Segregation of Areca Nuts Using Three Band Photometry and Deep Neural Network

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Abstract. In the Malnadu region of Karnataka state in India, often tender Areca nuts of five to eight months old are harvested together, manually separated according to ripeness based on their colour, dehusked, sliced and boiled before marketing. This is a tedious process involving skilled labour and due to the remnant pesticides on the arecanut surface, the health of the worker is adversely affected. Hence to aid the farmers, a technique is developed to carry the task of segregation based on Three Band Photometry and Machine Learning. Light green to fully ripe orange Areca nuts from two different regions were used for Training as well as Testing, using state-of-the-art YOLOv3 Object Detection Deep Neural Network model. They were studied at various stages after plucking between fresh from harvest to one week old. The method developed was found to be effective for both samples at any of these stages.

Keywords: Machine learning · Deep Learning · Computer Vision · Artificial Intelligence · Fruit sorting · Agricultural informatics · Galaxy classification

1 Introduction

Areca nut (*Areca catechu*) is an important cash crop in some states of India, due to its commercial and social significance. India is the largest grower and consumer of Areca nut, with over 700000 tons of annual production having commercial value of over 3 billion US dollars. The major grower, Karnataka produces ripe sun dried (Chali) as well as tender red boiled (Red Supari) nuts. Processing Areca nut to produce Red Supari is time critical:

1. The tender green nut of less than 5 months since flowering to yellowish ∼8 month old mature ones only are useful for this type of processing. The fully ripe orange or red ones have to be segregated from them, dried for about 45 days and dehusked to produce Chali.
2. Due to rain, labour scarcity and other operational reasons, plucking is feasible only limited number of times in the year.

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K. K. Patel et al. (Eds.): icSoftComp 2021, CCIS 1572, pp. 15–27, 2022.
https://doi.org/10.1007/978-3-031-05767-0_2

3. Within three or four days of plucking from the palm, the very tender green ones, slightly grown greenish yellow and mature yellow nuts have to be segregated, peeled, sliced and suitably boiled.

It is a labour intensive skilled task and hence there is good scope for Artificial Intelligence and Machine Learning. There is acute labour shortage, partly because some residual fungicide Bordeax mixture, used to control the disease affecting the crop in rainy season, remains on the surface of the nut which has adverse health effect on the worker handling it. Consequently, automization of the process of segregation and peeling becomes a necessity. There is work describing segregation of the Areca nut after boiling and drying [1], but it does not solve the health issue, apart from the fact that the tender ones and the ripe ones, though might appear similar, have different taste and other intrinsic characteristics which the farmer is very conscious of. Also, for the least damage during peeling, it might be desirable to segregate before dehusking.

Our project to design a machine to segregate and dehusk arecanut started when the arecanut farmers' association of Sirsi requested Indian Institute of Technology Dharwad for help and one of the authors visited their office in 2018 for a detailed discussion followed by an examination of the arecanut processing. The present project aims on classifying freshly plucked Areca nuts based on their ripeness level which are traversing on a conveyor belt in an Areca Nut Processing equipment and sending them to various containers based on the ripeness level using the images of the fruits. Implementing an AI technology for this purpose by making use of a Deep Learning model to work in real-time would not only improve the performance but also reduce the human effort required and enable the farmer to finish this time critical process on–time. An accuracy close to 90% was achieved for the classification of the nuts by making use of Machine Learning Algorithms such as Logistic Regression, Support Vector Machine and YOLOv3. It is no surprise that these results are comparable [2] and our task remains to implement efficiently a feasible algorithm. In this paper, we would focus on the implementation of YOLOv3 model considering the deployment results.

The paper is arranged as follows: The essential idea of color determination from three band photometry is described in the second section. The data collection, sample preparation and data augmentation is described in the third section. The custom–trained YOLOv3 Deep Learning model based segregation is explained in the following section along with refinements, where the implementation of the scheme on a conveyor belt is also shown. The summary is given in the last section along with prospects.

We have to mention that this is not a work in Computer Science, but a project in response to request from farmers based on methods developed in Astronomy.

