CashNet-15:An Optimized Cashew Nut Grading Using Deep CNN and Data Augmentation

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***Abstract*—Since there is a great demand for the quality of agricultural products in the global market. It is very important to improve the quality and standards of agricultural products to competent in the business world. Furthermore cashew is a significant produce in India as well as it takes the major part in the global export market for cashew nut. But the most of the methods proposed for grading system is wouldn't reach the better accuracy. Hence to improve the performance, we proposed the Optimized cashew nut grading using Deep CNN and Data augmentation. This *CashNet-15* work consists of totally 15 layers of CNN. Here we used 8 convolution layer and 4 Max-poolong layer for feature extraction and remaining are 1 fully connected layer, 1activation function and 1dropout layer. To attain the better performance we used data augmentation methods. To optimize the network, hyperparameter like SGD with Beta momentum and Leaky rectified linear unit was used to reduce the loss function and to obtain the non-linear property.**

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I. INTRODUCTION

Cashew is an important crop in India as well as it plays the major part in the global export market. There is gradual growth in contemporary commerce with the extensive development of high speed technologies. Major reason for the increase in heavy contest is the product quality, which has a great demand for the quality of products in the worldwide global market. The cashews quality was determined by its physical characteristics like shape, texture, size, color, weight and it was sorted into different grades. The different grades of cashews are white wholes, scorched wholes, desert wholes, splits, buts, white pieces, scorched pieces, dessert pieces [2].

Hence grading is an important process among the entire cashew processing stages which provides the standardization in cashew kernels export commodities[2]. Cashew processing includes various stages and they are roasting to take away the external shell, shelling the external shell, peeling and grading [1]. The traditional cashew grading was manual inspection which includes labor demanding, time consuming, lot of variations between workers, complex to predict, ineffective.

A. Research Gap:

Only few algorithms are proposed for cashew grading system in the last decades. Narendra. V.G and Hareesha K.S developed automated model by comparing the morphological features and color features in [3], Hue (H), Staturation (S), Intensity (I) in [7] ,geometric parameters in [6], for classifying the cashew kernels using artificial neural networks. Arun M.O et. al., developed an computer vision based cashew grading system by computing the color distribution features like mean (μ), standard deviation (σ) and skewness(γ) of the cashew nut. It evaluated and compared the accuracies of different classification algorithms [4]. Mayur.T implemented a fuzzy logic based grading system for classifying the whole cashew kernel. In this work the morphological features like length, width, and thickness are extracted and classified using Fuzzy Inference System (FIS) [5].

For the most part of the prior works are based on the color and morphological features of the cashew nut. On the other hand it wouldn't reach the better accuracy and didn't reach the high detection rate. The most important factor is that there exists more number of cashew varieties with different features for each variety. Hence it is complex and very exigent task to classify the cashew kernels.

B. Contribution :

At present time the computer vision based approach and deep learning models are non-destructive method, which provides reliable, sensibly precise, less time overwhelming and cost efficient resolution for many vision recognition applications. Hence to improve the performance, we proposed *CashNet-15,* an Optimized cashew nut grading using Deep CNN and Normalization.

The ultimate aim the proposed work is to classify the white whole and others. The defected cashews, splits, pieces, SW, butts will comes under others category.

The contribution of this work was famed into:

❖ *CashNet-15:* To optimize the conventional CNN some hyper parameters are added in the *CashNet-15* architecture.

❖ To decrease the false rate and to avoid the overfitting issues, data augmentation methods like flip, rescale, shear range, rotation are used.

❖ To optimize the network, hyper parameter like SGD with Beta momentum and Leaky rectified linear unit was used to reduce the loss function and to obtain the non-linear property. It will improve our network performance.

❖ This proposed work will classify Wholes and other (Scorched Whole, splits, and butts, pieces).

The remainder of paper is organised as follows. The related works are described in Section II. In Section III, the proposed method is presented. The Experimental setup and result are presented in Section IV. In Section V provides the conclusion and future work.

