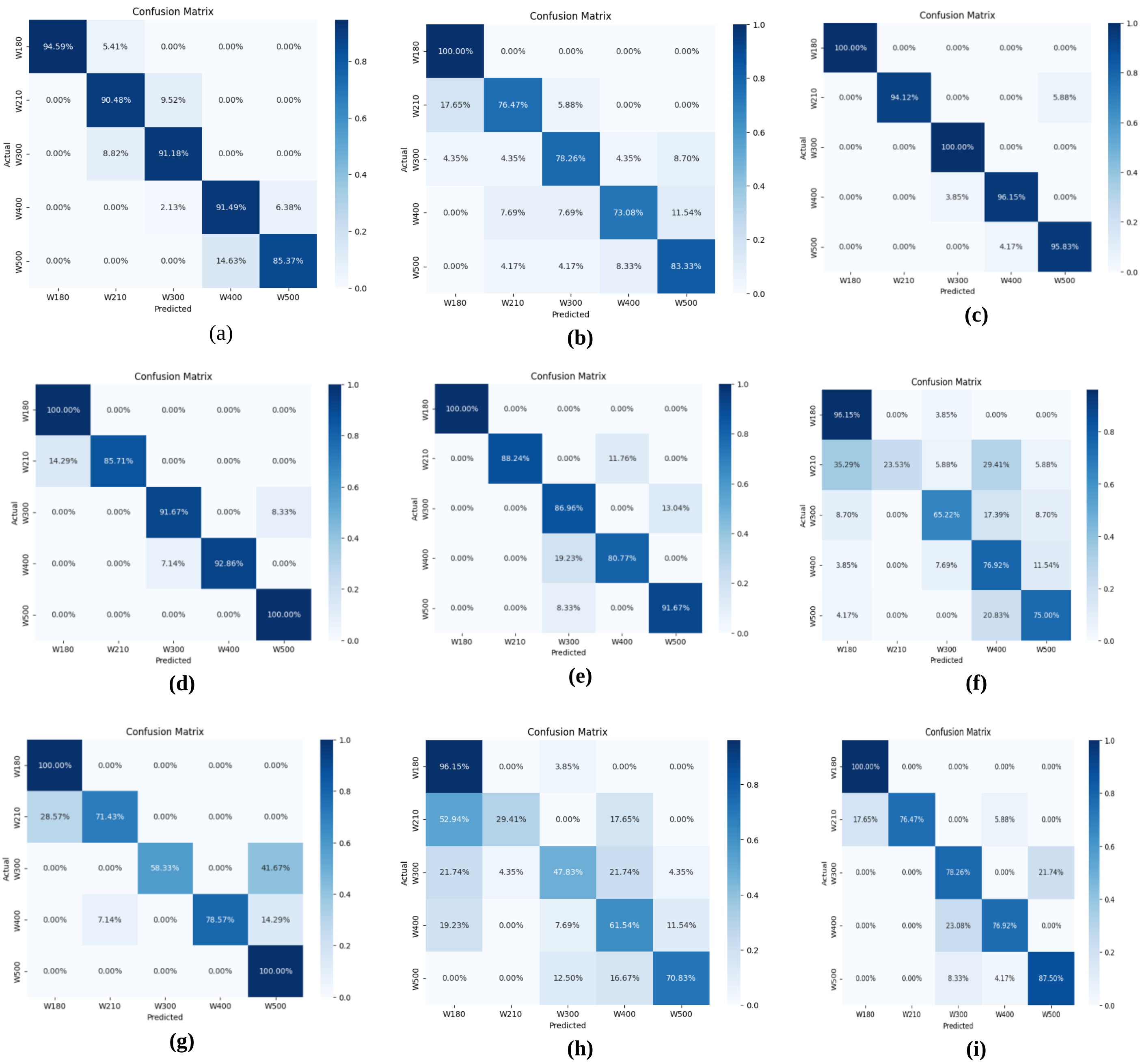

Fig.8. Confusion matrix of Hybrid models :(a) VGG16 + SVM. (b) Inception-V3 + SVM. (C) ResNet50 + SVM. (d) VGG16 + RF. (e) Inception-V3 + RF. (f) ResNet50 + RF. (g) VGG16 + KNN. (h) Inception-V3 + KNN. (i) ResNet50 + KNN.

