International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

A Framework for Grading of White Chali Type Arecanuts with Machine Learning Algorithms

Kusumadhara S, Ravikumar M S, Raghavendra P

Abstract*: Grading of arecanuts before marketing fetches better prize. There are two universally accepted grading systems for arecanuts namely grading at the producers' level and grading at the wholesale traders' level. The major work in this paper is devoted to generation of a standard image database for the White Chali Type arecanuts and constructing a frame work for their grading by exploring the features of White Chali Type arecanut images for the first time. Further, two separate datasets are developed for the above grading systems by employing image feature extraction methods with 3500 and 4132 instances respectively. The arecanuts are graded using popular machine learning algorithms and the results are validated using ten fold cross validation. Multinomial logistic regression as classifier outperformed with classification accuracies of 98.8% and 92.69% for the producers' level and the whole sale traders' level grading systems respectively. Also the performances of various machine learning algorithms for the above two datasets are evaluated using weighted average values of True Positive rate, False Positive rate, precision, recall, F-measure and Cohen's Kappa coefficient.

***Keywords* : Arecanut grading, Cohen's Kappa Coefficient, Cost sensitive classification, Machine Learning.**

I. INTRODUCTION

The arecanut is one of the perennial commercial crops in most of the tropical countries. According to the statistics of Food and Agriculture Organization of United Nations in the year 2017 India's contribution for the world arecanut production is 54.07 %. The other major contributors in decreasing order of their contribution are Myanmar, Indonesia, Bangladesh, China, Sri Lanka, and Thailand [1]. In India arecanuts are marketed under three categories, such as Raw arecanuts, Red Boiled Type (RBT) arecanuts and White Chali Type (WCT) arecanuts. These categories differ in their method of processing. Consumers generally prefer either RBT or WCT arecanuts which are the dried kernels of Raw arecanuts, while in the East of India consumers mostly prefer Raw arecanuts. Grading of arecanuts according to their quality fetches good market prize. At present arecanuts are graded manually, which is laborious and requires skilled labors.

This paper presents a frame work for grading of WCT arecanuts using machine learning techniques. The algorithmic approach for grading also helps to establish common understanding and trust among producers, traders and customers.

Ajit Danti and Suresha M discussed machine vision techniques for classification of Raw arecanuts using three sigma control limits on YCBCr images of Raw arecanuts. They also discussed the classification of RBT arecanuts using kNN and decision trees [2], [3]. Still, to the best of authors' knowledge no frame work is outlined for grading of WCT arecanuts. There are two universally accepted grading systems for arecanuts such as traditional grading or grading at the producers' level and commercial grading or grading at the wholesale traders' level. This paper deals with both the producers' level as well as wholesale traders' level grading of WCT arecanut produce of South Canara district in India. The arecanut produce of this region is regarded as Grade –1 arecanut as no region in India other than South Canara district produces a durable and qualitative WCT arecanuts [4].

II. WCT ARECANUT GRADING SYSTEM

Grading of arecanuts is an art as there are large intra class variations and low inter class variations among few classes. Hence grading is mainly affected by skill and knowledge of classifying labor. In addition, there are slight variations in grading methods among the producers, local retail merchants, whole sale traders and the consumers. Among several organized arecanut marketing boards in India, Central Arecanut and Cocoa Marketing and Processing Co-operative (CAMPCO) Ltd. is the largest WCT arecanut marketing board with a network of more than 400 co-operative societies [4], which was established in the year 1973. Hence to obtain an authentic knowledge of arecanut grades, a large number of samples under each class are collected from CAMPCO Ltd. branches located at 14 distinct geographical locations of South Canara district in India. The grading of arecanuts according to producers' level and wholesale traders' level are explained in the following sections.

Manuscript received on February 10, 2020.
Revised Manuscript received on February 20, 2020.
Manuscript published on March 30, 2020.

