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Chilli Dryness and Ripening Stages Assessment Using Machine Vision

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Abstract: The quality of chilli is prime concern for farmers, traders and chilli processing industries. The effective determination of chilli dryness and ripening stages are important factors in determining its quality and chilli shelf life with respect to manual estimation of ripening/dryness that are complex and time consuming. Chilli dryness and ripeness prediction at post-harvest stage by non-destructive machine vision technologies have potential of fair valuation for chilli produce for the chilli stalk holders. Chilli pericarp color values calculated from RGB, HSV and CIE-L*a*b* color space, texture properties using edge-wrinkles parameters are described by histogram of oriented gradients (HOG). LDA(linear discriminant analysis), RF(random-forest) and SVM(support vector machine) classifiers are analysed for performance accuracy for chilli dryness identification and chilli ripening stages using the machine vision. The chilli dryness identification accuracies of 83%, 85.4% and 83.5% are achieved using chilli color and HOG features with LDA, Random Forest and SVM classifiers respectively. Chilli ripening stage identification with combined chilli feature set of {color, HOG, SURF and LBP} using Support Vector Machine (SVM) average classifier accuracy is 90.56% across four chilli ripening stages. This work is simple with rapid, intelligent and high accuracy of chilli dryness and ripening identification by using machine vision approach has prospect in real-time chilli quality monitoring and grading. The results yielded were promising quality measurements compared previous studies.

Index Terms: Chilli; Machine vision; Ripening; dryness identification; Color features; Texture features.

1. Introduction

Dry chilli widely used as spice for coloring and flavoring agent for different cuisines. Chilli is associated with health benefits like anti-inflammatory, antarthritic, antioxidants, anticancer, antioxidants and antifungal characteristics and chilli byproducts are used in pest repellants and pesticides [1]. India is catering to half of the world’s consumption demand for dry chilli and is largest exporter of chilli. Red Chilli is produced across India as quality differs from region to region. Chilli with high color value and less pungency quality are known for high oleoresin content (chilli oil). The post-harvest loss of vegetables in the developing countries is about 20-50% [2,23]. Dried chilli doesn't spoil and pose a health risk, as passage of time they lose taste and hotness. As chilli is important commercial crop and most susceptible to postharvest loss due to moisture parameter hence effective chilli dryness identification is need of the hour. Manual ripness and dryness identification are often inconsistent leading to mould growth(mycotoxins/aflatoxins) or discoloration of chilli produce. As currently no tools are available so nondestructive machine vision based approach for chilli dryness identification are appropriate and suitable to reduce the post harvest losses of chilli produce.

As chilli produce can spoil by different ways, it is necessary to apply one of preservation methods to expend the shelf life of chilli. Ripening in same maturity stages guarantees better quality chilli produce of same batch and with good shelf life [3]. The green to red color development in climacteric red chilli is due to transition of chloroplasts to chromoplast. Color and moisture are important attributes. Moisture content is important parameter for storability and dryness of food product [4]. Color is not judged as direct quality attribute but perceived as nondestructive strong physiological maturity parameter. The post-harvest retention of this color is a key trait that governs the price of the produce. The chilli color changes from green to red are measured by devices based on the CIE La*b* color space [5,18].

Food products mostly affected by moisture changes which impact shelf-life and quality when consumed. Dry Chilli attains desirable texture characteristics, when moisture below 10%, Chilli moisture ratio expressed as fraction of 1.00 and defined as water-activity(Aw) defined as: Aw = Ps / Pw. Ps is the vapor pressure of a product, Pw is the vapor pressure of pure water. Aw ranges from 0.00 (absolutely dry) to 1.00 (pure water) [5]. Maturity is highest point of edible quality, related to taste and aroma at consumption.

Moisture Ration with machine vision combined with ML regression methods, gives for effective control on drying process in dryers. A computer vision-based system to recognize maturity of blueberries into mature, intermediate and young, reported an average accuracy of 92.07%, using L*a*b* color and HOG feature attributes. Identifies maturity of blueberry applying template matching algorithm [6,21].