2 Separation Based on Three Band Photometry

The color of a perfect blackbody can be determined from two band photometry because the flux of radiation emitted from it obeys the Planck Spectrum, varies as the fourth power of its temperature and is proportional to the total emitting surface area. Consequently, the ratio of the flux received per unit solid angle per unit time by a detector in two fixed wavelength bands is a monotonic function of the blackbody temperature. Hence the three Principal Components of a color–color diagram of stars of specified chemical composition are the following:

– The color indices of a star are monotonic functions of the surface temperature.
– A deviation from the black body relation is caused by the surface gravity of the star, which depends on its mass.
– The observed color of a star is further modified due to absorption of the starlight by intervening medium in a characteristic way.

Consequently, the color-color diagram of stars in a star cluster tells us about the temperatures, an idea of their mass and possible extinction due to interstellar medium. cf. [3], Chap. 6. The arecanut color - color diagram is more similar to that of galaxies, the emission from which is composed of contribution from stars of a range of mass and age as well as the interstellar gas. Due to observational noise as well as model uncertainties in some of these processes, stellar type analysis is tough and consequently, Machine learning and Artificial Neural Network has been efficiently employed for classification of galaxies since 1980's. An illuminating discussion of the early methods is given by Lahav et al. [4]. We shall explain the essentials of their Principal Component Analysis using our figure for Arecanuts, later in this work. But the basic idea of our method is: The three band RGB (Red-Green-Blue) images taken with a Camera connected to a Raspberry Pi turns out to be a good indicator of the color, based on which we can get a measure of the age of an Areca nut. For example, Green indicates a tender nut of about five months old while a deep Yellow one is the mature one which is more than seven months old from the flowering time and an Orange or Red one, the fully ripe nut.

One hurdle we face for any such classification of a fruit is the abrupt change in the color with age and the skewness of the distribution of the fruits of a given class in the RGB space. Consequently, the Areca nuts of about 6 months age from flowering, which show abrupt change from Green to Yellow colour are hard to classify. To illustrate the problem, the classwise cluster distribution for our samples is plotted using median RGB values. It turns out that due to colour variation on the surface of the nut and occurrence of yellowish spots on the green nuts, the position of Greenish Yellow nuts in the RGB three color space will show significant separation between two instances of the same nut captured at different orientations. However, for a normal Green or a Yellow nut, the variation caused by orientation effects is almost negligible as the samples occupy the same region in the RGB space. Classification based on this approach requires imaging of the same nut at least twice.

The color defined by the Astronomer is not identical to that of a Computer Vision scientist. So, we use the Hue-Saturation-Value of Computer Vision researcher to get the RGB of Astronomer or directly use it for our Principal Component Analysis.

There have been rapid advances in object detection methods, both for static and moving objects, thanks to Computer Vision. The YOLO (You Only Look

Once) object detection model [6–8] is highly effective to detect an object on the conveyor belt and from the features of the image sample, it can determine the color of an object.

3 Data Collection

3.1 Sample Selection

Two samples of freshly plucked Areca nuts were obtained. A first sample of about 150 nuts of a range of ages and colour from green to red were procured locally from Dharwad region and another sample of about 260 nuts from Yellapur region one day after plucking. Using such varied sample, we can ensure that the result will not be restricted to specific type of Areca nuts grown in a certain region, having limited reflection properties.

The nuts are carefully manually classified into 5 distinct classes - namely light Green tender nuts, about one month older Greenish Yellow, fully grown Yellow nuts, ripe Orange (or Red) and Broken nuts. There was a small ambiguity between Green and Greenish Yellow or Greenish Yellow to Yellow. Due to age difference and consequent peeling issues, we continue with having them as separate classes despite the errors observed in the initial results. The Broken nuts could be dried ones, decomposed or those with one end split and hence any of these cannot be used for Red Supari (Fig. 3).

Prototype of the Design. A prototype of the set up for imaging and segregation of the Areca nuts is shown in Fig. 1. The nuts are placed in the container in the top, which is given a slow rotating motion. The Areca nut flow is controlled and when each nut enters the conveyor belt a light signal prompts the imaging action. The camera over the belt is shown and the exit for the segregated Areca nuts. But the software back-end including the Raspberry Pi and breadboard with trigger to rotate the segregating panel, is not shown here.

Fig. 1. Set up for arecanut segregation

The set up is yet to be fine tuned and the design finalised. Due to abrupt termination of the project due to the pandemic, both in March 2020 and April 2021, the final touch to the segregation task awaits.

Multiple images of resolution 1280×720 pixels were taken for each Areca nut over a week to obtain a total of 1454 images, using a Raspberry Pi Camera and each image is annotated. 4 images having multiple Areca nuts were taken from the internet to take into account different lighting conditions as well as different colour distribution.