* Correspondence Author
Kusumadhara S*, Department of Electronics and Communication Engineering, K V G College of Engineering, Sullia and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. Email: kusumadhara5@gmail.com
Ravikumar M S, Department of Electronics and Communication Engineering, K V G College of Engineering, Sullia and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. Email: perajeravi@yahoo.com
Raghavendra P, Senior Manager, CAMPCO Ltd., Sullia, South Canara District, Karnataka, India. Email: rpkuntar2233@gmail.com

A. Producers' Level Grading System

Producers generally classify the arecanuts with the decreasing order of quality as, Bazar Chali, Bazar Fator, Bazar Ulli and Bazar Karikoka. The prominent visual features of each class are shown in Fig. 1, however various

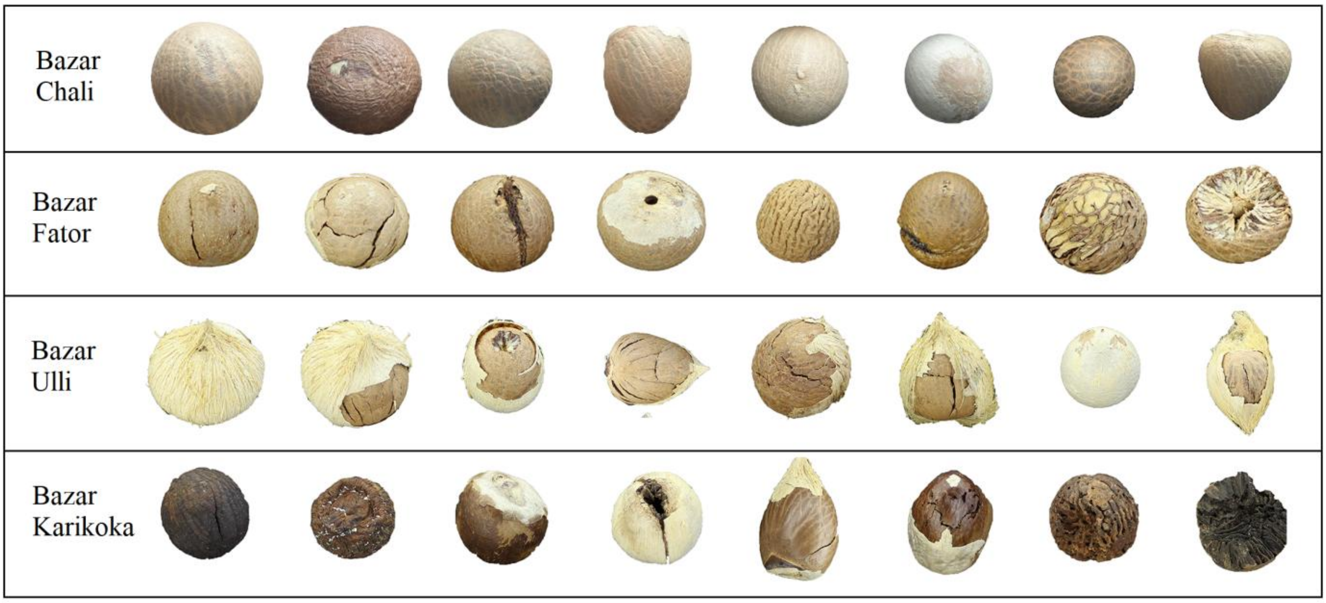

Fig. 1. WCT Arecanut Grading System at Producers' Level

combinations of these features are observed among the samples. Weight is a significant feature in classifying the arecanuts. A low density indicates inferior internal quality. Irrespective of the visual appearance, low density arecanuts are graded into the last category.

B. Wholesale Traders' Level Grading System

The CAMPCO Ltd., the largest WCT arecanut marketing board, follows the grading method adapted by the producers, and in addition it grades the Bazar Chali type as indicated in Fig. 2. The Garbled Rash type is further classified into six classes according to their size. They are Mora, Moti, Vachras (Sevardan), Jamnagar, Jeeni and Lindi in their decreasing order of size. The second quality Bazar Chali with minute cracks and artifacts is classified as Rash Fator. The Rash Fator class is further graded it into six classes as indicated in Fig. 2.

The Koka Fator is the third quality in Bazar Chali and is mainly characterized by little husk over the nuts. Tukda is formed during cutting of Bazar Chali for the purpose of internal quality inspection of pile of arecanuts by the local retail merchants or wholesale traders. The Rejection Fator is nothing but Bazar Fator miss classified by the producers as Bazar Chali.

III. WCT ARECANUT IMAGE DATABASE

A. Image Acquisition

Arecanut being hemispheroidal in shape rests mostly on its face. An image is captured for every 120 degree rotation of a sample. Images are captured using Canon DSLR 1300D camera with arecanut on its stable resting position. Three captured images of a sample with camera placed at 60 degree with respect to the sample plane covers entire surface area of the arecanut except its resting surface. The images are captured with a diffused lighting to have almost uniform illumination.