With rapid development of computer vision technology in food industry, visible image is used in detection of texture, color and shrinkage in food products. Solar drying is used for drying chilli [2,3,4]. To decrease moisture of by 10-15% requires 7-20 days based on weather conditions. Machine learning approaches for modeling drying applications have been performed for different fruit products [7, 22].

Destructive and non-destructive methods to identify the fruit ripening stages are reported in literature. Methods of non-destructive fruit ripening stages have advantages to conventional methods. The properties of destructive methods are fruits analytical and chemical features, while non-destructive methods adopt sensors based optical and multispectral properties [8,21]. Most recent research works are based on development of non-destructive methods by considering internal or external attributes like surface color, texture and spectral reflectance are implemented in a computer vision model. Dry chilli pepper classification is increasing in importance owing to international markets offering a price advantage for high-quality products [9,19].

Main objectives of the work are as follows:

- Fast and efficient Nondestructive method for chilli dryness identification and chilli ripening stages classification.
- To create dry chilli and chilli ripening stages datasets.
- Using ML approaches to experiment chilli dryness and assess the ripening stages of chilli based on color, edge and texture features.
- Analyze the chilli dryness and ripening stages classification with different machine learning models

2. Methdology

The aim of work is to study approaches to identify chilli dryness and ripening based on color and texture features using machine vision method. This work has potential scientific way to determine chilli dryness for benefit of growers, traders and chilli processing industries.The proposed model consists of two machine learning models for chilli dryness and chilli ripening stage identification. The input is RGB chilli image and machine learning models predict chilli dryness and ripening stages of chilli.

The algorithm builds color and texture features using training set of 1100 chilli images, details are shown in the next section. LDA, random-forest (RF) and SVM classifier were trained with Color and HOG features to predict chilli dryness of chilli test sample as shown in Fig.5. To detect chilli ripening stages, chilli image with Color, HOG, SURF and LBP vision features and external features were extracted as shown in Table 1, are used with SVM classifier.

A. Dataset

In consultation with experts of Sarpan Agri-Horticultural Research centre Dharwad, the chilli dataset was created. The varieties are labelled according to chilli dryness and ripening stages.The green to red color in red climacteric chilli is due to transformation of chloroplasts to chromoplasts [10]. Different chilli ripening stages are identified as shown in Fig.1.

a)Green b)Breaker c) Red d) DryRed

Fig. 1. Chilli Ripening stages

Table 1. External properties of chilli for each ripening stage.

External properties	Ripening stage	Min	Max	Mean
Moisture (%)	RS1	85%	90%	87.5
	RS2	75%	85%	80
	RS3	75%	85%	80
	RS4	60%	90%	75
Wrinkle-edges	RS1	4456	10135	7295
	RS2	4867	11287	8077
	RS3	14576	15225	14900
	RS4	16845	18133	17489
Pericarp Color				
L∗ (lightness)	RS1	26.1	55.287	40.70
	RS2	15.46	24.45	19.95
	RS3	8.72	16.65	12.685
	RS4	8.96	10.575	9.76
a*(green-red)	RS1	-12.5	-15.63	-14.06
	RS2	-4.5	1.08	-1.71
	RS3	0.44	10.00	5.22
	RS4	8.96	22.67	15.81
b∗ (blue-yellow)	RS1	1.720	26.01	13.91
	RS2	2.176	5.033	3.60
	RS3	-.30	-1.20	-0.75
	RS4	2.5	5.25	3.87

1. Fresh Green stage: The chilli fruits are fully developed but are green and suitable for sending to markets for green chilli mash and green chilli sauce.

2. Breaker/Turning Stage: Some portions of chilli are red or brown and the chilli is not fully ripe. It is most suited for local markets.

3. Red: The fruits develop maximum color and turn red. Such fruits are suitable for red chilli mash and red chilli sauces purposes.

