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Research Article

Efficient Deep Learning model for de-husked Areca nut classification

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Abstract
Areca nut is a widely used agricultural product in India and even over the globe. Areca nut, a fruit of areca palm (*Areca catechu*) is grown widely in the Asia-Pacific region.. Areca nut segregation is of prime importance in the areca nut industry. The quality segregation of peeled/de-husked nuts requires skilled workers. This process of manual segregation is time-consuming and can lead to erroneous classification. Recent deep learning (DL) advances have improved the performance in multi-class problems. The present work presents the classification of de-husked areca nut among five classes using an efficient deep learning customized Convolutional Neural Network (CNN) and the results of this model were compared with the standard AlexNet architecture. The new CNN model was customized to obtain classification accuracy higher than the existing ones. A dataset of 300 nuts (60 per class) was created using a specially designed instrumentation setup. The areca nut images were then pre-processed and fed to these models to learn the features of the areca nut from different classes. The confusion matrix and Area Under the Curve - Receiver Operating Characteristics (AUC- ROC) were employed to assess the results of these models and cross-validated with 5 and 10-fold. The experimental results show that the CNN outperformed the AlexNet model with an average accuracy of 97.33% and 98.34%, F1 score of 97.48%, and 98.45% for 5 and 10 folds, respectively.

Keywords: AlexNet, Area Under Curve (AUC), Areca nut; Convolutional Neural Network (CNN), Deep Learning, Receiver Operating Characteristics (ROC)

INTRODUCTION

Areca nut is a fibrous seed of the areca palm, grown in the Asia–Pacific region over thousands of years. It is popularly known as "betel nut" or "*Supari*" in India. The nut is generally placed in the buccal cavity and is often consumed as a "quid" with tobacco, slaked lime, and a plant leaf. When chewed, the nicotinic-acid–based alkaloid arecoline present in the nut gives a stimulant effect that boosts alertness and, in some, produces a mild euphoria (Moss, 2022). The significant constituents of areca nut are polyphenols, fat polysaccharides, fiber, and protein. It also contains alkaloids such as arecoline (0.1–0.7%) and others in smaller concentrations like arecadine, guvacoline, and guvacine. Tannins, a by-product after the processing of immature nuts, are used as a dye in the clothing industry. The fat content (8-12%) in the nut is extracted and used for confectionery purposes. Vagbhata (in the 4th Century AD) described the medicinal significance of areca nut and is an effective drug against various ailments. It also finds its medicinal significance in the metabolic system as a digestive and carminative Anti-diabetic, improving eyesight and relieving asthma.
The crop has such a vast commercial and religious value in India and, hence, is grown on a commercial scale along the western coast of India (Karnataka, Goa, Maharashtra), Kerala, Tamil Nadu, and eastern regions like West Bengal, Assam, Meghalaya (Ramachandran, 2014). Though the areca nut is assumed to have originated from Malaysia and the Philippines, the crop has taken deep roots in India to the extent that India has become the largest producer of it for over 60 years. India contributes to approximately

50% of the total world areca nut production.

The essential stages in producing Areca nut are Harvesting, Drying, De-husking, and quality nut segregation. Among all the stages, nut segregation is a tedious and time-consuming one. For many farmers and agriculturalists in the state of Goa and neighboring states (India), growing areca nuts is one of their primary sources of revenue. Goa Bagayatdar, a leading cooperative society, and other private vendors collect the de-husked nuts from the farmers. At the collection centers, nuts are classified into seven categories, viz. *Supari, Safed, Laal, Vench, Kharad, Tukada,* and *Baad*. This classification is necessary as there is a considerable variation of rates/kg across the various classes. The classification process takes much time since there is a shortage of skilled laborers for the above-said work. This delays the payment and can degrade the quality of nuts over a long period. Also, the classification may vary slightly from labor to labor. Hence, there is a need to develop a segregation unit to classify the nuts based on their quality. This will solve the issue of skilled labor scarcity and farmers' time.

Automation and computer vision have become integral to fruit or nut segregation (Hameed *et al.,* 2018; Edan *et al.,* 2009). Many industries, including agriculture, have come to understand the usefulness of artificial intelligence (Ayoub Shaikh *et al.,* 2022). This can be achieved effectively using image processing. Image processing is a robust tool frequently used to identify agricultural goods. Images are frequently evaluated for quality using color, geometric, and texture attributes (Huang, 2012). Image processing and machine learning for the identification, classification, and grading of agricultural produce have been the Areas of research in recent times (Alzubaidi *et al.,* 2021; Naranjo-Torres *et al.,* 2020). The Deep Learning (DL) technique, which is a specialized branch of Machine Learning (ML), is very popular in vision science due to high levels of abstraction and the ability to learn patterns present in images automatically (Naranjo-Torres *et al.,* 2020; Madani *et al.,* 2018). Convolutional Neural Network (CNN) is one of the most popular DL architectures used for image processing (Goodfellow *et al.,* 2016; LeCun *et al.,* 2015; Zeiler and Fergus, 2014). CNN is an Artificial Neural Network (ANN) that uses convolution operations in at least one of its layers (Goodfellow *et al.,* 2016). Park *et al.*(2004) have used content-based image classification using a NN with texture features, such as contrast, diagonal moment, energy, entropy, homogeneity, second diagonal moment, and uniformity, as input nodes.

Huang (2012) used NN and Image processing techniques to classify areca nuts using machine vision. To sort the quality of areca nuts, a back-propagation neural network (BPNN) classifier was used and achieved an accuracy of 90.9%. Danti and Suresha (2012) have worked on segmenting and classifying raw areca nuts based on three sigma control limits with an accuracy of 97.63%. Chandrashekhara and Suresha (2019) have worked on classifying healthy and diseased areca nuts using an SVM Classifier with LBP features and attained an accuracy of 98%. Mallaiah *et al.* (2014) classified diseased and undiseased areca nuts using texture features of Local Binary Pattern (LBP), GLCM, Gabor, and Haar Wavelets with an accuracy of 92.00%. Cai and Liu (2019) have proposed the betel nut classification method based on transfer learning using AlexNet. They achieved a classification accuracy of 89.4% using 189 images.