II. BACKGROUND

In recent years CNN has evolved in many visual recognition applications and achieved its excellent performance[2]. It is a feed forward multilayer perceptron, which is powerful implementation of deep learning model, used for many image classification, object detection problems. It is computationally efficient with capability of run on any device. It has a three general steps and they are convolution, pooling, fully connected layer. The convolution and pooling layer would be act as a feature extractor. With the traditional network, a new layer called normalization layer was included to attain the better performance. So many different CNN models are developed for visual recognition applications. Most famous CNN models are LeNet [10], AlexNet [8], VGGNet [9], ResNet[12], GoogleNet[11]. The development of various deep CNN for various image recognition and classification has been achieved its excellent results in various fields like remote sensing [21], agriculture [20], manufacturing [16], medical image analysis [19], food products classification[17,23, 25,26] Intelligent traffic analysis system[18]. In [16] the imbalanced classification problems are concentrated and overcome by DNCNN was proposed to detect the fault diagnosis of machinery. Here the ReLU and weight normalization is used for training the DNCNN model. B-CNN was developed in [21] for classifying the hyper spectral images using AL. From the input data this model takes the advantage of spectral and contextual information for classifying the hyper spectral images with the help of AL. In field of medical image analysis CNN is used as feature extractor in [13] for classifying the breast density and in [14] it is for recognising the epidemic pathogens. For optimizing the CNN architecture in data augmentation is used for classifying the coral texture images [15] and for identifying the real world species [24]. In [17] the spatial pyramid pooling layer was used with changed receptive fields and strides to manage the density of the network for classifying the foods. RGB, HSV, CIE xyz, CIE lab, are the different color spaces were used in [18] to recognise the color of the vehicle by developing 16 layers of CNN. The CaffeNet network was used for detecting the weeds in the soyabeans crops in [20] with overall accuracy of 98% and it was compared with adaboost, SVM, and random forest classifier. The exploitation of deep CNN has lead to step forward in visual categorization applications like fruits and vegetables grading [26], detecting defects in mango [25], and categorizing different fruits [22].

III. PROPOSED WORK

A. Preprocessing: After capturing the images, it was prepocessoed by three steps. The captured images were croped for the to plcae the cashew at the center point by reseizing the image size into 200 x 200. The wiener filter was used to eliminate the smudge effects. It has lower SNR and higher PSNR. Sobel filter was used to perform the segmentation, which is good in edge detection. Background subtraction method was used to separate the ROI from the background. The details about the dataset is given in table1.

TABLE1: DETAILS ABOUT THE DATSET

SI.NO	Purpose	Count
1	Description	Binary classification
2	Classified	Wholes and others
3	Training set	600 (W-250 , O-350)
4	Validation set	300 (W150, O-150)
5	Testing Set	100 (W-50, O-50)
6	Total	1000

B. Data Augmentaion: To improve the performance of deep learning model, it is very important to gather large amount data for the traninng the model [23],[22]. Since there is a variation among the shapes of whole cashews and others, which could lead to subjective near to some grades. Here we performed some four transformations to relatively increase the dataset and to attain the different factors of the dataset; the transformations are flip, rescale, shear range, rotation. The values of the data agumenation methods are given in the table2. The image size is rescaled to 1/255 from the original image. The range for applying shearing transformations is 0.1. The range for zooming the images is 0.1. The boolean variable 'True' is used for both horizontal anf vertical flip. The range for applying rotation for the images is 60 degree.

TABLE2: DATA AUGMENTATION VALUES

SI.NO	Description	Values
1	Rescale	1/255
2	Shear range	0.1
3	Zoom range	0.1
4	Horizontal / Vertical flip	True
5	Rotation	60

C. CashNet-15 Architecture: There are many existing pretrained networks are available for many image classification applications. The pretrained networks are trained for learning the features for very particular objects or things. To overcome these issues instead of using the pretrained models, a new architecture could be built which included necessary particulars for learning the various features of present problem. We propose a CashNet-15 model for identifying the whole cashew from others. Our proposed architecture CashNet-15 consists of totally 15 layers. Here we used 8 convolution layer and 4 Max poolong layer for feature extraction and remaining are 1 fully connected layer, 1activation function and 1dropout layer. The CashNet-15 architecture was shown in figure1.