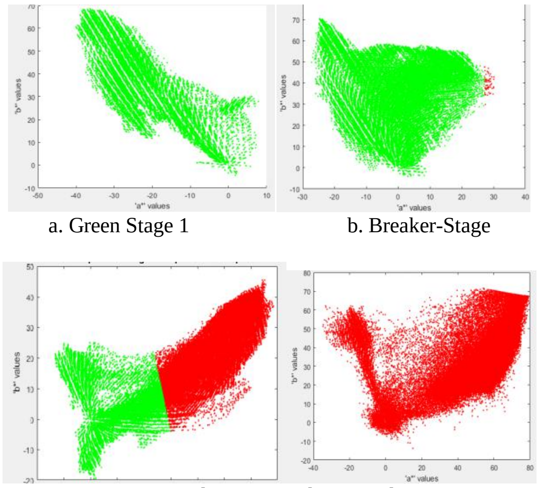
4. Dry Red: Fruits are mature & dry and are suitable for spices & dry red chilli powder which can be stored for a longer period of time to fetch income.

A digital camera with 20 mega pixels was used to capture the chilli images and stored in JPEG format . The images are resized and normalized due computing reasons. Sample dry chilli varieties are shown in Fig. 5. Eleven different dry chilli varieties with different color, texture and wrinkle characteristics are chosen. Two chilli training sets are created for chilli dryness and for chilli ripening stage identification.

In the first training set for chilli dryness identification model, 1100 chilli images with a size of 200 X 200 pixels resolution are cropped from 440 chilli sample images. The chilli varieties under varying illuminations are considered for training set. A total of 550 chilli samples which contained in the first month are acquired in the same way after one month of storage. The second chilli training set (for color analysis) contains four ripening stages (Fresh, Breaker, Red-mature and Dry chilli), around 450 samples for every class are considered. This work uses Otsu method for preprocessing to achieve good identification accuracy as shown in Fig.2, which shows color scatter plot and mapping of color pixels.

B. Chilli color and edge features

Using a* and b* components of La*b* model and chilli ripening stage images after background segmentation as in Fig. 3. The chilli wrinkle edges are also considered as shown in Fig.4, using.



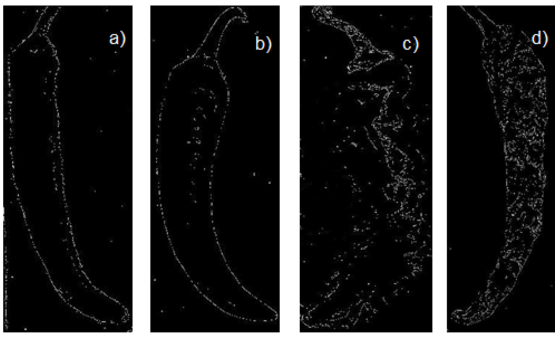
a. Green Stage 1 b. Breaker-Stage

c. mature red stage d . Dry red stage

Fig. 2. Chilli Ripening Stages color scatter plot in a*b* space

a. RS1 b. RS2 c. RS3 d. RS4

Fig. 3. Chilli Ripening stage images after background segmentation.



a. Green-stage b. Breaker-stage c. Mature-red d. Dry-red

Fig. 4. Chilli wrinkle edges for different ripening

C. Hog features

Texture features are wieldy applied for object recognition. Problems in texture feature extraction are due to variations in image resolution which leads to texture error, illumination problems, texture window and computational cost that affect the process of texture analysis.

Histogram of Oriented Gradients (HOG) algorithm detects and computes gradient orientation in chilli image and generalizes so that, same chilli sample produces similar feature descriptor for different conditions. Chilli samples have wrinkles on surface and consists irregular gradient frequencies and surface orientations in pericarp region of chilli.

Fig. 5. Dry Chilli Varieties.

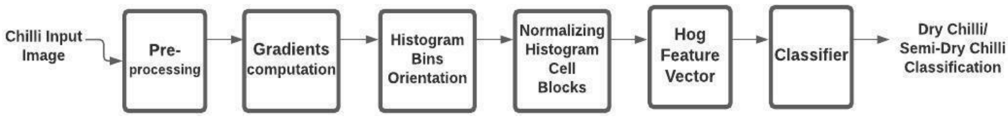


Fig. 6. Chilli HOG Feature Extraction process

HOG concept in this work is applied for extracting edges of chilli sample image. After applying normalisations it is found that they are invariant for shadowing and illumination effects. HOG feature extraction process is shown in Fig. 6.