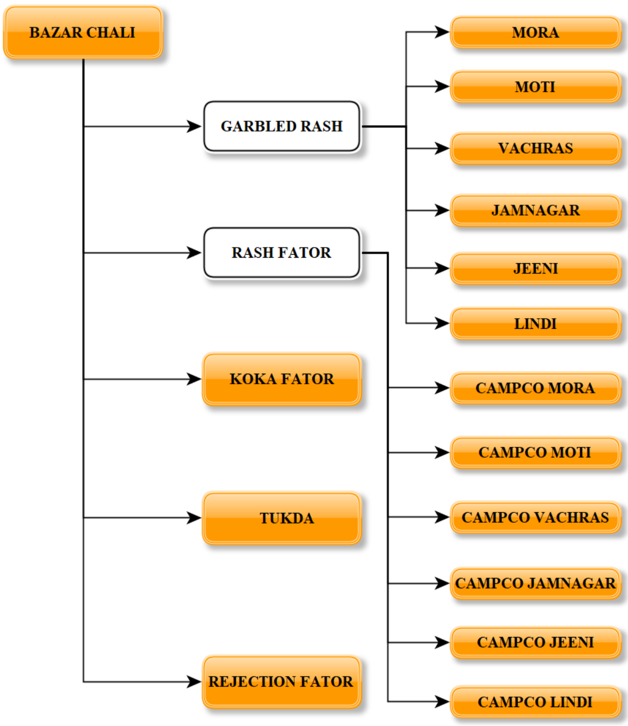

Fig. 2.Bazar Chali Grading System at CAMPCO Ltd.

Fig. 3.Image Aquistion System

A large WCT arecanut image database with 5862 images is generated for the first time. The experimental result shows that an expert human classifier can grade 98.77% arecanuts of the database using arecanut images and their densities. Rest of the portion is miss classified due to unrecognized significant features on the invisible side.

IV. FEATURE EXTRACTION

In fruit or nut grading systems usually a white or black background is set in order to avoid diffusion of background color into the region of interest. Nevertheless, in case of arecanuts both white and black backgrounds lead to a low contrast backgrounds as the arecanut images are almost gray in color and vary from high light to high dark. Segmentation of ROI from a low contrast background is crucial task and affects the performance of the grading system. Hence a segmentation method is designed using morphological filtering followed by active contour, which gives better performance in case of low contrast arecanut images. Then several geometric, color and texture features are extracted from the segmented images. The important relevant features are discussed in the following section.

A. Area Density

The area density of an arecanut can be calculated by measuring its mass and the total pixel area in the region of interest of its image. As area of pixels remain constant, the area density is proportional to mass of arecanut per pixel. It is expressed in grams per pixel. The experimental result justifies that the area densities above a threshold of 3×10^{-5} grams/ pixel have good internal quality.

B. Crack Density

The crack density is one of the major features of Fator class. In order to determine the crack density, the ROI is subjected to thresholding followed by morphological operations such as thinning, dilation and skeleton analysis. The crack density is estimated using equation (1).

$$Dc = \frac{1}{N}\sum_{i=1}^{n} Ai \qquad (1)$$

Where Dc is crack density, Ai is the area of i^{th} crack and N is total number of pixels in the ROI.

C. Haralick Features

These are the statistical measures of normalized Gray Level Co-occurrence Matrix (GLCM) of the given image. The GLCM gives texture information as it represents relation of each pixel with its neighborhood. It is normally computed by scaling the given gray scale image into a fixed number of levels. Fig. 4 illustrates the calculation of GLCM in the horizontal right direction. The rotational invariance Haralick features are obtained by considering average of GLCM in horizontal, vertical, left, right and diagonal directions.

D. RIHOG Features

The HOG features are sensitive to image rotation. To overcome this Minkyu Cheon proposed Rotation Invariant HOG (RIHOG) features [5]. This method involves two steps.