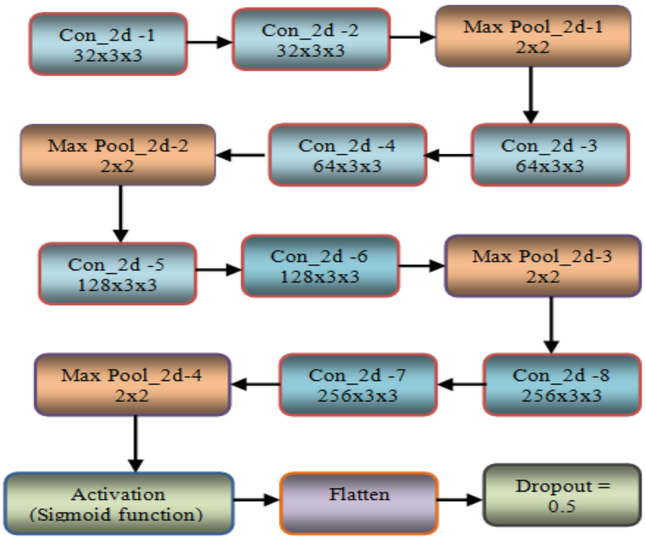

Figure1: Proposed CashNet-15 Architecture

1. *Convolution layer:* Convolution layer is the main building blocks of CNN, which combines the two sets of information [2]. Kernel is a small matrix combined with the input matrix and provides the feature map as the output. To make the model further great, non-linearity property is used and here it was achieved by Leaky Rectified linear unit (LReLu). This activation function could progress the training time and performance by put back the entire negative values into 0.
$$Y_k = f(W_k * x)$$
2. *Pooling layer:* After completing the two successive convolution layers, feature map which is obtained as the output in the previous layer is feed as the input to the polling layer. In this layer the spatial resolution or dimensionality is reduced by performing the down sampling operation. It will reduce the parameters size and could improve the training time. There are many pooling methods are there, they are, max-pooling, min-pooling, average-pooling, mixed-pooling, ect,. In deep learning, max-pooling method is used very frequently, which selects the maximum value in the receptive field for down sampling. In our approach 4 max-pooling layers is used alternatively after 2 convolution layers.
$$Y_{kij} = \max_{(p,q)\in\Re_{ij}} x_{kpq}$$
3. *Fully connected layer:* Last layer is the fully connected layer, which is act as classification layer by using the activation function. Here we used sigmoid function and to avoid the over fitting, the fast dropout method is used. The product of weight matrix and input of the fully connected layer is added with the bias vector. Here the sigmoid activation function is used for binary classification. For multiclass classification, softmax function is used.

IV. Experiments and Results

A. *Materials and Methods:*

The cashew dataset was collected from the local cashew industries. We collected 1000 images of Whole cashew, splits, and butts, pieces, defected through the digital camera. The collected images are splitted into three dataset for training, testing and validation. Deep learning libraries like tensorflow and keras are used to construct, train and test the deep *CashNet* network model. This *CashNet* architecture is deployed in Google Colaboratory platform.

B. *Training:*

It is important to train the *CashNet-15* model. Before training the model we have to determines the networks hyperprameters for efficient trianing. Stochastic gradient descent (SGD) with Beta momentum is used as learning algorithm for training the various features and to minimize the loss funtion. Regularization method is selected for avoiding the overfitting in the networks. Random weight, batch size, epochs, learning rate sholud be selected to determine the time taken to update the parameters, number of samples shown to the network. The details of the hyperparameter was given in table 3. The details of accuracy and loss function obtained during training and validation is given in table 4 and table 5.

TABLE 3: DETAILS OF THE HYPERPARAMETER

SI.NO	Descriptions	Values
1	Image size	200
2	Filter size	3x3
3	Number of filter	256
4	Pooling method	Max-pooling
5	Activation function	LReLu and Sigmoid
6	Initial Learning Rate	0.0001
7	Batch size	17
8	epochs	20
9	Drop out	0.5
10	Stride	1

TABLE 4: DETAILS OF ACCURACY OBTAINED

Accuracy	min	max	cur
Training	0.878	0.934	0.934
validation	0.886	0.977	0.943

TABLE 5: DETAILS OF LOSS FUNCTION OBTAINED

Log-loss	min	max	cur
Training	0.148	0.264	0.148
validation	0.043	0.288	0.079

C. *Performance evaluation:* To determine our performance evalution, we compare our accuracy result with the previous methods. Our proposed model obtaines the overall accuracy of 97.7% for classifiying the whole cashew and others. And we evaluated the accuracy rate by calucalting the Detection rate (D_R) and Error rate (E_R) of cahsews. The performance evaluation for the classification results was given in table 6.

$$D_R = (D_W + D_O / W+O) *100 \%$$

$$ER = (E_W + E_O/W+O)*100\%$$

TABLE 6: PERFORMANCE EVALUATION OF CLASSIFFICATION

	Detection rate (D_R)	Error rate (E_R)
Other (O)	97.45%	0.30
Whole (W)	97.73%	0.27

TABLE 7: COMPARISION WITH REVIOUS WORKS

S. N O	Features extracted	Classification method	Accuracy	Ref
1	Colour	Feed-forward neural network	80%	[6]
2	morphological features	Multi-Layer Perceptron	86%	[7]
3	16 Morphological, 24colour	Multilayer Perceptron ANN and Back propagation	88.93%	[3]
4	morphological features	Fuzzy logic	89%	[8]
5	Texture	Multilayer feed - forward neural network	90%	[11]
6	color, texture, shape, size	Back Propagation Neural Network	96.8%	[5]
7	*CashNet-15*	15 Layers of CNN	97.7%	

V. CONCLUSION

To improve the cashew grading system, we propose *CashNet-15* for classifying the whole cashew and others. Our network uses 15 layers of CNN for efficient classification of cashews. Our experimental results show the accuracy of 97.7% for classifying the cashews. The performance was also compared with the previous works, which attains the highest accuracy was given in table 7. Here we used data augmentation for improve our model performance. We enhance our work by classifying the different grades of cashews and also could discover improved architecture for cashew grading system.

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