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Deep Learning Based System for of Grading Cashew Kernels

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***Abstract*—Cashew nuts are cultivated widely across the globe and are categorized into various classes according to their size and quality. Currently, cashew kernels are sorted and graded manually, which is time-consuming and labor-intensive. This research proposes hybrid models to automate and accelerate the cashew classification process by integrating classifiers with deep convolutional neural networks (DCNNs). The proposed hybrid models categorize cashew kernels into five groups: W180, W210, W300, W400, and W500. Various hybrid models, including RCNN + OpenCV, were implemented and evaluated based on specificity, accuracy, and other metrics. The results demonstrated that the RCNN model paired with OpenCV achieved a maximum accuracy of 90%. This study's findings highlight that automating cashew grading can be significantly enhanced by combining DCNNs with classifiers in hybrid models. These hybrid models improve efficiency by enabling automatic, effective, and precise classification of cashews. By leveraging advanced machine learning techniques, the process becomes faster, more accurate, and less dependent on manual labor. Overall, the integration of deep learning technologies with traditional classifiers offers a promising approach to modernizing and optimizing the cashew grading industry. Future research could further refine these hybrid models to achieve even higher accuracy and efficiency, potentially revolutionizing agricultural sorting processes beyond cashew nuts.**

***Index Terms*—DCNN, OpenCV, RCNN, Hybrid Models**

I. Introduction

Although they are native to Brazil, cashew nuts—scientifically known as Anacardium occidentale—are now grown all over the world. Cashews are a great source of proteins, healthy fats, vitamins, and minerals. Their culinary allure is matched by their substantial nutritional value. Eating cashews has been associated with a number of health benefits, such as defense against heart disease, cancer, high blood pressure, and age-related degenerative disorders [1]. Brazil is not the only nation that produces cashews; other major producers include India, Vietnam, Nigeria, and Indonesia. In actuality, India surpassed all other countries in 2018 as the world's top producer of raw cashew nuts (RCN) [2]. Karnataka is a key player in the Indian cashew production business, which is a major player in the global market.

There are various phases involved in cashew harvesting. The cashew apples are harvested and then pressed to extract juice, which is then used in jams and drinks. To lower the moisture level of the cashew nuts, they are subsequently dried, either in the sun or with mechanical techniques. The cashew kernel is edible when the outer shell is properly removed after it has dried. In [3], a number of techniques for CNSL extraction are highlighted. To protect the fragile kernel throughout this operation, accuracy and caution are crucial. [4] [5] discuss the physicochemical properties and chemical makeup of cashew nut oil and cashew nut shell liquid.The cashews are then graded, sorted, and packaged in preparation for consumption and distribution.Cashew nuts are graded according to size, shape, color, and quality, among other characteristics. While each region has its own grading system, common varieties include Splits (cashew kernel halves), Pieces (broken or irregularly shaped kernels), Butts (broken and irregularly shaped kernels), and Scorched Wholes (slightly darker whole kernels). Furthermore, there are variations in the grading system between regions. Every grade has a specific usage, ranging from gourmet goods to food processing, and is employed in a variety of industrial and culinary applications, including baking, spreading, toppings, snacking, and as ingredients in various food products. Whole cashews are regarded as the highest quality cashews and come in a variety of grades, such as W180, W210, W240, W300, W320, W400, W500, and so on. The grade system for cashew kernels is denoted by W180, which means that there are roughly 180 whole cashew kernels per pound. Higher values correspond to larger cashew nut kernels. It is a measurement of cashew nut size.

The conventional approach to classifying cashews is expert workers manually sorting and grading the nuts. Each kernel is visually inspected, any faulty ones are removed, sizes are sorted, quality parameters are graded, and packaging is done. Although this method allows .It involves subjective assessment and personalization, requires a lot of work, takes a long time, and is prone to human mistake.For a variety of reasons, manual classification may nevertheless be used in traditional or smaller-scale activities. Cashew grading has been transformed by machine vision and artificial intelligence algorithms, which automate image capture, processing, classification, flaw identification, and sorting. Cashew nuts are analyzed according to size, shape, color, and flaws using high-resolution cameras and sophisticated image processing algorithms. Machine vision techniques are used in [6] to assess the areca nut quality. For the grading process, six geometric features, three color features, and the fault area were taken into account. A 90.9% accuracy rate was attained. AI systems, like as deep learning and machine learning models, extract useful information and divide cashews into several quality groups.In order to grade cashew nuts using machine learning, models are trained using labeled cashew nut photos.