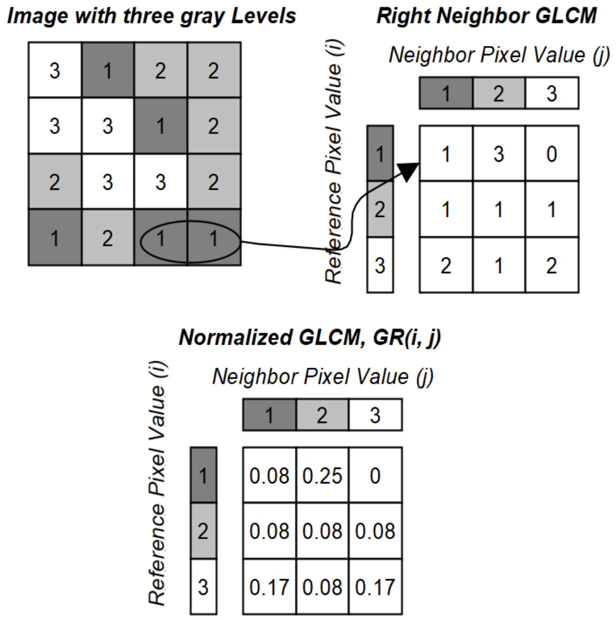

Fig. 4.GLCM in Horizontal direction

First computation of image gradient using two 1D filters [-1 0 1] and $[-1\ 0\ 1]^T$. Second construction of an 8 bin histogram by considering 8 relative orientation and magnitude values between a pixel and its neighboring pixels. The pixels which are 1, 2, 3 and 4 pixels away from the pixel of interest are considered for the calculation of relative orientation and magnitudes. The histograms obtained by these four neighborhoods are then concatenated to obtain 32 bin features.

E. Rotated Local Binary Pattern (RLBP) Features

LBP is a powerful tool to extract texture features, but like HOG, this is also sensitive to image rotation. Mehta R and Egiazarian K proposed methods to obtain its invariance which involves computing the dominant direction and shifting the weights associated with the neighboring pixels circularly with respect to the dominant direction [6].

F. Log Gabor Filters

The Gabor filter for image feature extraction is a sinusoidal plane modulated by a 2D Gaussian function. It can be used to find whether there are any specific frequency components along the specific directions in the region of interest. This is an important feature extractor as the local regions of arecanut image generally differ in their textures leading to inter class similarity.

The advantage of Log Gabor filter over Gabor filter is the elimination of DC component in its frequency response.

It also dynamically changes the frequency scale by over representing the low frequency components and under representing the high frequency components.

V. CLASSIFICATION

In this work, the grading of WCT arecanuts is carried out with machine learning algorithms using Weka workbench [7]. Separate datasets with 830 features are generated for producers' level and wholesale traders' level grading systems with 3500 and 4132 instances respectively.

The performance of the classifiers is evaluated using generally accepted 10-fold cross validation. The classifiers are evaluated with the same number of instances and features, and performances are compared using evaluation metrics such as classification accuracy, weighted average of True Positive rate, False Positive rate, Precision, Recall, F measure and Cohen's Kappa coefficient. The following section gives details of the classifiers used in this work.

A. Multinomial Logistic Regression

The extension of Logistic regression classifier from binary to multi-class classification is done by using logistic model trees which combines the logistic regression and tree induction [8]. This simple logistic regression involves fitting of logistic models by repeatedly calling LogitBoost algorithm for a fixed number of iterations, which is determined by the cross-validation. That is, the iteration is stopped when there is no error minimization in the last heuristic stop.

B. Naïve Bayes

The random numeric attributes may be modeled as nominal attributes by using a supervised discretization called kernel density estimation. Even though this method is more accurate, it is more prone to noise in the dataset. Hence a Gaussian distribution model is assumed for the random numeric attributes.

C. Linear Discriminant Analysis (LDA)

There are total of 6 and 15 classes for producers' level and wholesale traders' level grading systems respectively. LDA uses a multivariate Gaussian distribution on each class to find the feature subspace. These distributions are obtained by pooling the covariance matrices for each class that maximizes class separability. Then it uses Bayes' rule for classification.

D. k Nearest Neighbors (kNN) Classifier

In this instance based supervised learning algorithm, the optimum value of k which is computed using cross validation are found to be 5 and 6 for producers' level and wholesale traders' level grading systems respectively. This method employed inverse squared distance weighting method for the determination of incoming instance. The indexing method used by the classifier accelerates the search for nearest neighbors.