Here is the flowchart of the various steps we have taken. YOLOv3 allows imaging of the nut without stopping the conveyor belt (Fig. 2).

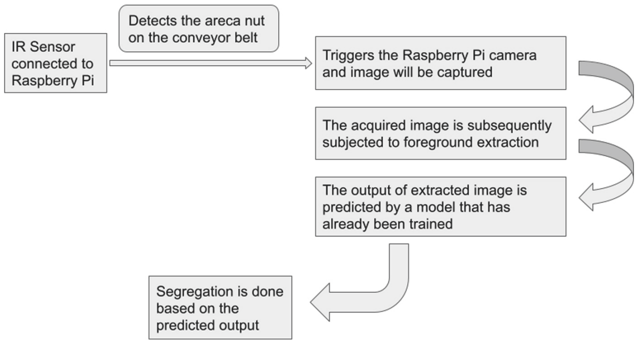


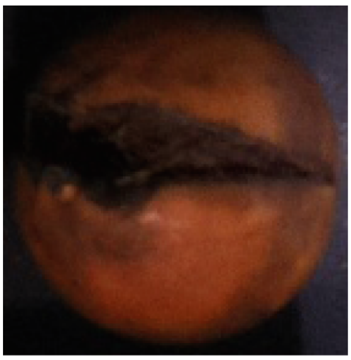
Fig. 2. Operation of our set up for Areca nut segregation

3.2 Data Preparation

We have in total 1458 images for the ∼410 Areca nuts, taken over a period of a week. Each image is manually annotated with bounding box coordinates and the class labels to define the location of the object as well the class using a library called *labelImg* from GitHub repository. The annotations are required for training the Deep Learning Model.

Based on the data set analysis, the HSV (Hue-Saturation-Value) range of areca nuts in our sample is from [5, 80, 25] to [100, 255, 180]. From this, we have extracted the foreground or the Region of Interest (ROI), which is the Arecanut. The cropped images were later used for the RGB color space as well as the Principal Component Analysis (PCA) plots.

Some of the sample ROI images are shown in the Figs. 3 and 4 below. But the image of a given day is not exactly comparable to the one taken next day because of the lighting as well as orientation of the nut in the conveyor belt.

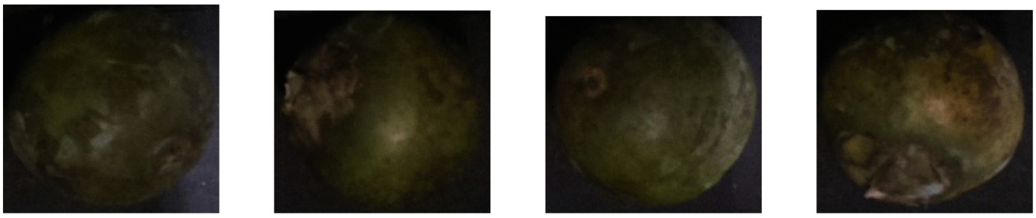


(a) Broken Ripe Areca nut

(b) Broken Tender Areca nut

Fig. 3. Sample of two broken Areca nuts, indicative of some problem with the crop which need remedial action.

The images of two typical undesired Areca nuts with split end and hence damaged or diseased kernel are displayed in Fig. 3. Evidently, they could have any mixed color, and more importantly, color might vary substantially depending on the orientation when the image is captured while in motion on the conveyor belt. There are also fully dried Areca nuts in the same category. Consequently, you do not expect them to occupy a well defined region in the RGB space of the Areca nuts. However, in the conveyor belt if you have two or multiple images captured of the same object at two different angles, they may occupy vastly different position in the RGB space. Consequently, this range of variation can be used to infer confidence level in classification. But the fraction of such Areca nuts in any sample is small and hence, we feel we have are able to segregate them reasonably well with single image using YOLOv3. This will become clear from the graphs later, where our 90% accuracy for the unusable Areca nuts is very similar to what we achieved for Green ones (Figs. 8 and 11).



