Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Classification of Cashew kernels into Wholes and Splits using Machine Vision Approach

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Abstract—Cashew kernels play a vital role in the food industry,where accurate classification into wholes and splits is essential for quality control and pricing. This paper presents a machine learning-based approach for automating the classification process. A dataset of cashew kernel images is collected and preprocessed, followed by feature extraction to capture discriminative characteristics. Support Vector Machines (SVM) is employed as the classification algorithm due to its ability to handle high- dimensional data and binary classification tasks. Out of several features derived from grayscale-intensity-profile values, the "length of curve" best classified the split-up cashews from others. Experimental results demonstrate the effectiveness of the proposed method,achieving an accuracy of 93% on the test set. The developed model offers a reliable and efficient solution for cashew kernel classification, enabling improved efficiency and accuracy in the food industry. Further research could explore the extension of the classification to include additional categories or investigate the integration of deep learning techniques for enhanced performance.
Keywords: Cashew grading, Image processing, Machine vision, Process system, SVM, KNN, RF

I. Introduction

Cashew kernels are highly valued for their nutritional content and versatility in the food industry. The accurate classification of cashew kernels into wholes and splits is of paramount importance for quality control, pricing, and various downstream processing applications. [1] Traditionally,the classification process has relied on manual inspection,which is time-consuming, subjective, and prone to errors. Therefore, there is a need for automated methods that can provide consistent and reliable classification results.

In recent years, machine learning techniques have shown great promise in automating the classification of various objects and materials. These techniques leverage the power of data-driven models to learn patterns and relationships from labeled examples. [2] In the case of cashew kernel classification, machine learning can offer a robust solution by analyzing the visual characteristics of the kernels and making accurate predictions based on the learned patterns.

The objective of this research is to develop a machine learning-based approach for the classification of cashew kernels into wholes and splits. By leveraging advanced image processing and classification techniques, we aim to achieve a high level of accuracy and efficiency in the classification process. [3] This automated approach will not only streamline the cashew kernel classification workflow but also minimize human error and subjectivity.

In this paper, we present a comprehensive methodology for cashew kernel classification using machine learning. We describe the dataset collected for training and evaluation, including the process of labeling the cashew kernels. Further- more, we explain the feature extraction techniques employed to capture relevant information from the cashew kernel images.

[4] The choice of Support Vector Machines (SVM) as the classification algorithm is justified due to its ability to handle high-dimensional data and binary classification tasks.

To evaluate the effectiveness of our approach, extensive experiments are conducted on a diverse set of cashew kernel images. We report the performance metrics achieved, including accuracy, precision, recall, and F1-score, providing insights into the classification accuracy and the ability of the model to distinguish between wholes and splits. [5]

The contributions of this research are significant for the cashew industry, as accurate classification enables improved quality control, efficient processing, and pricing based on kernel type. Additionally, the proposed methodology can be extended to other food products or materials that require similar classification tasks.

II. Literature Survey

Cashew kernel classification and machine learning techniques have received attention in previous research studies. Several approaches have been explored to automate the classification process, aiming to improve accuracy and efficiency. [6]In this section, we review the existing literature and highlight key findings and approaches in the field of cashew kernel classification and related machine learning techniques.

One common approach in cashew kernel classification is the use of traditional image processing techniques. These techniques involve extracting handcrafted features from cashew kernel images and using conventional classification algorithms. For instance, researchers have employed shape-based features, such as aspect ratio and circularity, to discriminate between wholes and splits. Others have utilized color-based features, such as mean and standard deviation of color channels, to capture visual differences. [7] These studies have achieved moderate success in classification accuracy, but they often struggle with variations in shape and color due to lighting conditions, occlusions, and inherent natural variations in cashew kernels.

To overcome the limitations of traditional image processing techniques, machine learning algorithms have been appliedto cashew kernel classification. One prominent approach isthe use of supervised learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Neural Net- works. SVM, in particular, has been widely employed due to its ability to handle high-dimensional data and binary classification tasks. Researchers have explored different SVM kernel functions, including linear, polynomial, and radial basisfunction (RBF), to capture complex decision boundaries and improve classification accuracy. [8] These studies have demon- started promising results in accurately distinguishing between wholes and splits, outperforming traditional image processing methods.