E. Decision Trees

The C4.5 decision tree is a popular supervised classifier yet highly sensitive to noise in the training data. With 10 fold cross validation it produced 315 and 1941 leaves for producers' level and wholesale traders' level grading systems respectively. On the other hand, Random forest uses bootstrap aggregation ensemble method to avoid the overfitting. One hundred decision trees are used to make the learning more robust.

F. Rule Based Classifiers

The rule based classifiers may be built directly from the data set or from the decision trees. In this work, the performance of RIPPER (Repeated Incremental Pruning to Produce Error Reduction) and PART (Partial decision Tree) algorithms are evaluated, as candidates for direct and indirect methods respectively. The former consists rule generation to cover entire data set and then followed by pruning to minimize the error. It is then optimized to obtain minimum decision list with 33 rules for the producers' level and 136 rules for the wholesale traders' level grading systems. On other hand later constructs a rule in each iteration by partially constructing a decision tree and finding a leaf with maximum coverage. The covered instances are removed from the list for the next iteration. With 10 fold cross validation PART generated 69 and 261 rules for the two grading systems respectively.

VI. RESULTS AND DISCUSSION

The performances of above machine learning algorithms are evaluated for the two datasets by using classification accuracy or observed accuracy metric. Table I and Table II shows the confusion matrices for the produces' level and wholesale traders' level grading systems with multinomial logistic regression as classifier. Further, for better clarity of grading at producers' level, the low density Bazar Ulli which has inferior internal quality is classified as Bazar Ulli2 and all other low density arecanuts are classified as Bazar Karikoka2.

The classification accuracy of the classifier is given by the ratio of number of correctly classified instances to total number of instances. For producers' level grading system, using Table I, the classification accuracy = (1022 + 607 + 497 + 480 + 391 + 461) /3 500=0.988 and for wholesale traders' level grading system it is found to be 0.9269.

The accuracy alone cannot assess the performance of the classifier due to class imbalance of the dataset and hence metrics such as True Positive rate, False Positive rate, Precision, Recall and F measure are useful while evaluating the performance of the classifiers. These are listed in Table III for the above classifier and it reflects that the classifier performs almost the best.

The weighted averages for these metrics are calculated by considering the number of labeled instance under each class and the total number of instances. For example, Weighted average of True Positive rate TPR_{WA} is given by equation (2).

$$TPR_{WA} = \frac{1}{N}\sum_{k=1}^{K} TPR_k \times L_k \qquad (2)$$

where N is the total number of instances in the dataset, TPR_k is True Positive rate of k^{th} class, L_k is number of instances in the dataset labeled as class k and K is the total number of classes.

Another evaluation metric called the Cohen's Kappa coefficient *(Kp)* is often used to assess the performance of classifiers with imbalanced dataset. It is a robust statistical measure for evaluating the classifier performance. It depends upon the Classification Accuracy *(CA)* and the Expected Accuracy *(EA)* and is given by equation (3).

$$Kp = \frac{CA - EA}{1 - EA} \tag{3}$$

Table- I: Confusion matrix for producers' level grading dataset

		A	B	C	D	E	F	PREDICTED CLASS
ACTUAL CLASS	A	1022	15	3	0	0	0	A=BAZAR CHALI
	B	12	607	1	0	0	0	B=BAZAR FATOR
	C	4	2	497	0	0	0	C=BAZAR ULLI1
	D	0	0	0	480	0	0	D=BAZAR ULLI2
	E	1	0	1	0	391	0	E=BAZAR KARIKOKA1
	F	2	0	0	1	0	461	F=BAZAR KARIKOKA2