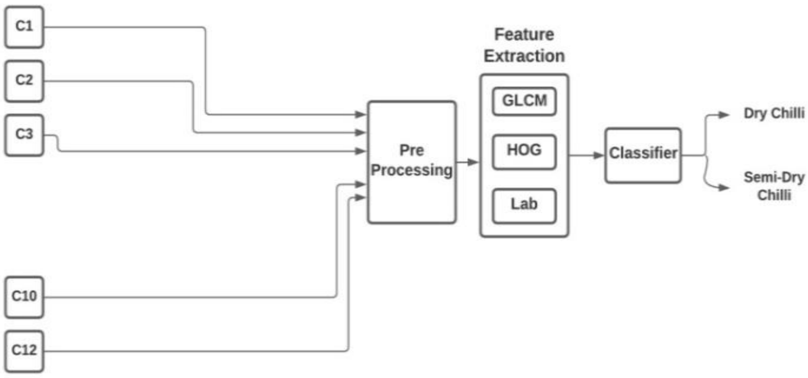


Fig. 7. Flow chart for Chilli dryness estimation.

In the first step, the chilli color image is reduced to gray image to make hog descriptor. In the second step, chilli scalar image used to convolve the gradients Gx and G_y with gradient masks Mx and My with chilli raw image I, as per Eqs. 1 & 2 which are later provided to histogram. We compute the gradient magnitude $|G(x,y)|$ and gradient direction $\phi(x,y)$ for pixel as per Eqs. 3 & 4.

$$Gx = Mx * I \ , \ Mx = [-1\ 0\ 1\ ] \quad (1)$$

$$Gy = My * I \ \ , \ My = [-1 \ 0 \ 1\ ] \tag{2}$$

$$|G(x,y)| = \sqrt{Gx^2 + Gy^2} \tag{3}$$

$$\theta = \tan^{-1}[gx]/[gy] \tag{4}$$

In the third step, cell histograms are created and normalized. The image is divided into cells of size 8 X 8. Each cell will have a defined number of pixels and then the histogram of gradients of each cell is computed. It is observed that the histograms spread evenly over 0◦ – 180◦. The normalization is applied to eliminate the illumination variations by considering 2x2, 4x4, 8x8 block size**.**

In the fourth step, the feature vector of HOG is computed by concatenation of feature vectors of all blocks in an image. A vector of chilli features is generated. HOG feature length, N, based on image size and the function parameters is given by Eq(5):

$$\mathrm{N} = (\frac{size(l,1)}{cellsize} - 1) \ \mathrm{x} \ (\frac{size(l,2)}{cellsize} - 1) \ \mathrm{x} \tag{5}$$

Block size x Num-Bins

For object detection HOG features are widely used [15,27]. HOG divides the image as square cells and computes HOG gradients of each cell, normalizes using a block pattern and returning a descriptor of a cell[11]. Squared stacking of cells used as image window descriptor for chilli detection as shown in Fig 12,applying SVM classifier.

D. LBP Features

Local binary pattern is simple texture operator that labels image pixels by thresholding each pixel in neighborhood resulting into binary number. The LBP operator main characteristic lies in its robustness to gray scale illumination variations and computational simplicity [13, 26].