Jyothi *et al.* (2022) worked on grading areca nuts using ML techniques. They used an SVM classifier and got an accuracy of 77% using LBP feature extraction and 79% using LTP feature extraction. Mallikarjuna *et al.* (2021) have developed a CNN-based approach for classifying images of diseased areca nuts. They have classified nuts with husk into four classes. Meghana and Prabhudeva (2022) have worked on image processing based on areca nut disease detection using CNN. With the help of this technique, it is possible to identify many areca nut diseases, including mahili and stem bleeding yellow leaf spot. A dataset containing 241 diseased and healthy images is used to train and test the CNN model. The proposed model achieved an accuracy of 93.3%.

Bharadwaj *et al.* (2021) worked on Areca nut Grading and Classification for four classes using Texture-Based Block-Wise LBP using SVM and achieved an accuracy of 94%. Siddesha *et al.* (2015) have worked on the texture-based classification of areca nut (7 classes) using various feature extraction techniques and achieved an accuracy of 91.43% using the Nearest Neighbour (NN) classifier with Gabor wavelet features. Shedthi B *et al.* (2023) have classified healthy and diseased areca nuts by applying ANN with density feature and got an accuracy of 98.8%. The literature survey shows that many researchers have proposed the classification of areca nuts with husk. But very little work has been done in classifying de-husked Areca nuts. In the previous work, a binary classification of de-husked areca nuts using CNN and MobileNet was done. It was observed that MobileNet outperforms CNN in all performance matrices (Patil *et al.,* 2023). This proposed work created a dataset containing 300 images of five categories of areca nuts employing two deep learning algorithms, a customized CNN and AlexNet to categorize Areca nuts.

MATERIALS AND METHODS

This paper deals with the quality classification of Areca nut, a fruit of areca palm (*Areca catechu*) from the Konkan belt of India, particularly from the state of Goa. A framework of the proposed Areca nut classification system is depicted in Fig. 1. The proposed system is divid-

Fig. 1. *Framework of the proposed method*

ed into five main steps: Image acquisition, Pre-processing, Image segmentation, Classification models with CNN and AlexNet, and Model performance analysis.

Image acquisition system

A unique setup was designed to create a primary database, as there was no publicly available database of the Areca nut images. In this setup, a camera was mounted at the top, and a sample table was placed below. A radial arrangement of 20 white LEDs evenly illuminating the sample surrounds the camera. The sample and the camera were shielded from stray light by using a hollow cylinder pasted with black matt paper on its inner side, as shown in Fig. 2 a. An AC power source of 220V, 50 Hz, was applied to the LEDs through a constant current DC converter. Also, a 220 µF/ 450 V capacitor was connected to the DC output to reduce flicker in the illumination. This setup used a low-cost 5MP lightweight Pi camera module, which communicates with the Raspberry Pi 3 B+ board using the MIPI camera serial interface protocol. A sample (areca nut) was placed over a black cloth to reduce the backscattered light. Fig. 2 shows the data acquisition setup designed for capturing images of Areca nuts.

Dataset description

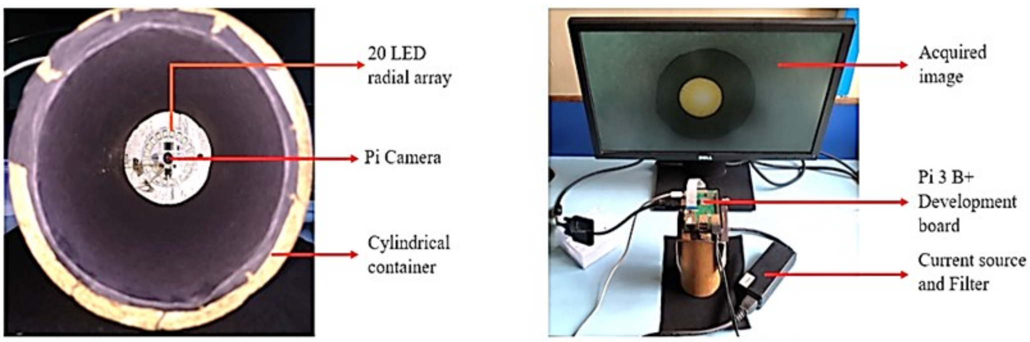
This work created a dataset of 300 nuts (60 per class) using a specially designed setup shown in Fig. 2 consisting of five classes. *Supari, Laal, Tukada, Kharad*, and *Baad*. The images acquired from all the mentioned categories are shown in Fig. 3.

Fig. 3(a) is an image of the Supari class nut. This class of nut is the costliest among all and has no defects. Fig. 3(b) shows the second class of nuts called *Laal*. This nut has a hole at the bottom. This class nut is priced marginally below *Supari* class. Fig. 3(c) is a picture of *Tukada*. These nuts are a broken variety of *Supari* and *Laal* class and are priced below them. The *Tukada* variety is mainly generated when nuts are peeled using an automatic de-husking machine. Fig. 3(d) shows the *Kharad* class nut. This variety has a husk on a significant portion of the nut. Due to improper drying, this husk remains on the nut and is primarily available in nuts peeled using an automatic peeling/de-husking machine. Since processing this class of nut in the industry requires additional steps, this class is priced below *Tukada*. The *Baad* class shown in Fig. 3 (e) is the lowest quality of nuts and is priced least. This nut has less weight, is uneven mainly in shape, and is porous.

Image Pre-processing

Image Pre-processing is a series of actions or manipulations performed on an image, depending on the application, to enhance the image quality. The noise and distortion are reduced by performing these processes on the image, and the relevant features are enhanced for further analysis and classification. For pre-processing the images captured by the Pi camera, an Anisotropic diffusion edge-preserving filter is used to protect image characteristics like edges, lines, and other image structures while filtering out image noise (Veerakumar *et al.,* 2014).