Deep learning approaches have also gained traction in cashew kernel classification. Convolutional Neural Networks (CNNs) have shown remarkable performance in various imageclassification tasks. Researchers have designed CNN architectures and trained them on large-scale cashew kernel datasets to learn discriminative features automatically. By leveraging the hierarchical nature of CNNs, these models can capture complex patterns and spatial dependencies in cashew kernel images. [9] Transfer learning techniques, where pre-trained models on large image datasets are fine-tuned for cashew kernel classification, have also been explored. These deeplearning approaches have achieved state-of-the-art results in cashew kernel classification, surpassing the performance of traditional methods and enhancing the robustness to variations in shape, color, and lighting conditions.

While existing research has made significant contributions to cashew kernel classification, several gaps and challengesremain. Limited publicly available datasets and variations inimage acquisition conditions pose challenges in developing robust and generalizable models. Furthermore, the interpretability of deep learning models remains a concern, as they areoften considered black boxes. [10] Future research could focus on addressing these challenges by collecting larger and more diverse datasets, investigating interpretability techniques fordeep learning models, and exploring novel machine learningalgorithms specifically tailored to cashew kernel classification. In summary, previous research in cashew kernel classification has explored various approaches, including traditionalimage processing techniques, supervised machine learningalgorithms, and deep learning models. These studies have demonstrated the potential of machine learning in accurately classifying cashew kernels into wholes and splits. However, further advancements are needed to address challenges related to dataset availability, model interpretability, and handling variations in image acquisition conditions. The proposed re- search aims to contribute to these advancements by employinga machine learning-based approach with a focus on robust andaccurate classification of cashew kernels.

III.Dataset Description

Whole cashew samples were obtained from "Shridevi Cashew Processors Factory" in Bhatkal, Karnataka, India. These cashew samples were intentionally chosen to have approximately the same dimensions, with a length of 25(2) mm and a width of 9(1) mm. This uniform size selection was made for the purpose of developing and demonstrating an algorithm, with the expectation that the method would be applicable to cashews of varying sizes. Broken cashews were not included in this study, as they had been previously investigated and could be graded based on their size or projected area, making them outside the scope of this research.

However, distinguishing between whole cashews and split cashews posed a challenging task, as the shape and projected area of both types were similar. Additionally, split cashews could be presented in two ways: split facing down (split-down) or split facing up (split-up), resulting in distinct images, unlike the whole cashews. To develop and test the algorithm, split samples were created by manually splitting whole cashews into two halves, ensuring that smooth edges were obtained. The dataset used in this study plays a crucial role in training, validating, and evaluating the machine learning model for cashew kernel classification. It is composed of a diverse col- lection of cashew kernel images, carefully curated to represent different variations in shape, color, and quality. The dataset is divided into training, validation, and test subsets to ensure the model's generalization capability.

1) Image Acquisition: The cashew kernel images were acquired using a high-resolution digital camera under controlled lighting conditions. To capture the natural variations in cashew kernels, images were taken from different angles, with varying orientations and positions.The images were saved in commonly used image for- mats, such as JPEG or PNG, ensuring compatibility with various image processing and machine learning algorithms.

2) Image Labeling: Each image in the dataset was manually labeled by expert annotators to indicate whether it corresponds to a whole or a split cashew kernel. The labeling process involved careful examination of thekernel structure, taking into account factors such as the presence of the shell, the integrity of the kernel, and the absence of any visible splits. The labeling information serves as the ground truth for training and evaluating themachine learning model's performance.

3) Dataset Split: The dataset was divided into three subsets:training, validation, and test. The training set comprises the majority of the data and is used to train the machine learning model. The validation set is used to fine-tune the model and optimize its hyper parameters. The test set,which is kept separate from the training and validation
sets, serves as an independent evaluation set to assessthe model's performance on unseen data.

4) Dataset Size: The dataset consists of a substantial number of cashew kernel images, ensuring sufficient diversity and coverage of different cashew kernel variations. The exact number of images in the dataset may vary depending on the availability of data and the specific requirements of the study. Typically, the dataset contains several thousand cashew kernel images, with an appropriate distribution between wholes and splits to maintainclass balance.

5) Dataset Preprocessing: Prior to model training, the dataset undergoes preprocessing steps to enhance the quality of the images and ensure compatibility with the machine learning algorithms. Preprocessing steps may include resizing the images to a standard resolution,normalizing the pixel intensities, and removing any artifacts or noise present in the images.