This automated approach has the benefit of being impartial and standardized.grading according to particular standards, which results in higher grading process scalability, uniformity, and efficiency. The results of the study in [7] indicate that the-Sorting cashews into different grades using a Random Forest classification model yields a 94.28% accuracy rate when compared to SVM. A system to categorize five grades of cashews utilizing form, size, color, and texture data together with Back Propagation Neural Networks (BPNN) was proposed in research paper [8]. The system showed a 96.8% accuracy rate. According to the results in [9], SVM performed better in terms of accuracy rates for cashew grading applications than BPNN. When it comes to cashew grading, deep convolutional neural networks (DCNN) outperform traditional machine learning (ML) techniques in a significant way. Four models of deep convolutional neural networks were used in the paper [10], including Inception-V3, ResNet50, It was determined that the generated DCNN models were able to achieve automatic, quick, and accurate cashew classification using VGG-16 and a bespoke model. In terms of cache grading, there are a number of benefits to combining classic machine learning (ML) methods for classification with Deep Convolutional Neural Networks (DCNN) for feature extraction. DCNNs are highly effective in extracting hierarchical features from unprocessed picture data and identifying complex patterns in cashew nuts.

By obtaining these attributes, machine learning algorithms can take use of their advantages in categorization and structured data processing to produce precise grading results. This hybrid method, which combines the strengths of DCNN and ML for the best cashew grading outcomes, enables improved feature representation and interpretability. The classification of flower photos was found to be greatly enhanced by the use of hybrid models. Among the numerous models that were used, the integration of a support vector machine and ResNet-50 as a feature extractor(SVM) classifier attained a 90.01 accuracy rate [11].In nut classification, the use of DCNN and machine learning together has not received much attention.

For this reason, this study presents a strong methodology that combines DCNN and machine learning approaches to achieve outstanding accuracy in cashew kernel grading and categorization.The fruit grading systems listed above employ a wide range of techniques [12], [13], [14], [15], [16], and [17].Digital image analysis is utilized in [18] to quantify twelve crucial kernel morphological characteristics of wheat cultivars. These characteristics most likely included 80% accuracy-achieved kernel size, shape, color, and texture. The Backpropagation Neural Network (BPNN) outperformed the array of machine vision classification algorithms developed, attaining an accuracy of 85% [19]. In [20], an innovative method utilizing the ”shadow to total-area ratio” effectively addressed the classification difficulty of differentiating between whole and split-down cashews, obtaining an impressive degree of accuracy. Fruit grading is done in [21], [22], and [23] utilizing spectrophotometry, a machine vision technique, and mobilenet V2.A system based on digital image processing techniques was proposed by the study [24] to identify faulty grains in a sample of rice grains. Apple browning was detected by a computer vision system that used textural and color features [25].In a paper [26], the four primary cashew grades were graded using the fuzzy logic toolbox. The computation time of 0.53 seconds was found, which is substantially faster than the fuzzy classifier done in Python.

This research uses feature extraction from to precisely identify cashew kernels. a number of DCNN neural network models, including a bespoke model, ResNet50, VGG-16, and Inception-V3.Additionally, the cashew kernels are categorized using the SVM, RF, and KNN algorithms into five different grades. Another goal of this study is to compare how well they classified data. One important result of this work is the creation of hybrid models, which outperform separate ML and DCNN models in terms of efficiency.The knowledge gained from this study has the potential to improve not only the industry’s ability to precisely classify cashews but also other varieties of nuts with a high degree of accuracy.

II. Materials and Methods

A. *Data Collection for an Efficient Classification Model*

This study’s main goal was to create a system for classifying whole cashews based on their form and whiteness. In order to do this, close cooperation was developed with the Karnataka cashew companies in order to gather a wide range of cashew samples. We acquired cashews from the Mahasathi Cashew Industry in Bhatkal, ranging in quality. The particular classes that were taken into consideration were W180, W210, W300, W400, and W500, which stand for various cashew kernel sizes and quality. For cashew grades, ”whole” is what the ”W” stands for. The size and quality of the cashew kernels are indicated by the letter ”W” followed by a number.