The contrast of the image is improved using the image processing technique Contrast-Limited Adaptive Histogram Equalization (CLAHE). Instead of processing the entire image, the CLAHE algorithm works on discrete, non-overlapping sections of the image (Patil *et al.,* 2022; Yakno *et al.,* 2021).



(a)Top view of imaging setup (b)Components of imaging setup

Fig. 2. *Data acquisition setup*

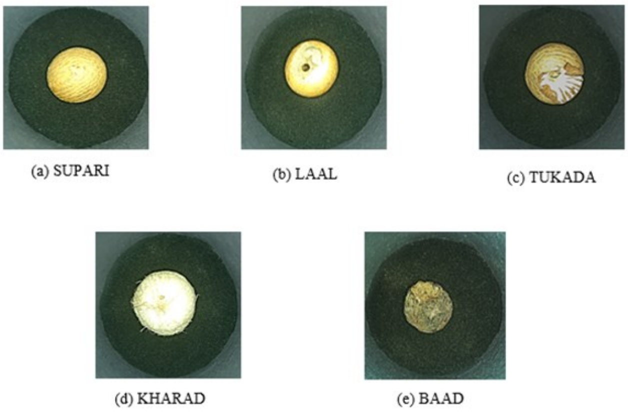


Fig. 3. *Various classes of areca nuts*

Image segmentation

Image segmentation is the process of dividing an image into pixel groupings, or segments, each represented by a label or a mask. The complexity of an image is reduced by segmentation, thus simplifying the analysis algorithm. Here 'k' means image segmentation method is used (Patil *et al.,* 2022).

Areca Nut Classification Models

The authors have used customized CNN and AlexNet models to classify areca nuts into five categories. The performance evaluation of these models is depicted in the result section.

Convolutional Neural Network (CNN)

In recent literature, CNN has received much attention (Jia *et al.,* 2020; Mai *et al.,* 2020). CNN is a subset of Deep Learning (DL) algorithms that is particularly effective in classifying data by identifying patterns in images. A CNN is a feed-forward network comprising fundamental components, including a convolutional layer, pooling layer, and activation layer, that are layered together in various ways. The CNN's feature extraction section comprises a variable configuration of convolutional layers, pooling layers, and activation layers (Khoshdeli *et al.,* 2017). A Fully Connected (FC) layer and the classification layer are then given the extracted characteristics (Khoshdeli *et al.,* 2017). Each layer type has a particular function. Fig. 4 shows the customized CNN architecture for areca nut classification.

Convolution layer

A convolution layer is an essential layer of CNN architecture. It is made up of several kernels or filters. These filters provide the input image's N-dimensional metrics-based function map (Alzubaidi *et al.,* 2021; Yamashita *et al.,* 2018).

Activation Layer (ReLU)

The activation ReLU layer helps to introduce non-linearity into the network. It takes the weighted sum of all the inputs from the previous layer and then applies an activation function. It converts the absolute values of the input to positive numbers (Alzubaidi *et al.,* 2021).

Pooling Layer

This layer takes a region of the input feature map and replaces it with the average value of all the pixels in the region. This reduces the size of the feature map, making the model more efficient and reducing the number of parameters used, thereby avoiding the overfitting image (Alzubaidi *et al.,* 2021; Yamashita *et al.,* 2018).

Fully Connected Layer (FC)

In the FC layer, all neurons in the preceding layer are connected to neurons in the subsequent layer. This layer is typically used in a network's output layers for classification (Alzubaidi *et al.,* 2021).

AlexNet

AlexNet is a deep convolutional neural network developed by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever. AlexNet uses ReLU as CNN's activation