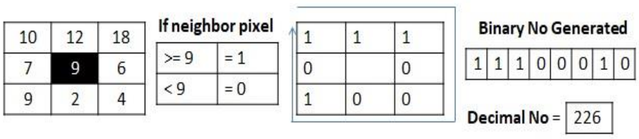
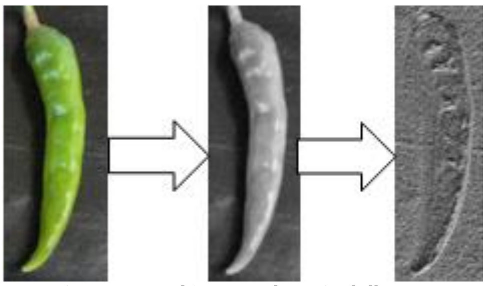


Fig. 8. LBP Feature Extraction process**.**

To compute the LBP value of the center pixel shown in Fig 8, we begin from top-right point and work clockwise, by accumulating the binary values. The binary string is converted to decimal value for all pixels. These values are stored in the output LBP 2D array, which we are shown in Fig. 9.



a)Input image b)*Grayscale c) Chilli LBP*

Fig. 9. Chilli LBP representation.

E. Surf features

For local, similarity invariant representation and comparison of images a fast and robust Speeded Up Robust Features(SURF) algorithm used[16]. The SURF uses box filters for fast computation of operators as in Fig. 10.

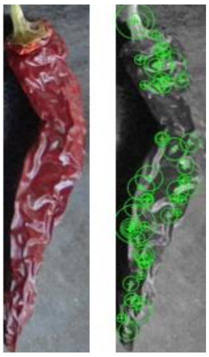


Fig. 10. Chilli SURF Key Points.

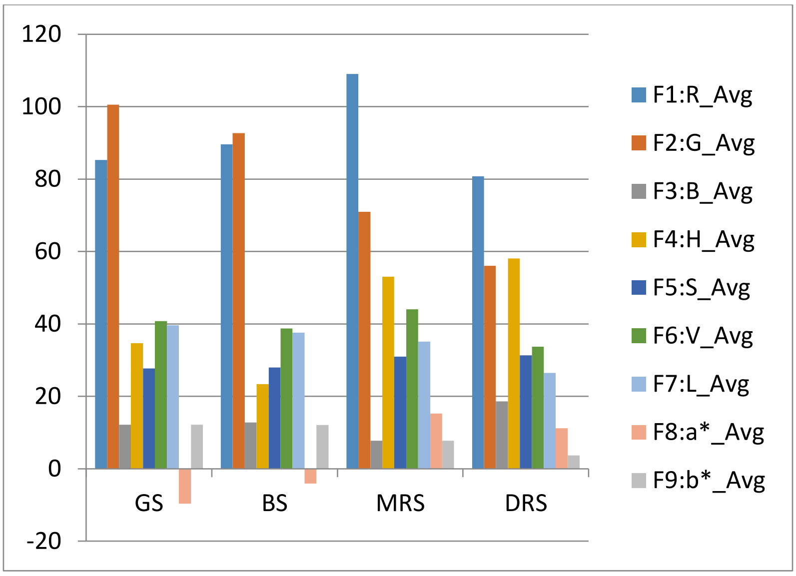


Fig. 11. Color features plot

F. SVM Classifier

A Supervised Support Vector Machine (SVM) is widely used ML classification algorithm . In Support vector Machine algorithm, each data point is plotted in p-dimensional space as p refers to number of features. The feature values of chilli categories are separated by clear gap. SVM maximizes the distance of hyper-plane and margins of closest data points among two classes called support vectors.These points perform classification by computing hyper-plane that splits the classes.

Each chilli sample image in training set is marked as semi-dry chilli or dry chilli using HOG features. The points of interest n, for chilli training dataset is expressed in form {(Xj, labj) were j = 1, 2, ...n} xj as feature vector and labi ∈ [−1,1] as class label of i^{th} chilli training dataset sample respectively. Each xi is p-dimensional vector computed from HOG features and the hyper plane defined by Eq. (10).

$$f(x) = w.x + m \tag{10}$$

where, w is normal vector to hyper plane. Considering the gap between margin of chilli training features, soft margin is adopted. Parameter 'c' for regulation is set for large or narrow margin checking [17]. Ten-fold validation parameter for better accuracy is adopted.