It indicates how many entire cashew kernels there are in a pound of cashews.Figure 1(a) shows W180 cashews, which have an average of 180 kernels per pound. W210, as illustrated in Figure 1(b), indicates slightly.Smaller cashews, with around 210 kernels per pound. Figure 1(c) shows W300, a lower size with approximately 300 kernels per pound. Figure 1(d) depicts W400 cashews, which have around 400 kernels per pound. Figure 1(e) shows that W500 cashews are the smallest grade, with an average kernel count of 500 per pound.The model’s dataset was created by taking photos of each kernel.

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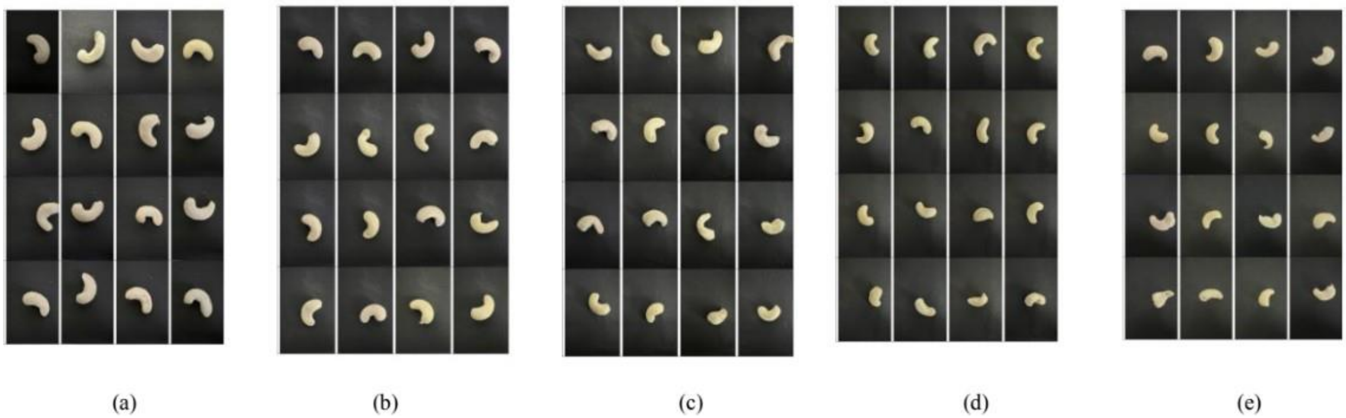

Fig. 1. Different grades of cashew kernels. (a) W180 (b) W210 (c) W300 (d) W400 (e) W500

B. Image Acquistion and Preprocessing

Using the mobile camera's superior capabilities, a methodical strategy was used during the image gathering procedure to guarantee correct portrayal. the cashews were shot with extreme caution and uniformity, with a consistent 6 cm gap between the camera and the cashew kernel. A dark backdrop was used to draw attention to the cashews' features and create contrast. Over the course of the roughly three to four week dataset collection process, every important detail was taken into consideration, such as lighting conditions, the distance between the cashew and the camera, backdrop color, image brightness, and capture angle. Thorough and varied images were obtained by carefully evaluating these factors in order to support the training of a strong deep convolutional neural network.The collection of data created for this reason included more than 2000 photos from various school levels, demonstrating how meticulous the photo collection procedure was.

Various preprocessing measures were taken into consideration following the image capturing process before the data set was fed into the models. These preprocessing actions included background and noise reduction, as well as image resizing. Additionally, image augmentation techniques were used to further expand the training data set and enhance the models' capacity for generalization.Using modifications including rotation, scaling, cropping, and flipping, these methods produced a wider and more varied set of training examples. The intention was to improve the DCNN models' precision and efficacy in cashew grade classification by implementing these techniques based on the obtained dataset. After obtaining the dataset, the next stage was to build hybrid models by fusing classifiers and deep convolutional neural networks (DCNNs).

C. Implementation of Detection Models

- OpenCV is an open-source library that serves as the foundation for many computer vision tasks. It offers a comprehensive toolbox for image processing, manipulation, and feature extraction. In our cashew nut grading system, OpenCV plays a vital role in preparing the images captured by the camera for R-CNN.Image Resizing helps standardize image dimensions to ensure compatibility with R-CNN's input requirements Color Normalization also Adjusts color variations caused by lighting inconsistencies to improve feature extraction. Mitigation of noise introduced during image capture for cleaner data feeding into R-CNN. By using OpenCV's functionalities, we ensure our cashew nut images are preprocessed effectively, allowing R-CNN to focus on accurate classification.
- R-CNN (Region-based Convolutional Neural Network) ideep learning architecture designed for object detection. It employs a two-stage approach to identify and localize cashews in our captured images. R-CNN utilizes a separate model to analyze the image and generate candidate regions (bounding boxes) that potentially contain cashews. These regions are like preliminary guesses about where cashews might be located. Classification and Bounding Box Regression for each proposed region, R-CNN employs a Convolutional Neural Network (CNN) – the workhorse of the system. The CNN analyzes the content within the proposed region and performs two crucial tasks one determines whether the region contains a cashew or not.secondly,refines the initial bounding box proposed in stage 1 to more accurately encompass the detected cashew nut.