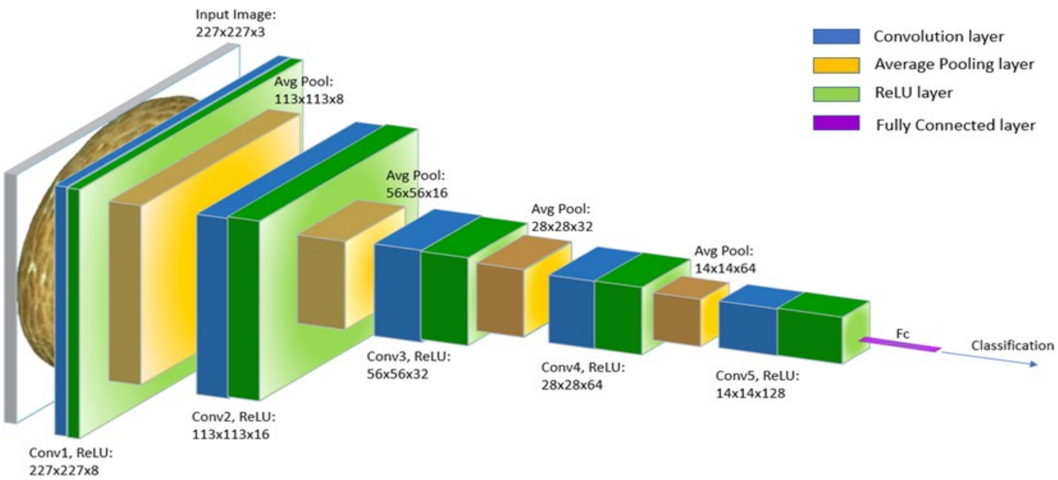


Fig. 4. *Customized CNN model*

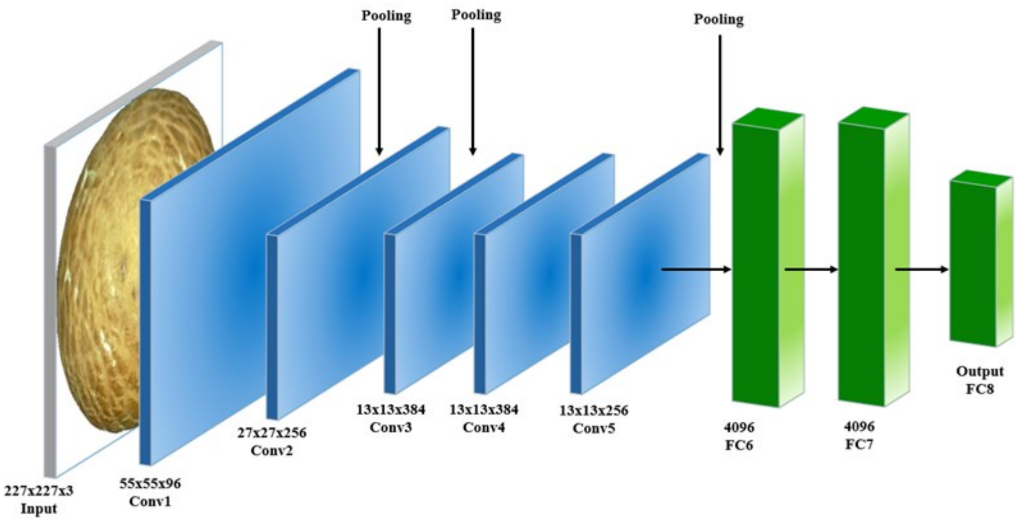


Fig. 5. *Standard AlexNet model architecture*

function, and it has been demonstrated that it performs better in deep networks than Sigmoid in terms of gradient dispersion . It consists of eight layers: five convolutional layers, two fully connected layers, and one output layer. To reduce overfitting in the FC layers, AlexNet employed a regularization method called "dropout," which is very effective and is widely used in many DL applications (Krizhevsky *et al.,* 2017). The AlexNet architecture is given in Fig. 5.

Performance of evaluation metrics

It is critical to evaluate the performance of the ML model that will describe, forecast, or evaluate outcomes after it has been constructed and the ground truth has been established (Boutaba *et al.,* 2018; Carbonero-Ruz *et al.,* 2017). The performance classification metrics are divided into three more categories (Ferri *et al.,* 2009). To evaluate the performance or quality of the model in the present work, metrics such as the Confusion matrix and AUC- ROC (Area Under the Curve-Receiver Operating Characteristic) curve are used.

Confusion Matrix

The confusion matrix is a crucial element used to measure the performance of the classification model. It is a table with two dimensions showing actual and predicted values (Visa *et al.,* 2011). These matrices are used to evaluate the accuracy of a model in predicting the correct class for a given input. The most common performance metrics are accuracy, precision, recall, and F1 score. Accuracy measures the overall efficacy of the model, precision measures the proportion of true positives to false positives, recall measures the proportion of true positives to false negatives, and the F1 score is the harmonic mean of precision and recall.

Accuracy is an evaluation metric that measures the number of correct predictions made by a model with the total number of predictions (Kamilaris & Prenafeta-Boldú, 2018). It is given by

$$\text{Accuracy}(A_{AN}) = \frac{TP_{AN}+TN_{AN}}{TP_{AN}+FP_{AN}+TN_{AN}++FN_{AN}} \quad \text{..............(1)}$$

Precision is a measure of how many of the positive predictions made are correct (Kamilaris & Prenafeta-Boldú, 2018). It is given by

$$\text{Precision}(P_{AN}) = \frac{TP_{AN}}{TP_{AN}+FP_{AN}} \quad \text{............(2)}$$

A Recall measures how many positive cases the classifier correctly predicted over all the positive cases in the data (Kamilaris & Prenafeta-Boldú, 2018). It is given by

$$\text{Recall}(R_{AN}) = \frac{TP_{AN}}{TP_{AN}+FN_{AN}} \quad \text{............(3)}$$

Where,

TP_{AN} = Correct positive predictions

TN_{AN} = Correct negative predictions

FP_{AN} = Wrong positive predictions

FN_{AN} = Wrong negative predictions

The F1 score is defined as the harmonic mean of the Precision and Recall (Kamilaris & Prenafeta-Boldú, 2018). It can be readily calculated from equations 2 and 3 as

$$\text{F1 Score} = 2 * \left(\frac{P_{AN}*R_{AN}}{P_{AN}+R_{AN}}\right) \quad \text{....................(4)}$$

AUC-ROC curve

The AUC-ROC curve is an evaluation metric for visualising a classification model's performance (Fawcett, 2006). The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The ROC curve is a valuable tool for visualizing, organizing, and selecting classifiers based on performance. It is also used to compare the performance of different classifiers. The Area under the ROC curve measures how well a parameter can distinguish between various classes of areca nut. Instead of relying on a single operating point, the Area Under the Curve (AUC) describes the entire position of the ROC curve (Hajian-Tilaki, 2013; Hanley and McNeil, 1982; Swets, 1979). A higher AUC indicates better classifier performance (Markoulidakis *et al.,* 2021).