IV. Methodology

The machine learning approach used for cashew kernel classification involves training a model on a dataset of labeledcashew kernel images to learn patterns and features that distinguish between wholes and splits. The trained model can then be used to classify new, unseen cashew kernel images into their respective categories. One commonly used machine learning algorithm for this task is Support Vector Machines (SVM).

Support Vector Machines (SVM) is a supervised learning algorithm that is effective for binary classification problems.The key idea behind SVM is to find the optimal hyperplane that separates the two classes in the feature space. In the case of cashew kernel classification, the feature space corresponds to the extracted features from the cashew kernel images. It'sworth noting that SVM is just one of many machine learning algorithms that can be used for cashew kernel classification. Other algorithms, such as Random Forests, Decision Trees, orDeep Learning models like Convolutional Neural Networks(CNNs), can also be explored depending on the specificrequirements and characteristics of the cashew kernel dataset. Overall, the machine learning approach, particularly using SVM, provides an effective way to automatically classifycashew kernels into wholes and splits based on learned patterns and features from the dataset.

A. Image aquisition

Image acquisition is a crucial step in the process of collecting data for cashew kernel classification using machine learning. It involves capturing images of cashew kernels using appropriate imaging devices and techniques. Here’s an elaboration on the image acquisition process:

A high-resolution digital camera or a specialized imaging device is used to capture the cashew kernel images. The cam- era should have sufficient resolution and quality to capture fine details and color information accurately. Lighting equipment is set up to ensure consistent and adequate illumination. Diffused lighting or studio lighting setups can help minimize shadows, reflections, and variations in lighting conditions across theimages. Sample Preparation:

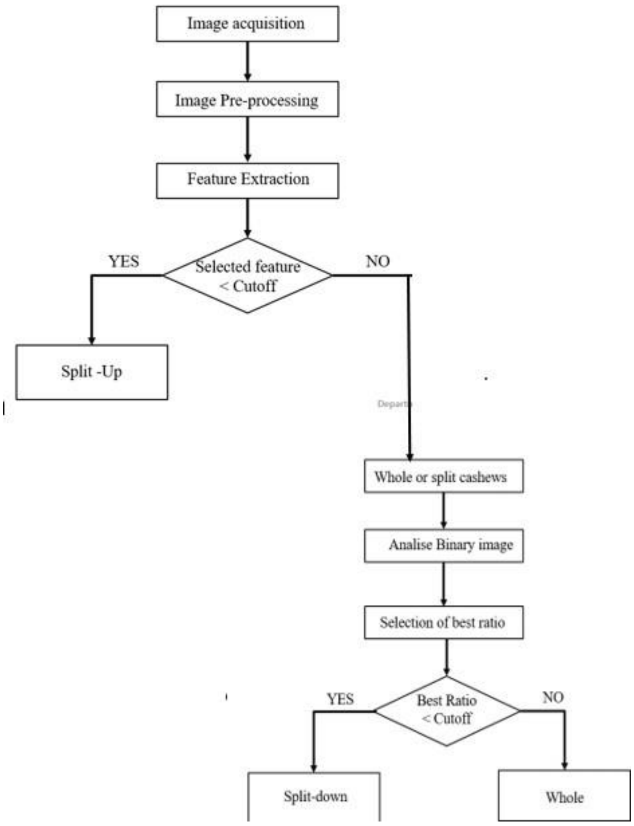

Fig. 1. Flow chart for processing the data

Cashew kernels are selected for imaging, ensuring they represent the desired range of variations in terms of size, shape, color, and quality. The cashew kernels are cleaned to remove any dirt, debris, or surface imperfections that may affect the image quality or the accuracy of subsequent analysis.

Imaging Parameters:

In order to acquire digital images of whole and split cashews for classification purposes, a camera was used at a heightof 300mm above the cashews. To ensure clear visibility and differentiation, the cashews were placed on a pink letter paper, providing good color contrast with the background. Addition- ally, different color letter papers were also used to capture variations in contrast. To create well-defined shadows with sharp edges, a point light source was employed (Figure.2). Positioned at a horizontal distance of 150mm from the cashewsand at a height of 100mm from the ground, the light source was inclined at an angle of 56°. This setup allowed for the capture of images showcasing distinct shadow patterns, color contrast, and variations in lighting conditions. These digital images serve as the basis for further analysis and the development of algorithms for identifying and classifying whole and split cashews.