G. LDA classifier

Linear discriminant analysis used for dimension reduction which is a supervised algorithm,. LDA maintains the class difference of dataset feature space (*m*) into subspace (l) where l ≤ (*m*-1). Statistical properties of chilli dataset are computed for each class. LDA projects the features from higher dimension space to lower dimension [21] using three steps:

i) Compute separability of classes, the mean distance among several classes, known as *between-class variance*.

$$Sb = \sum_{i=1}^{g} Ni(xi - x)(xi - x)T \quad (11)$$

ii) Compute distance between chilli sample and mean of each class, which is known as within-class variance [21].

$$Sw = \sum_{i=1}^{g}(Ni - 1)Si \quad (12)$$

iii) Build lower-dimensional space to maximize between-class variance were as to minimize within-class variance. P is called as Fisher's criterion(lower-dimensional projection).

$$Plda = argw \max \frac{WtSbW}{WtSwW} \quad (13)$$

Where, Sb refers to between-class variance
Sw refers within-class variance.

The LDA model shown in Fig. 13 consists of statistical properties of chilli dataset computed for each class and similar properties are used for multi-variate gaussian variables. Multi-variates given by covariance matrix and predictions are made by applying statistical LDA equation for chilli dataset. Lastly, the feature values are stored in a file to create LDA vector.

H. Random forest classifier

A supervised machine learning classification algorithm random forest, builds the forest with large number of decision trees as an ensemble. Each tree in random forest ouputs a class prediction for the class with maximum votes of trees in forest. The algorithm picks the classification with most votes among the trees in forest [22]. Trained with a "bagging" method, which is a combination of different models to improve overall accuracy.

I. Chilli colour feature analysis

Chilli HOG detector alone cannot differentiate different chilli ripening stages, the chilli regions identified needs processing . Color analysis for chilli identification using chilli RGB images is required. As RGB values are affected due to illumination problems, to address this chilli RGB samples are normalised. Normalised RGB values are transformed using Eq. (14)

$$r = \frac{Rc}{Rc+Gc+Bc}, \quad g=\frac{Gc}{Rc+Gc+Bc}, \quad b=\frac{Bc}{Rc+Gc+Bc} \quad (14)$$

Rc, Gc and Bc represent non-normalized values. Aquino, Diago, Millan, & Tardaguila have reported RGB , HSV and L*a*b* are most used color models for computer vision applications [23]. These color models were analyzed for best suitable model to capture color information for identifying different chilli ripening stages

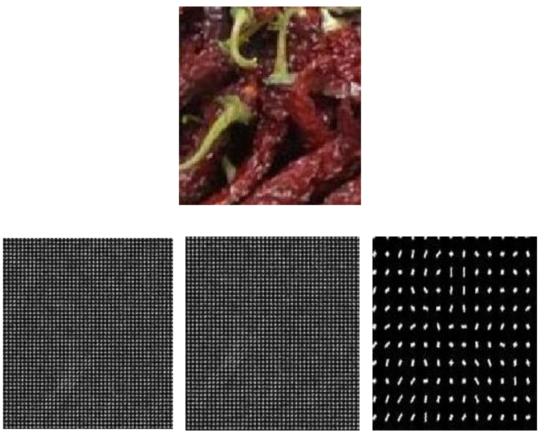


Fig. 12. Chilli HOG Features.

In this work, chilli training set for clustering purpose were normalized using color models like HSV, RGB, and L*a*b*. Each chilli training samples were represented by average values of RGB components for all sample images in training set in normalized space. L and V components of L*a*b* and HSV models were dropped to address the illumination variations.

Average Hue (H), Saturation(S) in HSV, a*chormacity and b*chormacity [25] of L*a*b models respectively are considered for feature extraction as given in Eq. (15) and (17).

$$R_{avg}=\frac{\sum_{i=1}^{n} Ri}{n} \tag{15}$$

$$H_{avg}= \frac{\sum_{i=1}^{n} Hi}{n} \tag{16}$$

$$a*_{avg}= \frac{\sum_{i=1}^{n} a\ i}{n}\ ,\ \ b*_{avg}= \frac{\sum_{i=1}^{n} b\ i}{n} \tag{17}$$

The average values of chilli categories namely, Ravg, Gavg, Bavg, Havg, Savg, a*avg, and b*avg are computed, for n pixels in each training image. Fig. 11 shows the distribution of RGB, HSV and CIE L*a*b* color models for chilli ripening stages.