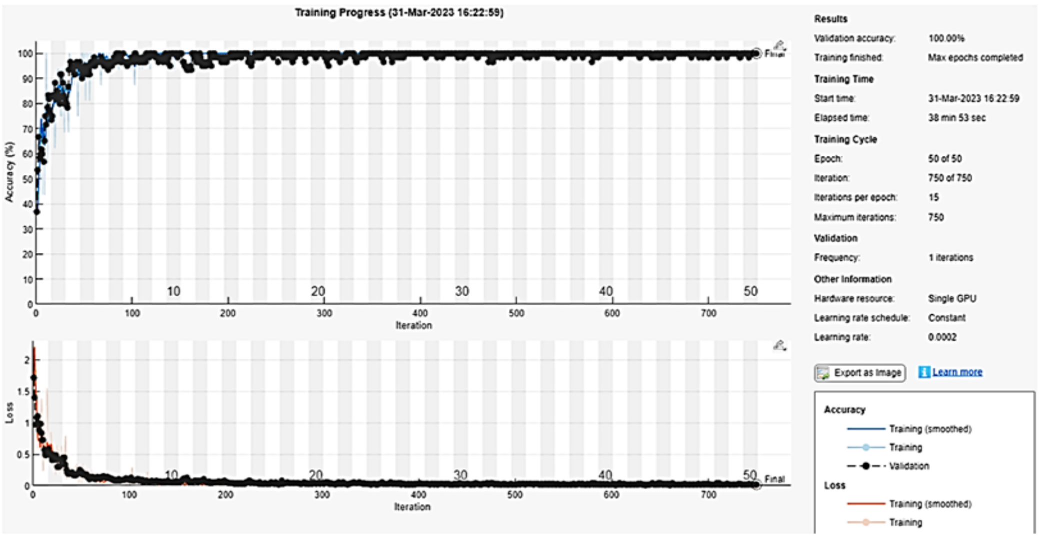
RESULTS AND DISCUSSION

The present study evaluates the classification of dehusked areca nuts into five categories, namely *Supari, Kharad, Tukada, Laal,* and *Baad,* using customized CNN and standard AlexNet Models. The segregated areca nut samples were collected from Goa Bagayatdar. A 5-fold and 10-fold cross-validation method are utilized for both the CNN and AlexNet architectures. Both models have been implemented successfully using MATLAB on an Intel i3 Core computer with an NVIDIA PCIc card having TU116 GPU with 6GB GDDR6 dedicated graphics RAM and 16 GB main RAM.

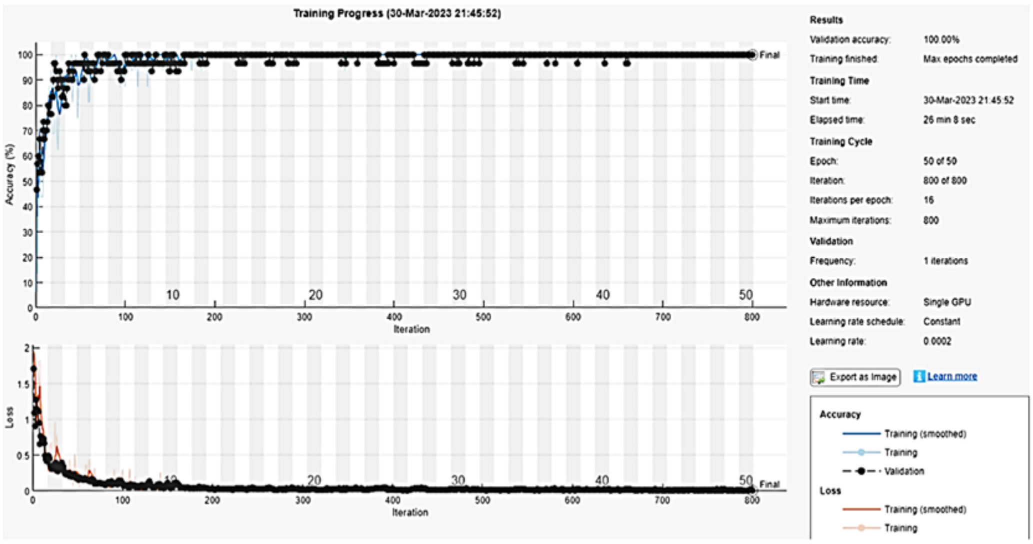
Performance measure of DL models using the k-fold technique

The present work utilises two DL classification models with Adam optimizer. The k-fold cross-validation is a popular method for assessing a DL algorithm's performance on a new dataset for a multi-class problem. In this method, a data set is randomly divided into k disjoint folds of roughly equal size, and each fold is used to test the model that a classification algorithm inferred from the other k folds (Kamble and Dale, 2022; Yu-Dong Zhang and Sangaiah, 2022; Wong, 2015).

Deciding the k value for cross-validation of a model in DL is very important. When the value of k increases, the model's accuracy also increases because the mod-