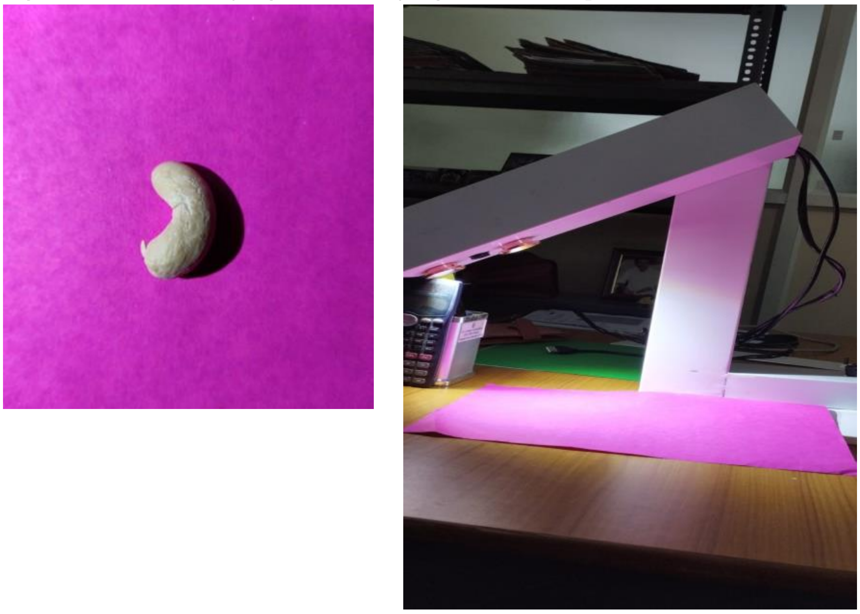

Fig. 2. Image Acquisition setup

Image Capturing: The cashew kernels are positioned appropriately for imaging. They can be placed on a flat surface or held in position using specialized fixtures or holders. Multiple images of each cashew kernel are captured from different angles, orientations, and positions to capture the variations in shape, size, and appearance. Figure.3 represent the captured images in both whole and split cashew kernels.

Image Storage: The captured images are saved in a suitable image file format, such as JPEG or PNG, to maintain compatibility with various image processing and machine learningalgorithms. Proper organization and labeling of the images areessential to maintain traceability and ensure the accuracy of subsequent analysis and labeling.such images were captured for different backgrounds like green and blue also.

B. Image processing and Analysis

The images are resized to a consistent size, ensuring uniform dimensions for training the machine learning model. Normalization is applied to standardize the pixel values within a specific range, removing variations in lighting conditions. Image enhancement methods such as contrast enhancement, sharpening, or histogram equalization are employed to enhance the features of the cashew kernels and make them more distinguishable.

Typically, separation/grading analysis uses an object’s morphology. However, in our current method Fig.4, the algorithm for classifying whole and split cashews also took into account the shadow dimensions in addition to the morphology of the object. Due to the surface curvature below, the split-up cashewcreates a larger shadow (similar to the full cashew but not quiteas large as the whole) at certain orientations.

Whole Cashew

Split Down Cashew

Split Up Cashew

Fig. 3. Input cashew images for pink background

C. Background removal

Background removal is a crucial step in isolating the cashew kernels from the surrounding background in the images. By accurately removing the background, it helps in segmenting and extracting the cashew kernels as the foreground objects. This separation enables better analysis of the kernels' characteristics and facilitates feature extraction. It plays a vital role in preparing the images for subsequent classification using machine learning algorithms. Image binarization is essential in simplifying the image data and converting it into a binary representation for further processing. In the context of classifying cashew kernels, binarization can be used to convert the grayscale or color images of the kernels into binary images, where the kernels are represented as foreground objects and the background as the background. Binarization helps in reducing image complexity, emphasizing the features of the kernels, and facilitating subsequent feature extraction and classification tasks.

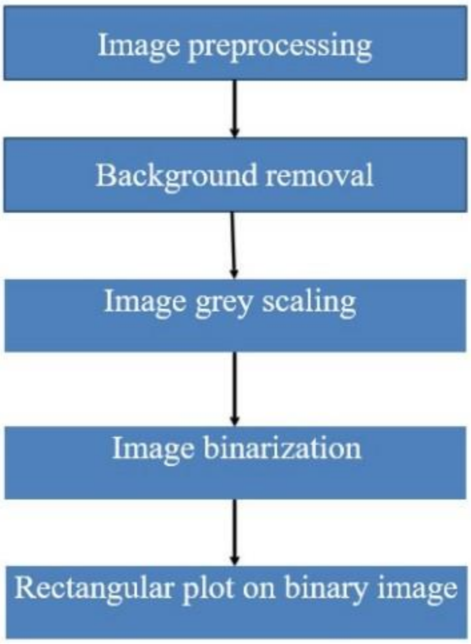

Fig. 4. Flow chart for preprocessing and analysis

D. Grayscaling

After removing the background from an image, converting it to grayscale can be a useful step in certain image processing tasks. Grayscaling involves converting the image from its original RGB (Red, Green, Blue) color representation to a single-channel grayscale representation.