(a) Tender Areca nut on first day (b) Tender Areca nut next day (c) Areca nut after four days (d) Areca nut after a week

Fig. 4. Tender Green Areca nut on four days. Orientation and lighting not identical. (Color figure online)

Displayed above is a sample of the images of a Green Areca nut over one week period. Most of the good Green, Yellow or Orange Areca nuts have very consistent image characteristics for different orientation. The images taken over a week period have a small shift in the RGB diagram but they occupy the same region in the diagram. The ambiguity between green and greenish yellow nuts is well known to farmers, but is sometimes important in classification. Our approach has been to use the irregular small yellow spots in Areca nuts just turning yellowish or the slight change of one part of the surface compared to another, and apply the deviation in the position in RGB diagram between two readings as a Data Augmentation technique. Since it is a continuous change due to age, segregation between tender arecanuts and those just turning greenish yellow is ambiguous. Typical sample of each class of Areca nut is shown below in Fig. 5.

The distribution of our sample in the RGB diagram is shown in Fig. 6. A tender Green nut and a ripe Yellow one are well separated in the RGB diagram and hence, Machine Learning can certainly help segregation and separate treatment for them as is evident from the diagram. The images taken over a week period have a small shift in the color, but still they all occupy the same color region of the RGB diagram.

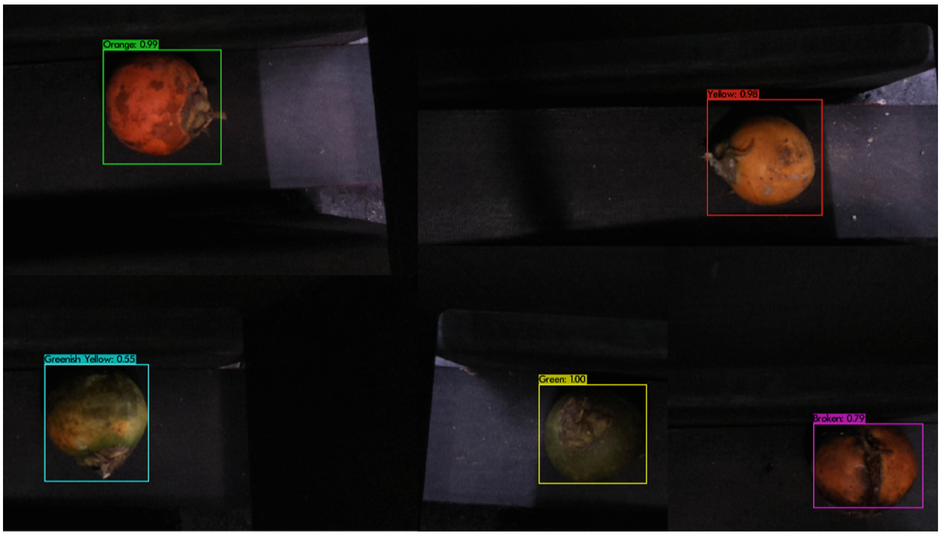


Fig. 5. Images of typical Areca nuts of various classes in our sample (Color figure online)

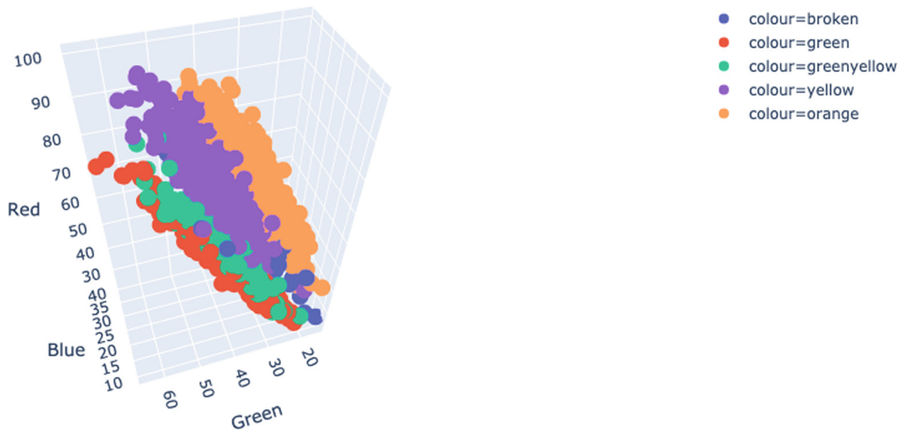


Fig. 6. Distribution of our sample of arecanuts in the RGB color diagram (Color figure online)

3.3 Data Augmentation

The Deep Learning approach requires considerable amount of data for each class for reliable training. In our sample, there were very few Areca nuts for the Broken set. There is a little bit of ambiguity in classifying as Green versus Greenish Yellow based on visual inspection only. So we tried Data Augmentation for these classes based on orientation of two images, the principle for which has been already explained.