The confusion matrix helps determine how well the model can predict the test image correctly. As shown in Fig 8, the elements of the matrix represent the counts or percentages of instances classified into each combination of true and predicted labels. Among the nine models developed for classifying cashews into different grades, the VGG16 model combined with SVM and RF stood out for its impressive performance. The VGG16 + SVM model consistently achieved high accuracy percentages across all grades, with noteworthy results for W180 (94.59%), W210 (90.48%), W300 (91.18%), W400 (91.49%), and W500 (85.35%) shown in Figure 8(a). Similarly, the VGG16 + RF model showcased excellent classification results, as shown in Figure 8(d), with a perfect accuracy of 100% for W180 and consistently high accuracy for other grades, such as W210 (85.71%), W300 (91.67%), W400 (92.86%), and W500 (100%). These models demonstrated the ability to accurately identify and classify cashews, making them reliable choices for cashew grading. On the other hand, the InceptionV3 model combined with SVM and RF encountered varying degrees of success. While the InceptionV3 + SVM model achieved perfect accuracy for W180, it faced challenges in accurately classifying W210 (76.47%), W300 (88.26%), W400 (83.08%), and W500 (83.33%), depicted in Figure 8(b). The InceptionV3 + RF model also displayed mixed results, with relatively high accuracy for W180 (96.15%) and W400 (86.92%) but struggling with W210 (23.53%), W300 (65.22%), and W500 (75%). These models showcased the potential of the InceptionV3 architecture but highlighted the need for further refinement to enhance their performance in cashew grading tasks.. The lower accuracy for some grades in the diagonal elements of the confusion matrix of some models could be due to the choice of models that may not be well-suited for the classification task. As one can observe in Figure 8(c), the ResNet50 combined with SVM performed very well compared to other hybrid models by predicting test images accurately.

Table 2 . Comparative analysis of the result using the cashew dataset with our work implementation.

Paper	**[9]**	**[7]**	**[6]**	**[6]**	**[26]**	**[27]**	**Our Hybrid models**			
Model used	Machine vision	BPNN	SVM	RF	ANN	Fuzzy logic	ResNet50 +SVM	VGG16 +RF	VGG16+ SVM	ResNet50+ RF
Accuracy	90.9%	96.8%	90.96%	94.28%	88.93%	89%	97.40%	95%	91%	90%

The classification accuracy of different Hybrid models used in this study was higher than that obtained in [9], where SVM and random forest classifiers were used to classify cashews and obtained 90.6% and 94.28% accuracies, respectively. As well as in [26], an artificial neural network (ANN) model was used to classify cashews and achieved 88.93% classification accuracy. In [27], a fuzzy logic-based computer vision system was implemented for the classification of whole cashew kernels and achieved 89% classification accuracy. The machine vision-based approach used in [6] yielded an accuracy of 90.90%, which is very low compared to the ResNet50+SVM hybrid model implemented in our study. Back Propagation Neural Networks (BPNN) were implemented in [7] for Automated cashew kernel grading and achieved an impressive accuracy of 96.8%, which is a bit more compared to our hybrid models except ResNet50 + SVM. Overall, the Hybrid models with specific combinations implemented in this study performed well compared with traditional machine learning and machine vision approaches.

7. Conclusion and Future Scope

The cashew grading process has benefited significantly from the integration of deep convolution neural network (DCNN) models and machine learning algorithms. The hybrid models, combining CNNs such as VGG16, InceptionV3, ResNet50 with classifiers like SVM, Random Forest, or KNN, have demonstrated their effectiveness in accurately classifying cashew kernels into different grades. The ResNet-50+SVM combination emerged as the superior model, achieving an impressive accuracy of 97.40%. The custom model with SVM yielded an accuracy of 89%, notably lacking in effectiveness compared to ResNet50 + SVM. These hybrid models leverage the feature extraction capabilities of CNNs to capture intricate patterns and characteristics of cashew nuts, while the machine learning algorithms contribute to the final classification based on these extracted features. The integration of CNN and machine learning offers enhanced feature representation, interpretability, and scalability in the cashew grading process, leading to increased efficiency and consistency. In the future, we will examine the combination of CNN models with the intersection of classifiers to achieve better result

Conflicts of interest

The authors declare no conflicts of interest.

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