Table- II: Confusion matrix for wholesale traders' level grading dataset

		L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	PREDICTED CLASS
ACTUAL CLASS	L	12	0	0	0	0	0	3	0	0	0	0	0	1	0	0	L = MORA
	M	0	219	6	1	0	0	1	27	1	0	0	0	1	0	0	M = MOTI
	N	0	8	303	3	1	0	0	0	8	0	0	0	3	0	0	N = VACHRAS
	O	0	3	4	222	5	0	1	1	0	4	1	0	1	0	0	O= JAMNAGAR
	P	0	1	0	4	214	0	0	2	0	2	6	0	5	2	0	P = JEENI
	Q	0	0	0	0	1	303	0	0	0	0	0	0	0	0	0	Q = LINDI
	R	7	0	2	1	0	0	316	6	1	0	0	0	0	6	1	R= CAMPCO_MORA
	S	1	40	3	0	0	0	4	144	10	1	0	0	3	7	0	S = CAMPCO_MOTI
	T	0	0	17	1	0	0	1	4	232	2	0	0	3	4	0	T= CAMPCO_VACHRAS
	U	0	0	0	8	3	0	2	0	3	203	0	0	0	1	0	U = CAMPCO_JAMNAGAR
	V	0	0	1	0	3	0	0	0	1	0	283	0	0	0	0	V = CAMPCO_JEENI
	W	0	0	0	0	0	1	0	0	0	0	0	207	0	0	0	W = CAMPCO_LINDI
	X	0	0	2	4	7	0	4	7	1	2	4	0	258	4	0	X = KOKA_FATOR
	Y	0	0	0	0	1	0	4	3	0	0	0	0	2	371	1	Y = REJECTION_FATOR
	Z	0	0	0	0	0	0	0	0	0	0	0	0	0	1	343	Z = TUKDA

Table- III: Performance metrics for producers' level grading

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
BAZAR CHALI	0.983	0.008	0.982	0.983	0.982
BAZAR FATOR	0.979	0.006	0.973	0.979	0.976
BAZAR ULLI1	0.988	0.002	0.990	0.988	0.989
BAZAR ULLI2	1.000	0.000	0.998	1.000	0.999
BAZAR KARIKOKA1	0.995	0.000	1.000	0.995	0.997
BAZAR KARIKOKA2	0.994	0.000	1.000	0.994	0.997
Weighted Average	0.988	0.004	0.988	0.988	0.988

Table- IV: Comparison of algorithms for producers' level grading

Evaluation Metrics	MLR	Naïve Bayes	LDA	kNN	C4.5	Random Forest	RIPPER	PART
Classification Accuracy	**0.988**	0.7946	0.9571	0.9663	0.9603	0.9511	0.9557	0.956
Kappa statistic	**0.9852**	0.7478	**0.947**	**0.9585**	**0.951**	**0.9398**	**0.9454**	**0.9457**
Weighted TP Rate	0.988	0.795	0.957	0.966	0.96	0.951	0.956	0.956
Weighted FP Rate	0.004	0.046	0.014	0.008	0.011	0.012	0.011	0.013
Weighted Precision	**0.988**	0.806	0.958	0.967	0.961	0.952	0.957	0.956
Weighted Recall	0.988	0.795	0.957	0.966	0.96	0.951	0.956	0.956
Weighted F-Measure	0.988	0.794	0.956	0.966	0.96	0.951	0.956	0.956
Time Taken to build model (seconds)	139.06	**0.07**	2.3	120.75	0.24	1.25	7.59	2.3

Where $$EA = \frac{1}{N^2}\sum_{k=1}^{K} L_k \times C_k \qquad (4)$$

where C_k is number of instances classified as class k. For the confusion matrix shown in Table I, the expected accuracy = 0.189426 and hence Cohen's Kappa coefficient is 0.985196. A Kappa coefficient more than 0.81 is considered to be almost perfect.

The performance metrics of eight candidate machine learning algorithms are tabulated in Table IV and Table V. The Multinomial Logistic Regression as classifier performs best among all the classifiers for both the datasets, however it takes longer time to build the model. From Table IV, it is clear that, kNN, C4.5, LDA, PART and the RIPPER classifiers too exhibit perfect Cohen's Kappa Coefficients.

Table- V: Comparison of algorithms for wholesale traders' level grading

Evaluation Metrics	MLR	Naïve Bayes	LDA	KNN	C4.5	Random Forest	RIPPER	PART
Classification Accuracy	**0.9269**	0.7035	0.7657	0.8926	0.8064	0.8284	0.7694	0.8032
Kappa statistic	**0.9215**	0.6813	0.7486	0.8845	0.7921	0.8156	0.752	0.7886
Weighted TP Rate	0.927	0.704	0.766	0.893	0.806	0.828	0.769	0.803
Weighted FP Rate	0.005	0.022	0.016	0.008	0.014	0.013	0.018	0.014
Weighted Precision	0.926	0.714	0.785	0.891	0.802	0.826	0.776	0.802
Weighted Recall	0.927	0.704	0.766	0.893	0.806	0.828	0.769	0.803
Weighted F-Measure	0.926	0.704	0.772	0.891	0.802	0.826	0.769	0.802
Time Taken to build model (seconds)	1609.46	**0.08**	2.71	461.54	0.56	2.93	37.42	12.28