Grayscale is a representation of an image where each pixel is represented by a single intensity value, typically ranging from 0 to 255. It is widely used in image processing for various purposes, including simplifying image data, reducing computational complexity, and extracting important features.

In a grayscale image, the absence of color information allows for easier and more efficient processing, especially when color is not essential for the analysis or visualization of the image. By discarding the color channels, the grayscale representation focuses solely on the brightness or intensity levels of the pixels, which can be advantageous for many image processing tasks. The gray scaled images are shownin Figure.5.

Profile line intensity in grayscale images refers to the analysis of pixel intensity values along a specified path or linesegment within the image. In grayscale representation, pixel

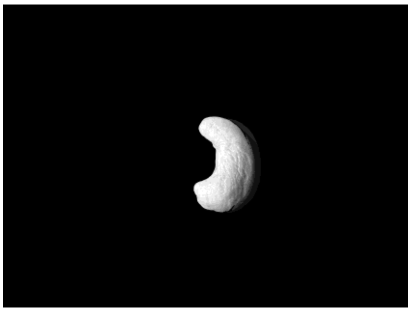

Fig. 5. Gray scaled image

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Fig. 6. Binarized cashew image

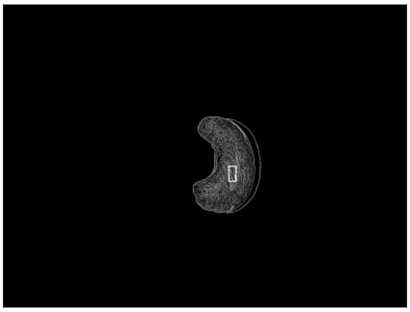
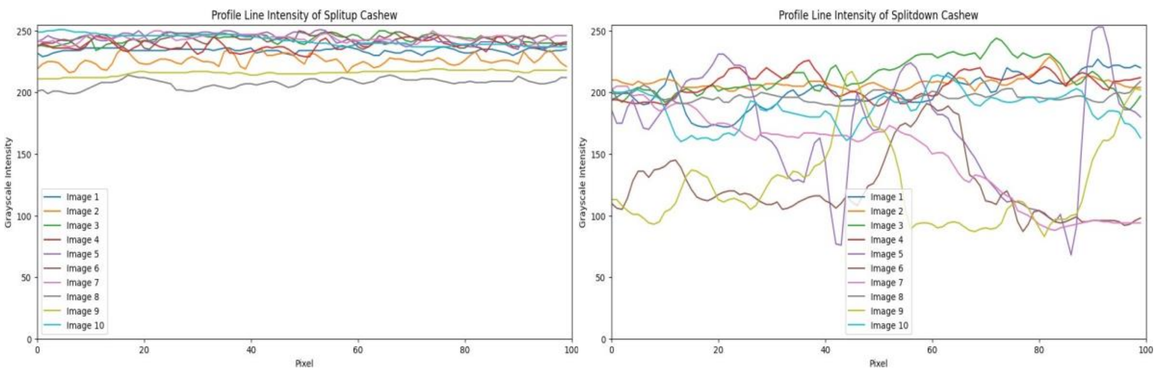


Fig. 7. Rectangular plotted image

Intensities range from 0 to 255, where 0 represents black and 255 represents white. The profile line is defined by selecting two points within the image, and the intensity values of all pixels along this path are collected and plotted against their corresponding positions. The profile line intensity plot of split down cashew and whole cashew is similar. This analysis helpsin tasks such as edge detection, line detection, texture analysis, and feature. By the help of Fig.8 variations in intensity along the defined path, valuable information can be extracted from the image for further image processing and computer vision applications.