D. Training and validation of datasets

To assess model accuracy, training and validation dataset curves were compared. The data needed for model construction is often separated into three parts: training dataset, validation dataset, and testing dataset. The three datasets are used at various stages of model building. The training dataset refers to the sample of data used to fit the model. The training dataset is used to train the model. A validation dataset is a sample of data used for unbiased evaluation.Fitting a model to a training dataset and tweaking hyperparameters or model architecture. The test dataset.A sample of data is utilized to offer an unbiased appraisal of the.The test dataset

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is independent.dependent on the training dataset, but follows the same probability distribution as the training dataset. It is only utilized when the model has been properly trained with the training and validation datasets. When the Overfitting is minimized when the model fits to both the training and test datasets. If the model fits better during trainingWhen comparing the dataset to the test dataset, Shah (2017) found evidence of overfitting. To prevent overfitting, include all three datasets in the model. The training and validation dataset curves were created by comparing accuracy and epoch (number of runs through the training dataset). The dataset was split into training and validation datasets with an 80:20 ratio (400 for training and 100 for validation). Models were iteratively trained and validated on each dataset.

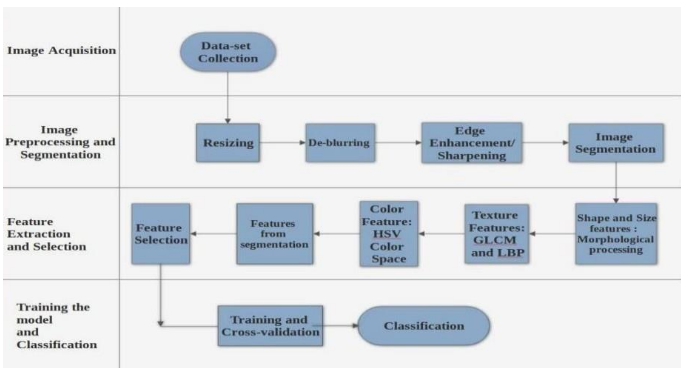

Fig. 2. Trainig and Classification Working

Compactness and Roundness were also employed to describe the overall shape and identify deviations caused by splits or deformities. The cluster distance ratio compared distances between clusters formed when analyzing the cashew image. This could be helpful in identifying cashews with significant defects that deviate from the typical shape or texture.

E. Evaluation of model (DCNN) performance

The DCNN model's performance was evaluated using statistical measures such as recall (TPR), specificity (TNR), precision (PPV), accuracy (ACC), and F1 score (Equations 1-5). Recall or sensitivity refers to the fraction of true positives properly identified by the model. Specificity refers to the proportion of genuine negatives correctly detected by the model. Precision is the ratio of correct positive predictions to total predicted positives, calculated as the number of true positives divided by the sum of true and false positives. Accuracy is defined as the percentage of correct predictions to total predictions (Jain, 2019). The F1-score represents the harmonic mean of precision and recall (sensitivity).

$$\text{Sensitivity}(TPR) = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Specificity}(TNR) = \frac{TN}{TN + FP} \tag{2}$$

$$\text{Precision}(PPV) = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Accuracy}(ACC) = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The F1 score is sometimes preferred since recall and precision are weighted equally. Model performance measures were calculated for each classifier using 100 photos for training.where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives.

True positives occur when one expects something positive and it comes true. True negativity refers to accurately predicting bad outcomes. False positive refers to incorrectly predicting a favorable outcome, whereas false negative refers to the opposite when one makes a pessimistic prediction that turns out to be wrong.