Further, the type I error is unethical in arecanut grading system and type II error leads to loss of profit for the seller. In order to minimize type I error a cost sensitive classification method is employed for Multinomial Logistic Regression classifier. Table VI shows the cost matrix for producers' level grading system to minimize type I error. This leads to a decreased False Positive Rate as shown in Fig.5 and hence the improvement in precision. The classification accuracy of MLR with cost sensitive classification are increased to 98.8857 % and 92.72% for the two grading systems respectively.

Table- VI: Cost matrix for producers' level grading system

		A	B	C	D	E	F	PREDICTED CLASS
ACTUAL CLASS	A	0	1	1	1	1	1	A=BAZAR CHALI
	B	2	0	1	1	1	1	B=BAZAR FATOR
	C	3	2	0	1	1	1	C=BAZAR ULLI1
	D	4	3	2	0	1	1	D=BAZAR ULLI2
	E	5	4	3	2	0	1	E=BAZAR KARIKOKA1
	F	6	5	4	3	2	0	F=BAZAR KARIKOKA2

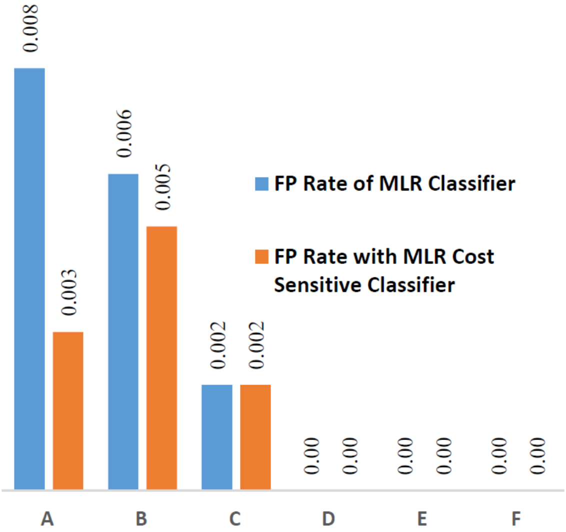

Fig. 5.Comparision of False Positive Rates

Fig. 6.

Further, the validity of size of the datasets are studied by using performance curves.

The performances of MLR classifier are evaluated using 10 fold cross validation by varying the number of instances in the dataset. The learning curves shown in Fig. 6 indicate the data dependency of the MLR classifier. As the percentage of instances in the dataset increases, the classification error becomes almost constant, which implies that the generated datasets are complete and substantial.

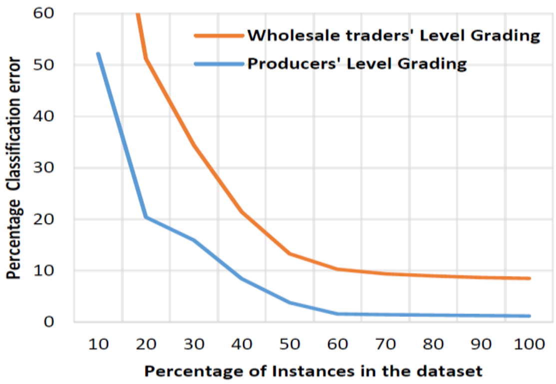

Fig. 7.Learning Curves of MLR Classifier

VII. CONCLUSION

In this work, WCT arecanuts are graded into six classes in producers' level grading system and fifteen classes in wholesale traders' level grading system. Using the general features alone, namely average pixel intensity, crack density and weight fails to classify the arecanuts into such a large number of classes. A deep intervention of WCT arecanut image features and feature extraction techniques resulted in 830 relevant features. Among several machine learning algorithms MLR as classifier performs the best for the producers' level and wholesale traders' level grading systems with 3500 and 4132 instances respectively. Further, by using cost sensitive classification, the classification accuracy of MLR classifier is increased to 98.89 % and 92.72% for the two datasets respectively. The MLR classifier also exhibits an acceptable classification error rate with respect the size of dataset which indicates that the generated datasets are complete and substantial.