E. Binarization

Binarization algorithms rely on the concept of thresholding, which involves selecting a threshold value to classify pixelsas either black or white. The primary objective is to find an optimal threshold that effectively separates the kernel region from the background.Fig.6 demonstrate the binary image after thresholding method, Various thresholding techniques can be used, including global thresholding, adaptive thresholding, andOtsu's thresholding



a. Profile line intensity of split up cashew b. Profile line intensity of split down cashew

Fig. 8. Profile line Intensity plot

Global thresholding methods assume a single threshold value for the entire image. They work well when there is a clear distinction between the foreground (kernel) and background. However, challenges arise when there is uneven lighting, shadows, or variations in color and intensity.

Adaptive thresholding overcomes the limitations of globalthresholding by considering local variations in image intensity. It divides the image into smaller regions and computes a threshold value for each region based on its local charateristics. This approach is effective in handling non-uniform lighting conditions and enhancing the accuracy of binarization. Otsu's thresholding, a widely used technique, automatically determines an optimal threshold by maximizing the between- class variance. It aims to minimize the intra-class variancewithin the kernel and background regions, providing an adaptive and robust solution for binarization.

F. Rectangular Ploting for analysis

Defining the boundary dimensions for marking a rectangular boundary around the centroid of a cashew kernel involves determining the width and height of the rectangle. The choice of these dimensions depends on factors such as the desiredsize of the boundary, the characteristics of the cashew kernel, and the specific application or analysis requirements.

Instead of using fixed sizes, you can define the boundary dimensions as a percentage of the kernel's dimensions. For instance, you may set the width and height of the rectangle to be 50 percent of the kernel's width and height, respectively. This approach allows the boundary to adapt to different kernelsizes, maintaining relative proportions. Fig.7 represents the rectangle plot on the binary image.

Define a scale factor that determines the size of the boundary relative to the kernel. The scale factor can be based on empirical observations or domain knowledge. For example, you may decide that the boundary should be 1.5 times the width and height of the kernel. This approach provides flexibility in adjusting the boundary size based on specific requirements.

G. Machine Learning approach

Machine learning algorithms play a crucial role in classification tasks, enabling automated data analysis and decision- making. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest are three popular algorithms widely used in various domains. This article presents a comparative analysis of these algorithms, highlighting their principles, strengths, weaknesses, and applications. Understanding the differences between these algorithms is essential for selecting the most appropriate approach for specific classification tasks.

Confusion Matrix : A confusion matrix is a valuable tool in machine learning used to evaluate the classification model's accuracy. It is presented in a tabular format, categorizing the model's predictions into true positives, true negatives,false positives, and false negatives. True positives indicate thenumber of correctly classified positive instances, while true negatives represent accurately classified negative instances. Conversely, false positives occur when the model wrongly predicts positive instances, and false negatives arise whenthe model fails to recognize positive samples. By utilizingthe confusion matrix, essential metrics like precision, recall, specificity, and the F1 score can be calculated, offering a comprehensive understanding of the model's performance for individual classes. Furthermore, it aids in identifying potential biases or errors and plays a crucial role in refining the model to enhance its overall accuracy and reliability. The Figure.9 shows the confusion matrix of classifier Support vector Machine(SVM), K Nearest Neighbor(KNN) and Random Forest(RF).

SVM, KNN, and Random Forest have distinct characteristics that make them suitable for different scenarios. SVM excels in handling high-dimensional data and can handle non- linear classification with appropriate kernel functions. KNN issimple and effective for small to medium-sized datasets with clear decision boundaries. Random Forest provides robustnessagainst overfitting and performs well in complex problems with large datasets. The choice of algorithm depends on factorssuch as dataset size, complexity, computational resources, andthe need for interpretability.