III. Results and Discussion

Multiple deep learning architectures were evaluated for classifying cashew grades. These included VGG16, OpenCv, and Yolov3 and RCNN. RCNN achieved the highest accuracy (90.4%) in combination with OpenCV, demonstrating its superiority for this task.VGG16 with Yolov3 yielded a accuracy of 84%, proving its effectiveness in cashew classification. The system demonstrated an average processing speed of 2 frames per second. This speed is adequate for small-scale operations, allowing multiple cashew nuts to be graded per minute. The processing speed ensures that the system can keep up with the pace of the conveyor belt, maintaining a continuous flow of graded nuts. This figure 3 visualizes the accuracy achieved using different deep learning models on the training data.The RCNN model was trained to classify cashew nuts. Data augmentation enhanced the model's ability to handle variations. A fixed strategy (like sliding window) for region proposals ensured efficient training on resource-constrained hardware. In figure 4, the object that has been detected is a W500. Our project can detect up to five different grades of cashew nuts which includes W180, W210 , W300 ,W400 ,W500.The

Fig. 3. Detection of W210 Using of YOLO v3

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next section discusses the potential differences between the different object detection models and their accuracies.

Fig. 4. Detection of W500 Using of Open CV

A. Model Accuracy's

The increasing training and validation accuracy indicate the model's improving classification performance.The validation accuracy is around 0.75,training loss is around 2 The validation loss is around 4. However, the higher training accuracy compared to validation accuracy suggests potential overfitting, where the model performs well on training data but poorly on unseen data. Both training and validation loss are decreasing, reflecting better model performance, but the lower training loss compared to validation loss further supports the overfitting observation as shown in Figure 5.

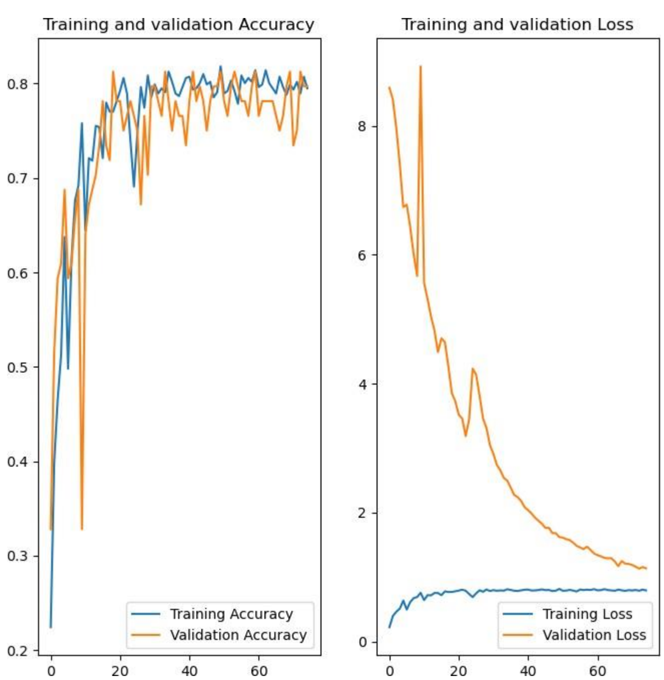

Fig. 5. Acurracy of Yolov3 Training

The CNN architecture described has 29,585,989 trainable parameters and no non-trainable parameters. Comparing RCNN and OpenCV methods, RCNN achieves higher accuracy, precision, recall, and F1 score due to its advanced architecture, though it requires longer training and inference times. Yolov3 methods offer faster training and inference times, making them suitable for real-time applications, but typically show lower performance with a precision of 70.00%, recall of 80.00%, and F1 score of 75.00%.Both Models are suitable for image classification tasks where the input images are of size 256x256 pixels and the output is one of five classes. The absence of non-trainable parameters suggests that neither model uses pre-trained weights or frozen layers.These architectures leverage the standard design principles of CNNs, optimizing feature extraction through multiple convolutional layers followed by spatial reduction via max-pooling, and leveraging dense layers for classification. The high number of parameters in the dense layers enables complex mappings from the extracted features to the output classes, potentially leading to more accurate classification.In conclusion, while models differ slightly in their initial convolutional layer configurations, both are capable of efficiently learning and classifying image data. Their identical architecture and parameter counts indicate similar performance capabilities, making them robust choices for tasks requiring image classification in computer vision applications.