ACKNOWLEDGMENT

The first and second authors would like to thank CAMPCO Ltd. Sullia for proving the arecanut samples for the research work and labeling the arecanut images according to the producers' level and wholesale traders' level grading systems. Special thanks are also due to Mr. Anil B V, Associate Professor, K V G College of Engineering, Sullia for his assistance in developing idea of this paper.

REFERENCES

1. Food and Agriculture Organization of United Nations, Rome, 'FAOSAT', 2017. [Online]. Available: http://www.fao.org/faostat/en/#data/QC/visualize [Accessed: January 18, 2020].
2. Danti and M. Suresha, "Arecanut grading based on three sigma controls and SVM", IEEE-International Conference on Advances in Engineering, Science and Management (ICAESM -2012), Nagapattinam, Tamil Nadu, 2012, pp. 372-376.
3. Suresha M and Ajit Danti, "Construction of Co-occurrence Matrix using Gabor Wavelets for Classification of Arecanuts by Decision Trees", International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868 Foundation of Computer Science FCS, New York, USA, Volume 4– No.6, December 2012, pp 33 – 39.
4. Ravindra Kumar, Production and marketing of arecanut a case study of South Canara, Ph.D. dissertation, Sir Parashuambhau College, Savitribai Phule Pune University, Pune, 2003, pp 181-192. [Online]. Available: https://shodhganga.inflibnet.ac.in/handle/10603/174913 [Accessed on: June. 03, 2019]
5. Minkyu Cheon, Wonju Lee, Chang-Ho Hyun and Mignon Park, "Rotation Invariant Histogram of Oriented Gradients." International Journal of Fuzzy Logic and Intelligent Systems, vol. 11, no. 4, December 2011, pp. 293-298, http://dx.doi.org/10.5391/IJFIS.2011.11.4.293, [Accessed: January 18, 2020].
6. Mehta, R & Egiazarian, K, "Rotated Local Binary Pattern (RLBP): Rotation invariant texture descriptor", 2nd International Conference on Pattern Recognition Applications and Methods, ICPRAM 2013, Barcelona, Spain, 15.-18.2.2013. International Conference on Pattern Recognition Applications and Methods, IEEE, pp. 497-502.
7. Eibe Frank, Mark A. Hall, and Ian H. Witten (2016). The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques", Morgan Kaufmann, Fourth Edition, 2016.
8. Marc Sumner, Eibe Frank, Mark Hall, "Speeding up Logistic Model Tree Induction", 9th European Conference on Principles and Practice of Knowledge Discovery in Databases, pp.675-683, 2005.

AUTHORS PROFILE

Kusumadhara S, received his B.E degree in Electrical and Electronics Engineering from Mangalore University in 1999. He received his M.Tech degree in Digital Electronics and Communication from Visvesvaraya Technological University, Belagavi in 2006. He secured 3rd Rank in M.Tech University examination under Digital Electronics and Communication. He has 20 years of teaching experience. His research interests include Machine Learning, Image Processing, Soft Computing and Pattern Recognition. Currently he is serving as Associate Professor in K.V.G. College of Engineering, Sullia, Affiliated to Visvesvaraya Technological University, Belagavi.

Ravikumar M S, received his B.E degree in Electronics and Communication Engineering from Mysore University in 1990. He received his M. Tech degree in Digital Electronics and Communication from Visvesvaraya Technological University, Belagavi in 2002. He received his Doctoral degree in 2012 from Visvesvaraya Technological University, Belagavi. He has 30 years of teaching experience and currently he is guiding six Ph.D scholars. He has been a reviewer for many National and International technical journals. His current research areas are Image Processing, Pattern Recognition and Soft Computing. Currently he is heading Electronics and Communication Engineering Department in K.V.G. College of Engineering, Sullia, Affiliated to Visvesvaraya Technological University, Belagavi.

Raghavendra P, received his master's degree from Mangalore University in 1993. He has served in various capacities at different branches of Central Arecanut and Cocoa Marketing and Processing Co-operative (CAMPCO) Ltd. since 25 years. He has excellent knowledge of grading and marketing of arecanut produce of India. He has worked as marketing manager in CAMPCO's arecanut marketing outlet at Ahmedabad for 4 years and at Kolkata for 2 years. Currently he is serving as Senior Marketing Manager at CAMPCO Ltd. Sullia, in Karnataka state of India.