4 Artificial Neural Network and Data Analysis

4.1 Detection and Classification

As described earlier, we shall discuss only the YOLOv3 based classification here, though the efficiency is comparable in the various methods we used. Custom–trained YOLOv3 is used to segregate Areca nuts. It is a Convolutional Neural Network and due to the heavy computational load, we adopt a two step process similar to Zheng at al. [9] (Fig. 7).

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Table 1. **Darknet-53.**

Fig. 7. Architecture of YOLOv3 with Darknet as the backbone (ref. [7] and [8]).

We train the YOLOv3 model on a data set of 1458 images, and we apply a transfer learning approach. We use the pretrained convolutional weights and train the final dense layers of the model and the detection is nearly 95% accurate using the non-max suppression criterion but the classification accuracy is low. We implement the YOLOv3 model on the entire dataset (80% of our sample which is used for training).

The entire data set containing 1458 images was divided into two parts: 80% (1168 images) for training and the rest (290 images) for testing purposes. The images having multiple Areca nuts were retained in the training data.

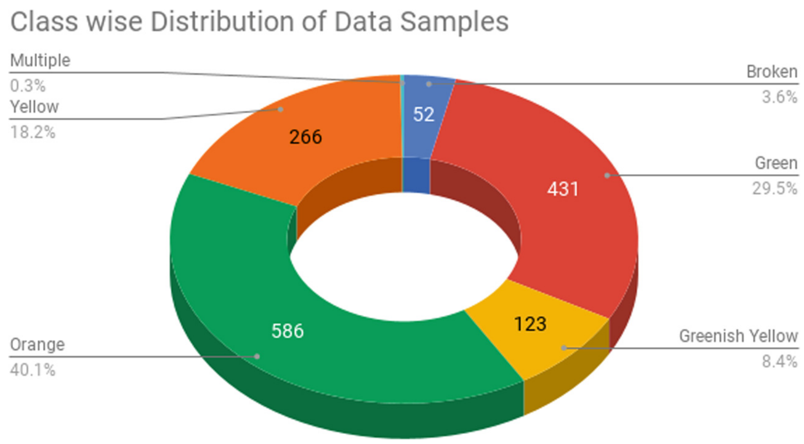


Fig. 8. Class wise distribution of Areca nuts used for training and testing

4.2 Refining the Analysis

The two major reasons for refinement are

- The broken type of Areca nuts are a collection of a variety of nuts unusable for boiling and processing. They do not occupy a continuous region in the RGB diagram, and also their position in the diagram will depend on the orientation of the nut in the conveyor belt while imaging.
- Only a small number of nuts appear Greenish Yellow visually. But this is an important class as the nut ripens. Based on the slight orientation based change in the image characteristics or possible occurrence of yellow dots, they have to be segregated into a single class (Fig. 8).

We use the OpenCV function called *findContours* to extract the Region of Interest (ROI) and use it for the refinement. We compare the pixel values for the B, G, R layers and find their mean pixel values. We used two algorithms for the refinement:

- t-Distributed Stochastic Neighbour Embedding (**t-SNE**) [10]
- Principal Component Analysis (**PCA**) [11,12]

We used the algorithms in the *sklearn* library for the analyses. The result was qualitatively similar for the two algorithms. The distributions of the images in the transformed 3-d space for the PCA algorithm is shown in Fig. 9 next page. There are three Principal Components in this figure.

- All the good arecanuts fall in a plane in the 3-dimensional PCA diagram. The points along the various bands only indicate the size of the arecanut or amount of white light used for imaging.
- The mean central line of various bands make an angle with the 3rd direction axis in this figure. This angle increases monotonically for red (or orange), yellow to green arecanuts in our sample. This angle is a measure of the color (or the age of the arecanut). Ideally, a farmer should be able to change the angular width to control the segregation as a function of the age of the nut.

- The broken or dry arecanuts with grey color or irregularities are, in general, distributed away from this plane, but sometimes they might fall in the plane and cause errors in our classification. The problem can be overcome with multiple imaging, but it is not feasible to do so in practice.