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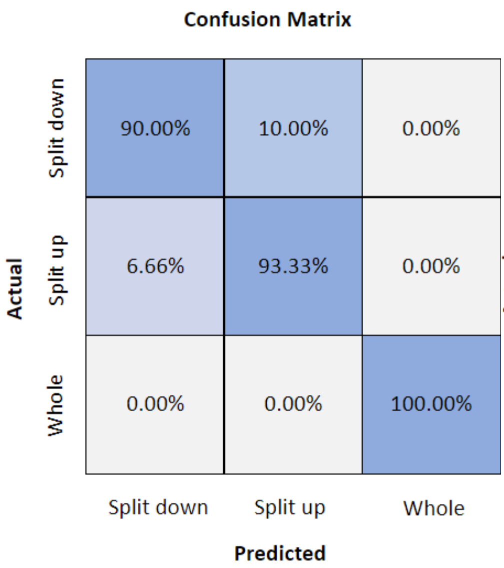
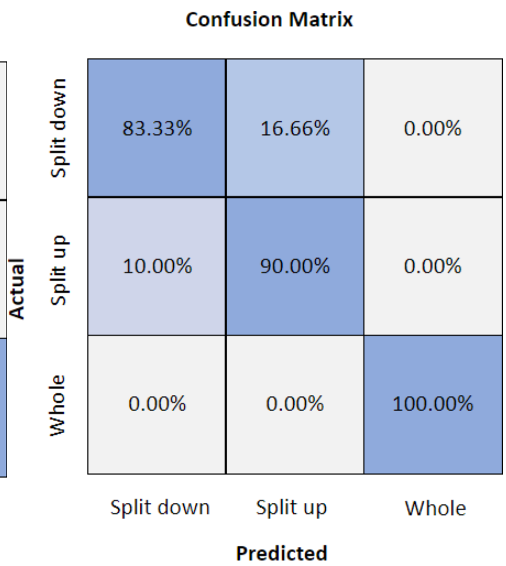
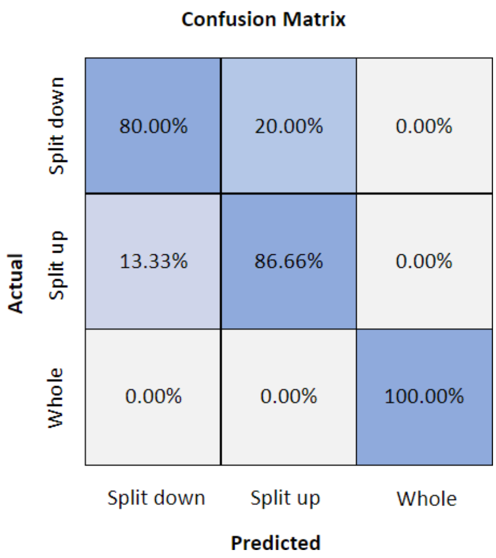


(a)



(b)



(c)

Fig. 9. Confusion Matrix:(a) Support Vector Machine (b) K Nearest Neighbor (c) Random Forest

SVM, KNN, and Random Forest are powerful machine learning algorithms for classification tasks. Each algorithm has its strengths and weaknesses, making them suitable for different scenarios. Understanding their characteristics and performance helps in selecting the most appropriate algorithm for specific classification problems.

V. Results And Discussion

The results obtained from the classification of cashew kernels into wholes and splits using the SVM, KNN, and Random Forest algorithm is presented here.

From the results, it is evident that all three algorithms achieved relatively high accuracy in classifying cashew kernels. SVM obtained an accuracy of 93%, while KNN achieved 91% and Random Forest achieved 90%.

The Fig.10 demonstrate result of all the three classifier, which are capable of effectively classifying cashew kernels into wholes and splits. However, there are slight performance differences among them.