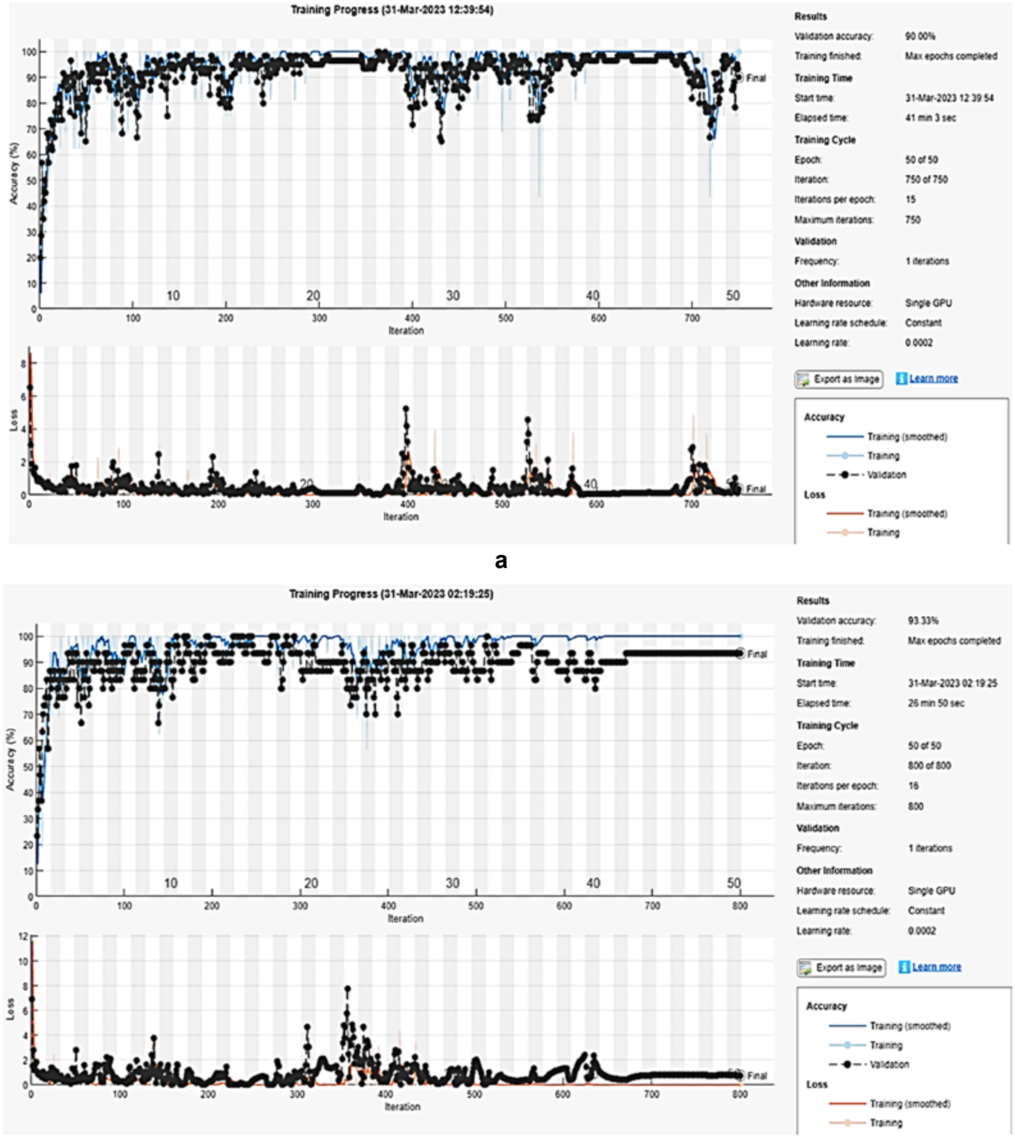


a



b

Fig. 6. *Training and validation accuracy and loss curves for CNN (a) 5-fold (b) 10-fold*



a

b

Fig. 7. *Training and validation accuracy and loss curves for AlexNet model (a) 5-fold (b) 10-fold*

el is provided with more training samples. Many researchers have explored the effect of different *k* values on the estimate of model performance (Lanjewar *et al.,* 2023; Nti, *et al.,* 2021). The database is divided into 5/10 unique folds for 5/10-fold cross-validation, of which 4/9 folds will be utilized for training and 1 for testing. In other words, each tested sample is now a part of the training set, and a sample from the training set is used in testing.

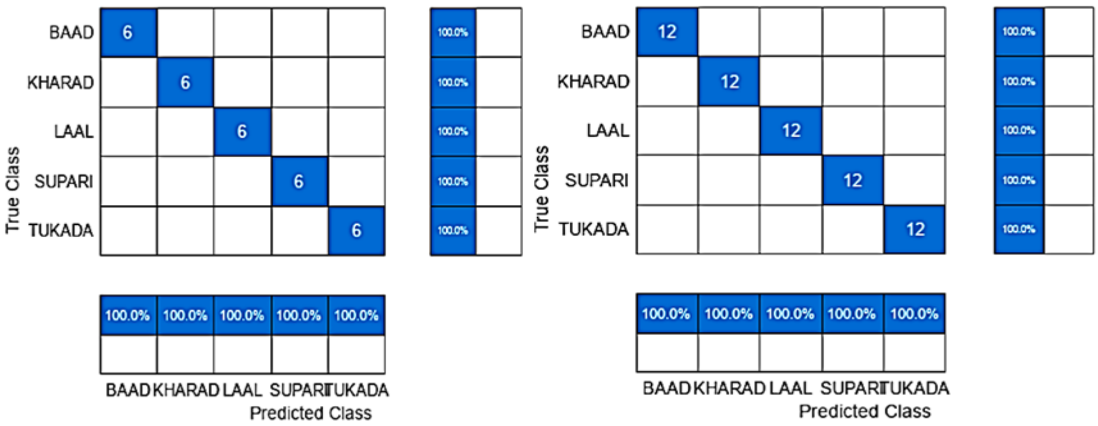
Training-Validation Accuracy and Loss Distribution

Fig. 6 and Fig. 7 show the training and validation accuracy with loss curves against the number epochs for CNN (k=5,10) and AlexNet (k=5,10) models, respectively. The hyperparameters tuned for this paper are: Learning Rate=0.0002, Optimizer=Adam, Batch size: 16, epoch=50. Fig. 6 shows that the training-validation accuracy stabilizes and follows each other after 15 epochs for CNN. For the AlexNet model, the distribution fluctuates during entire folds, as shown in Fig. 7. The training and validation loss for CNN is low compared to AlexNet. It is observed that the training-validation loss distribution is uneven for AlexNet. So, the designed CNN model performed better than the standard AlexNet model.

Confusion matrix:

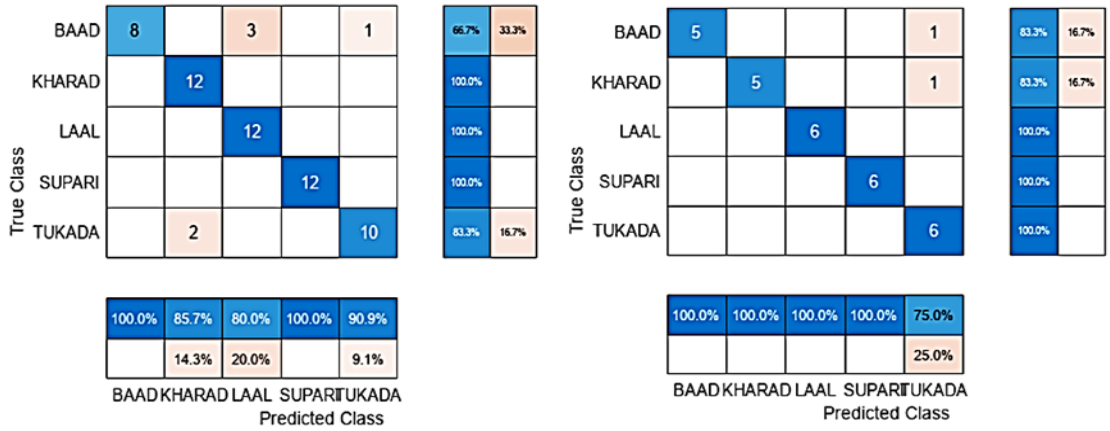
The comparative performance analysis of both models was checked using a confusion matrix. The confusion matrix for one of the 5/10-fold of cross-validation for CNN and AlexNet is shown in Fig. 8 and Fig. 9, respectively.