The irregular shape of the various bands in this figure and the thickness of the band are indicators of noise, both due to observation and irregularities on the surface of nuts. It is desirable to quantify the noise spectrum, but obtaining the nuts is time critical and so we are unable to repeat the work with more sample.

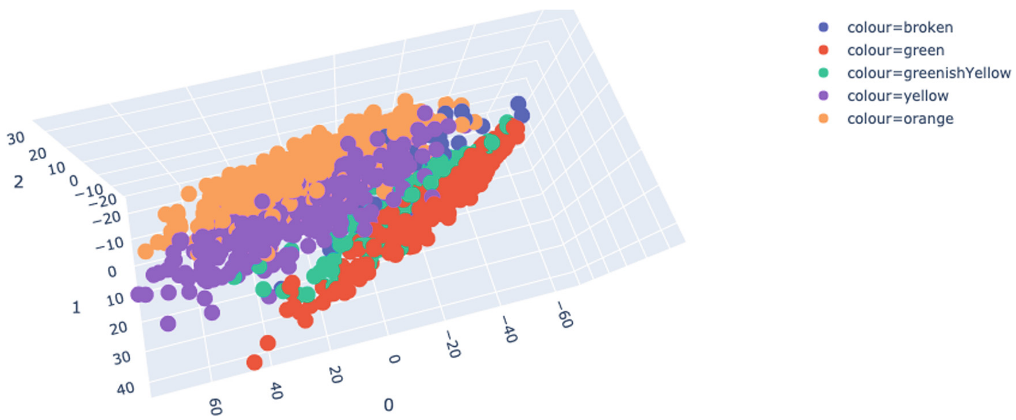


Fig. 9. Distribution of sample Areca nuts in the 3-color diagram after scaling based on the PCA analysis. (Color figure online)

The accuracy of the YOLOv3 neural network model as a function of the number of iterations is shown in Fig. 10. For our data set and refinements, 3500 appear to be the optimal number of iterations.

The final accuracy achieved for the various classes is shown in the Fig. 11. Generally this accuracy is ∼90%. For the class of Greenish Yellow nuts the value of 46% corresponds to ∼20 miss classifications which is mainly due to the large number in the neighboring classes. Refining the boundary between Green and Greenish Yellow class should be implemented after consultations of farmers as a subjectivity is involved for this class.

The final weights file was converted from float32 to float16 so that the file had manageable size and our model could be executable on the Raspberry Pi using TensorFlow Lite and camera interface for real–time detections.

The results obtained here are comparable to the other methods we tried as seen in Table 1: We have explained the reason for selecting YOLOv3.

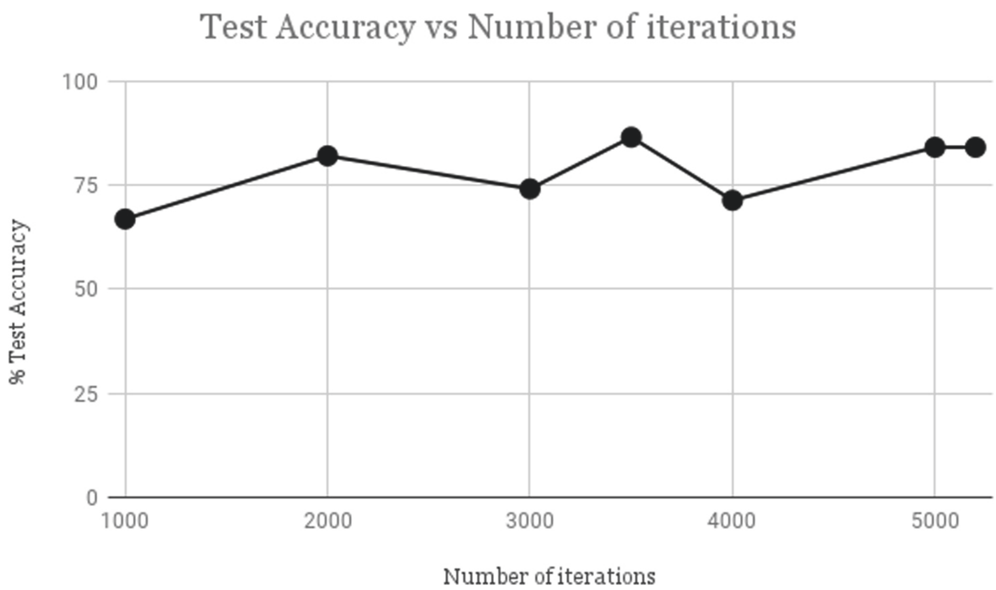


Fig. 10. Accuracy of the Machine Learning algorithm as a function of number of iterations