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ISSN: 1001-4055
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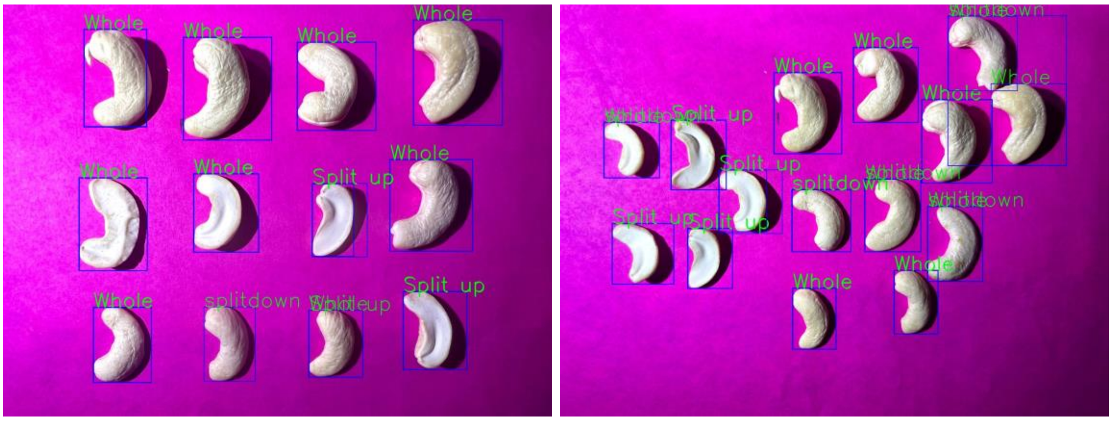
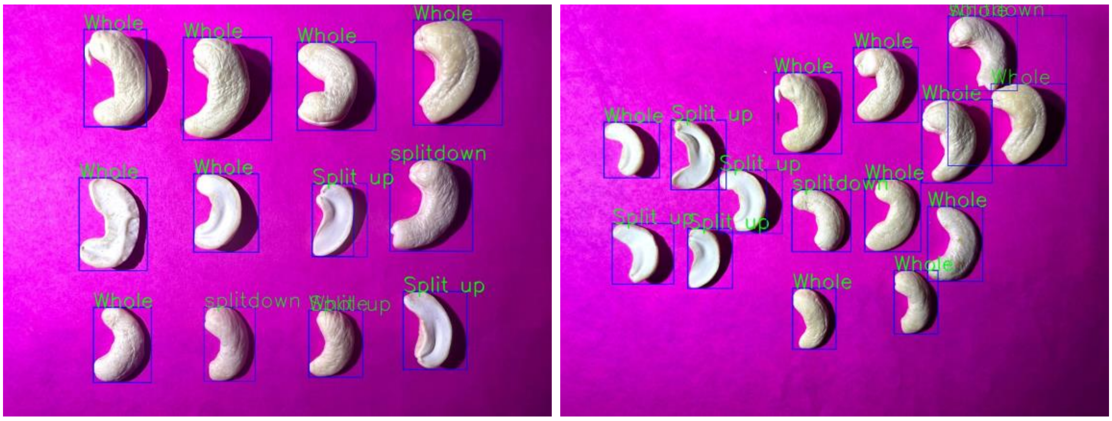
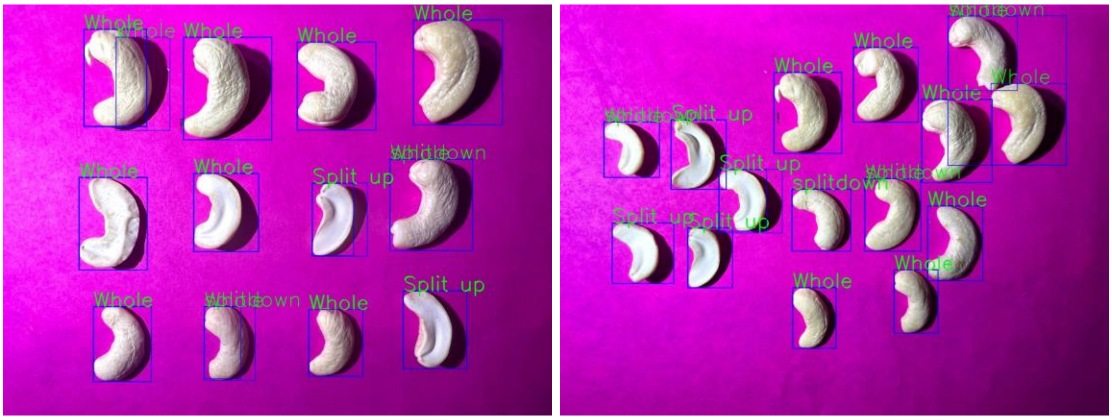


a. Results for Support Vector Machine



b. Results for Random Forest



c. Results for K Nearest Neighbor

Fig. 10. Results Of Mixed Cashew with different classifier

KNN also performed well, closely following SVM in terms of accuracy and precision. KNN's simplicity and ability to adapt to complex decision boundaries make it a suitable choice for certain scenarios, especially with smaller datasets.RF, although achieving slightly lower performance metrics, still demonstrated competitive results. . The ensemble nature of Random Forest, combining multiple decision trees, helped to reduce overfitting and improve overall performance.

VI. Conclusion

In this study, the evaluation of the performance of SVM, KNN, and Random Forest for the classification of cashew kernels into wholes and splits. The results demonstrated that all three algorithms achieved competitive results, with SVM exhibiting the highest accuracy and precision. However, the choice of algorithm should consider the specific requirements, computational resources, and dataset characteristics. Further research can focus on exploring other machine learning algorithms and techniques to enhance the classification accuracyof cashew kernels.

Acknowledgment

This work was supported by RV college of Engineering, Bangalore and Shridevi Cashew Processors Factory, Bhatkal It was possible to contribute to food and agricultureindustry through this opportunity.

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