From Fig. 8, the classification accuracy is 100 %, indicating that all five classes are correctly classified. For 5 -fold, 60 images are used for validation (12 from each class)



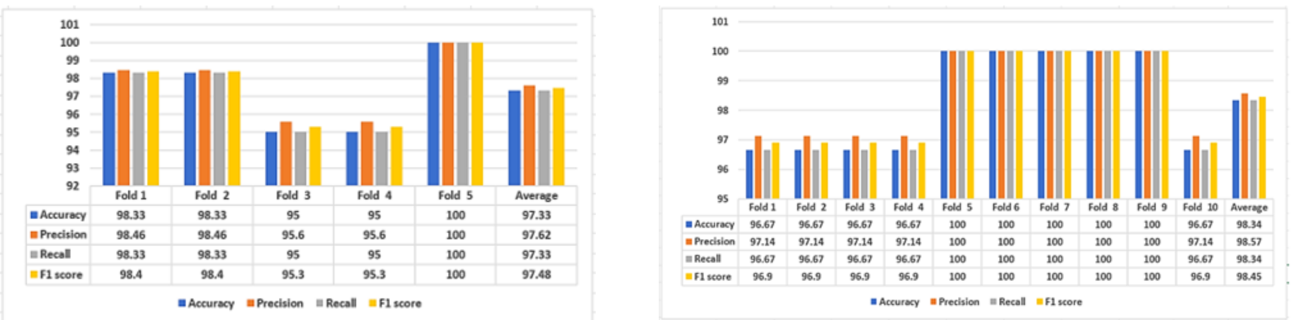
(a) **(b)**

Fig. 8. *Confusion matrix chart for CNN a) 5-fold b) 10-fold*



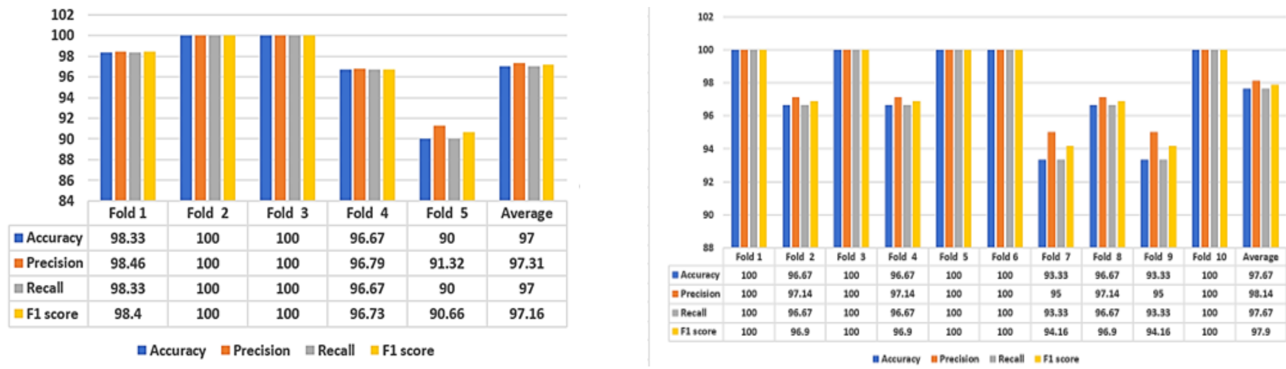
(a) **(b)**

Fig. 9. *Confusion matrix chart for AlexNet (a) 5-fold (b) 10-fold*



(a) **(b)**

Fig. 10. *Various metrices for the CNN model a) 5-fold b) 10-fold*



(a) **(b)**

Fig. 11. *Various metrices for the AlexNet model a) 5-fold b) 10-fold*

Table 1. Summary of all metrices for CNN and AlexNet

Model / Metrics		Average			
		Accuracy	Precision	Recall	F1 score
CNN	5-fold	97.33	97.62	97.33	97.48
	10-fold	98.34	98.57	98.34	98.45
AlexNet	5-fold	97.00	97.31	97.00	97.16
	10-fold	97.67	98.14	97.67	97.90

and 240 for training the model. Whereas for 10-fold, 30 are used for validation (6 from each class), and 270 are used for training. As shown in Fig. 9 (a), it is seen that *Baad* and *Tukada* are wrongly classified, thereby decreasing the accuracy to 90% for that fold. Similarly, for 10-fold, *Baad* and *Kharad* category nuts are classified wrongly, which gives an accuracy of 93.33%.

Figs. 10 and 11 show various performance matrices for CNN and AlexNet models. Summary of results for CNN and AlexNet models is depicted in Table 1.

CNN attains the highest accuracy / F1 score of 97.33% / 97.48% for 5-fold and 98.34% /98.45% for 10-fold, respectively. As the fold is reduced from 10 to 5, it is observed that the CNN model performs equally well.

AUC-ROC

The ROC curve for both the models for 5 and 10-fold is shown in Fig. 12. The AUC values for the CNN model are highest for 5-fold and 10-fold. Fig.s 12 (a) and (b) show the ROC curves for the CNN model with 100% accurate performance. At the same time, Fig.s 12 (c) and (d) show the 90% (5-fold) and 93.33% (10-fold) accurate performance for AlexNet. From Fig. 12 (a) and (b), it is clear that all the classes of areca nuts achieved