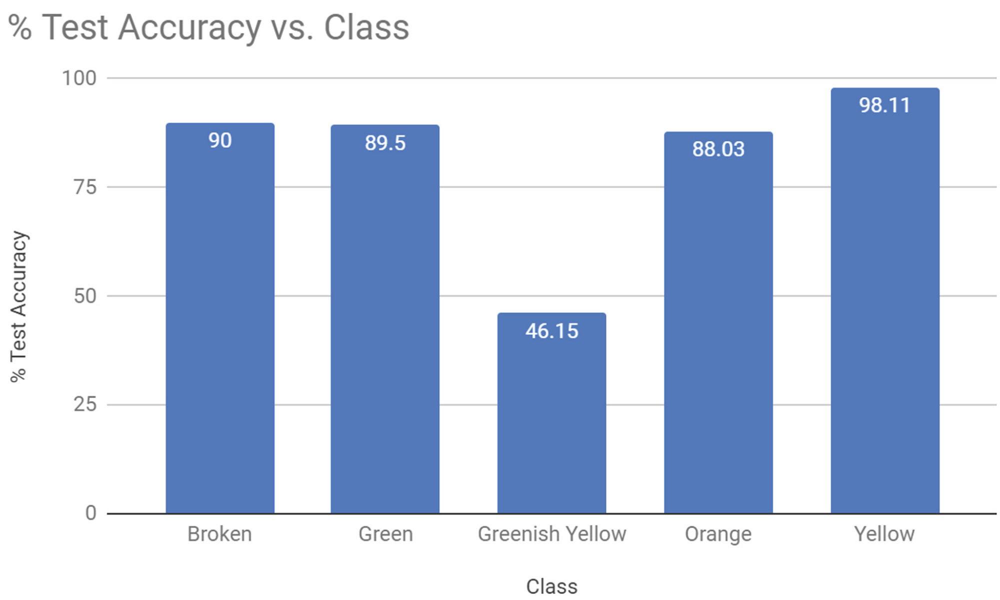


Fig. 11. Accuracy of classification of various classes of Areca nuts in our testing sample.

Table 1. Comparison of methods

Classifier	Accuracy
Logistic regression	96%
Convolution neural network	95%
Support vector machine	92%
YOLOv3	87%

5 Conclusions

Artificial Neural Network (ANN) based segregation of Areca nuts does more than what a human could do consistently, for a big set of Areca nuts.

Using the method developed here, the freshly plucked Areca nuts, within a week of harvesting, can be segregated into five classes, namely, Green tender ones, Greenish Yellow nuts about a month older, mature Yellow ones, fully ripe red or orange nuts which have to be separately processed and broken or diseased nuts which are to be discarded.

We used three band photometry based classification, incorporating statistical analysis of the skewness of the distribution as well as shift in the position of the three color diagram utilizing the powerful features of YOLOv3. But this requires substantial computational power.

The statistical tables of weights generated from this ANN were uploaded on a Raspberry Pi to drive the segregation mechanism on Areca nuts moving on a conveyor belt in real time. Some fine tuning of the mechanism is required.

The Data set we collected had specific lighting conditions. Possibly changing the lighting as well as background in the conveyor belt, the reliability of the scheme will have to be re-examined. Thus the robustness of our scheme can be tested and possible modifications can be worked out.

The size and shape information can be incorporated in the analysis because of the availability of the information of bounding box.

The method described here is fairly general. It can be used for classifying a variety of fruits or other objects based on Computer Vision. But the huge data set required in each class for reliable learning and the computational load implies that we can get the weight table from YOLOv3 with statistical additions, but it has to be uploaded in a device like Raspberry Pi for the actual classification in real time.

Acknowledgements. We thank Prof. Rajshekhar Bhat and Prof. Prabuchandran K. J. for their time and engaging discussions related to areca nuts are Machine Learning. Initial prototyping work for imaging of areca nuts done by Mr. Amit Kumar is acknowledged. We thank Mr. Aneesh, Mr. Manjunath, Mr. Rahul Maurya for offering their instrumentation expertise at a short notice. We are thankful to the referees for their constructive suggestions.

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