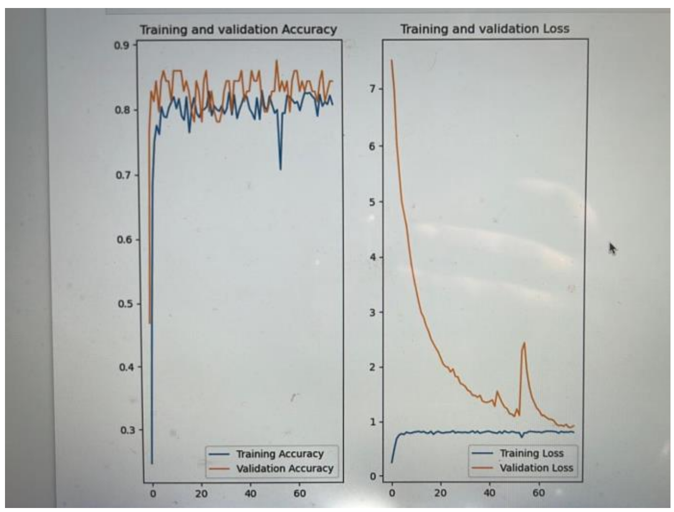

Fig. 6. Accuracy of RCNN Training

B. Conveyor Mechanism

The conveyor belt mechanism is a critical component of the cashew nut grading system, responsible for transporting nuts past the web camera for grading and then to their respective sorting bins based on the grading results. This mechanism is driven by an L298N motor driver and a 28BYJ-48 stepper motor, which together provide precise control over the movement of the conveyor belt.

1) Precision Movement: The 28BYJ-48 stepper motor is well-known for its precision, making it ideal for applications requiring controlled and accurate movements. In this system, the stepper motor's precise control ensures that each cashew nut is accurately positioned in front of the camera for image capture and grading. This precision is crucial for ensuring that the grading process is accurate and reliable.

2) Motor Driver Control: The L298N motor driver receives control signals from the Raspberry Pi's GPIO pins, translating them into the necessary power and directional commands for the stepper motor. This setup allows for fine-tuned control over the conveyor belt's speed and direction.The L298N motor driver is chosen for its ability to handle higher currents and provide stable control, ensuring that the conveyor belt operates smoothly and consistently. It's a dual H-bridge motor driver that can control the speed and direction of two DC motors or one stepper motor. For this application, it's used to control the 28BYJ-48 stepper motor, which is known for its low-cost, simple design, and accurate stepping.The system has demonstrated a swift response time in adjusting the conveyor belt based on the grading results. When the RCNN model grades a cashew nut, it sends a signal to the motor driver, which then adjusts the conveyor belt to sort the nut into the appropriate category. This rapid response time is essential for maintaining the flow of nuts and ensuring accurate sorting.

3) Synchronization: The synchronization between the motor control system and the grading model is crucial for the system's overall functionality. The conveyor belt must move in harmony with the grading decisions to ensure that nuts are sorted correctly. This synchronization ensures that the nuts are not only graded accurately but also placed into the correct sorting bins without delays or errors.System integration involves the seamless combination of all hardware and software components to ensure the grading system operates effectively and reliably. This integration is critical for achieving the desired performance and functionality the conveyor belt mechanism in the cashew nut grading system is a vital part of the overall operation. It utilizes an L298N motor driver and a 28BYJ-48 stepper motor to ensure precise movement, synchronized with the grading decisions made by the RCNN model. The system's rapid response time and synchronization capabilities are crucial for maintaining the flow of nuts and ensuring accurate sorting into the correct bins.

The integration of hardware components (Raspberry Pi, web camera, motor driver, and stepper motor) with software components (TensorFlow-based RCNN model and control scripts) ensures that the grading system operates effectively and reliably. This integration enables the system to function with precision, accuracy, and efficiency, meeting the requirements of the cashew nut grading process.

Overall, the conveyor belt mechanism, driven by the L298N motor driver and 28BYJ-48 stepper motor, exemplifies how precise control and synchronization contribute to the successful operation of automated grading systems in agricultural applications.

Fig. 7. Hardware Integration

TABLE I
COMPARISON OF METRICS: RCNN VS VGG16

Metric	RCNN	VGG16
F1 Score	85.00%	75.00%
Precision	86.00%	70.00%
Recall	84.00%	80.00%
Accuracy	90.00%	82.00%

IV. CONCLUSION

The system automates the sorting of cashews that don't meet quality standards, using cost-effective components. A camera captures images of each cashew kernel with artificial lighting for consistent image quality. These images are processed by a specialized onboard computer program that analyzes each nut for defects. Results are transmitted to a central control unit, automating actions such as removing non-compliant nuts. This improves operational efficiency and product consistency while reducing human error. The system facilitates data-driven decision-making, providing insights for process optimization. Overall, it offers a reliable, efficient solution to maintain consistent cashew quality and represents the future of nut processing.

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