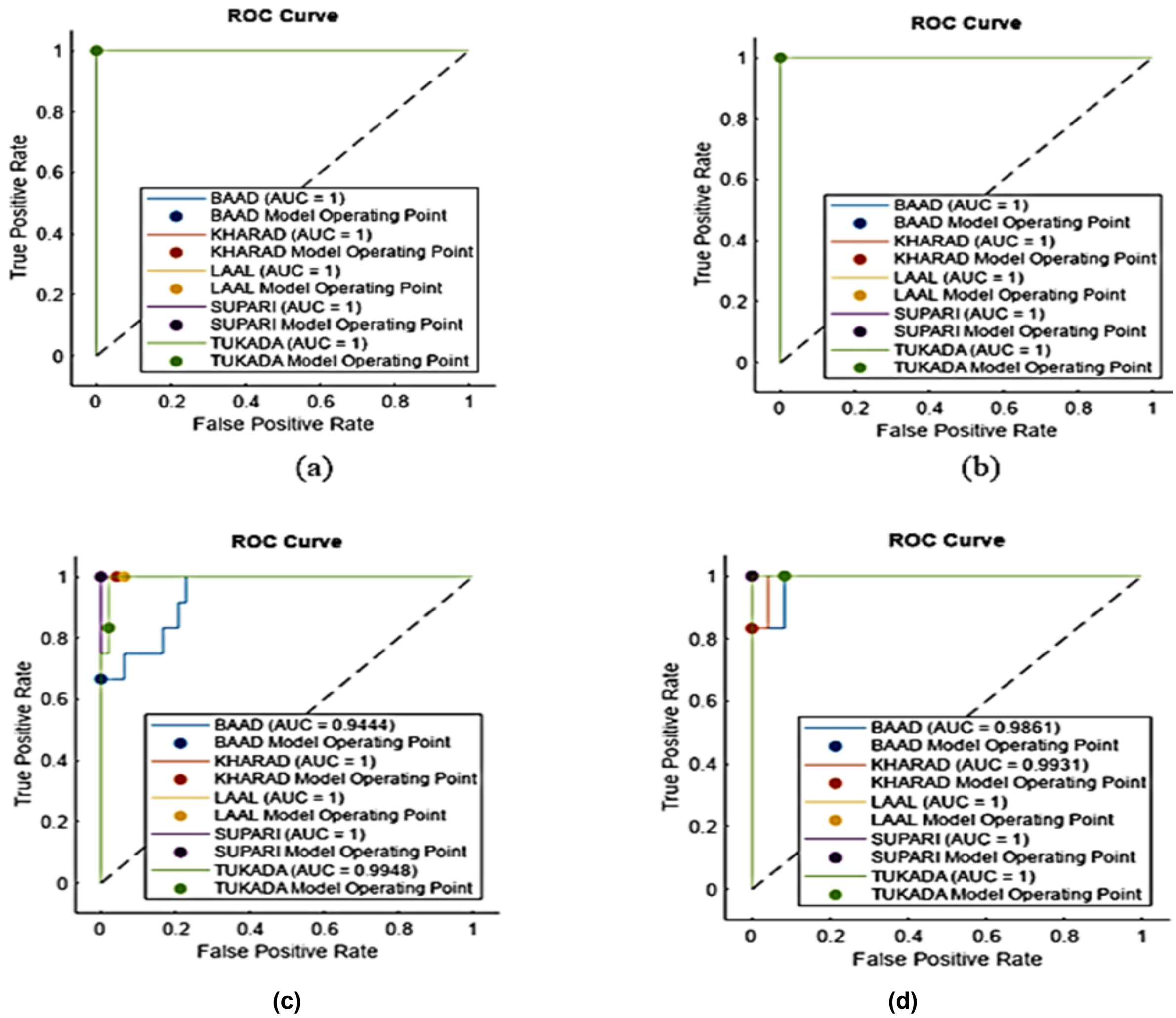


Fig. 12. *AUC- ROC curve of five classes;(a) CNN-5-fold, (b) CNN-10-fold,(c) AlexNet-5-fold, (d) AlexNet-10-fold*

Table 2. Work carried out by researchers on de-husked areca nut classification

Researcher	Methodology	Accuracy (%)	Classification
Shedthi *et al.*	Logistic regression, k-NN, naive Bayes classifiers, and density features with SVM and ANN	98.8	Binary
Bharadwaj *et al.*	Block-Wise LBP for feature extraction, Otsu thresholding for segmentation, and SVM classifiers	94	Multi-class
Siddesha *et al.*	Wavelet, Gabor, LBP, GLDM, and GLCM for feature extraction and NN classifier	91.43	Multi-class
Patil S. *et al.*	Mobile Net	100	Binary
Proposed model	CNN	97.33 (5-fold) 98.34 (10-fold)	Multi-class

an AUC of 1, which shows excellent performance of the CNN model. On the other hand, from Fig. 12 (c) and (d), it is seen that the value of AUC for *Baad*(0.94) and *Tukada*(0.99) for 5 fold, and *Baad*(0.98) and *Kharad* (0.99) for 10 fold in case of AlexNet respectively. This shows that CNN performs very well compared to AlexNet for areca nut classification.

Bharadwaj *et al.* (2021) used Block-Wise LBP for feature extraction, Otsu thresholding for segmentation, and SVM classifiers for grading and classification of areca nut into four classes and achieved an accuracy of 94%. S. Siddesha *et al.* (2015) used NN classifier for the texture-based classification of areca nut into seven classes and attained an accuracy of 91.43%. Shedthi *et al.* (2023) applied ANN with density features for classifying healthy and diseased areca nuts and got an accuracy of 98.8%. The present researchers, Patil *et al.* (2023) in their previous work for binary classification of areca nut (healthy and diseased) achieved 100% accuracy using the MobileNet model, which is the best among the literature reported. From Table 2, the proposed CNN model outperformed standard AlexNet and literature-reported results with average validation accuracy of 97.33 % and 98.34 % for 5 and 10-fold, respectively.

Conclusion

In conclusion, the proposed study has demonstrated that customized Convolutional Neural Network (CNN) and standard AlexNet architecture can accurately classify five categories of areca nuts. However, the size of AlexNet architecture was quite large compared to the customized CNN architecture. Hence, customized CNN will be more effective considering the required length of the conveyor belt and the required speed of segregation of the nuts when the automated system is designed. The proposed model could be used to further classify areca nuts into more categories, which could help farmers get a valuation of their produce done instantaneously, resulting in faster payments.

Conflict of interest

The authors declare that they have no conflict of interest.

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