J. Performance evaluation

Model performances are evaluated for chilli dryness identification and for chilli ripening stages classification. Performance measures are computed using Eqs. (18) thru (23):

$$Recall=\frac{Tp}{Tp+fn} \tag{18}$$

$$Precision=\frac{Tp}{Tp+fp} \tag{19}$$

$$F\_Measure = \frac{(2 * Recall*Precision)}{(Recall+Precision)} \tag{20}$$

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{21}$$

$$False\ negative\ rate = \frac{fn}{tp+fn} \tag{22}$$

$$False\ positive\ rate = \frac{fp}{fp+tn} \tag{23}$$

False negative rate or missed rate focuses on classifier effectiveness to classify positive labels. False positive indicate effectiveness of classifier to identify negative labels. Accuracy indicates correctness of the test performed . Tp is (correct identifications)true positive, fp is (incorrectly identifications) false positive, tn is (correct rejected)true negative, and fn is (incorrect rejections) false negative.

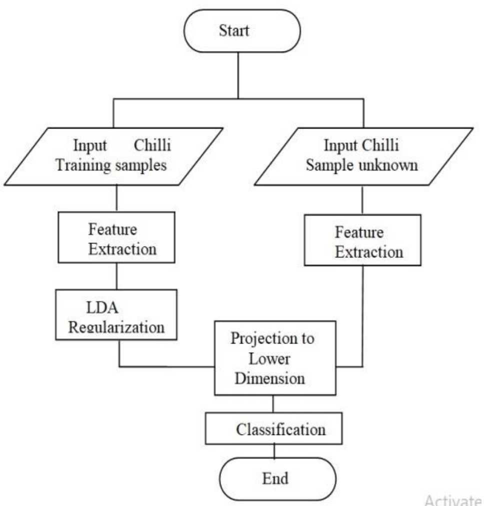


Fig. 13. LDA Classifier Model

3. Results and Discussions

A. Chilli Dryness Model

HOG features are extracted from chilli training set. The chilli samples data is encoded by HOG feature vector. As cell size of HOG affects, the information coded in the feature vector by visualizing HOG chilli detector of different cell size parameter. The visualization of HOG features for chilli ripening stages with different HOG cell sizes are shown in Fig.11. From the generated HOG features, we can observe that 2X2 cell size cannot contribute more about shape information. Likewise 4X4 cell size encodes more shape data thereby increasing the HOG feature vector dimension according to Eq. (5).

The confusion matrix for chilli dryness identification for various dry chilli varieties for second month is given in Table 2 and classification accuracies of LDA, Random forest and SVM are given in Table 3. Random forest classifier has yielded highest performance with 85.40% accuracy.

Table 2. Confusion matrix for chilli dryness for second month.

BN	81	2	2	2	4	0	0	0	3	3	3
BMD	1	87	5	4	1	0	0	0	1	1	1
BD	1	3	91	3	1	0	0	0	0	1	0
BSP	1	1	3	91	1	0	0	0	1	1	1
GNT	1	1	1	2	88	1	2	1	1	1	1
JLP	0	1	1	2	3	84	4	3	2	0	0
JWL	0	0	0	2	3	3	86	3	3	0	0
KSR	0	0	0	1	2	2	3	90	2	0	0
MND	1	1	2	2	2	0	2	3	82	3	2
RSP	2	2	2	2	2	2	2	2	2	79	3
SMK	0	1	1	2	3	1	0	0	1	1	90

Table 3. Chilli dryness identification using LDA, SVM & Random forest classifier.

Classifiers	**Recall (%)**	**Precision**	**F-Measure (%)**	**Accuracy**
LDA	83	83	82.90	83.03
Random Forest	86	85.30	84.20	85.40
SVM	85.4	82.70	82.70	83.50

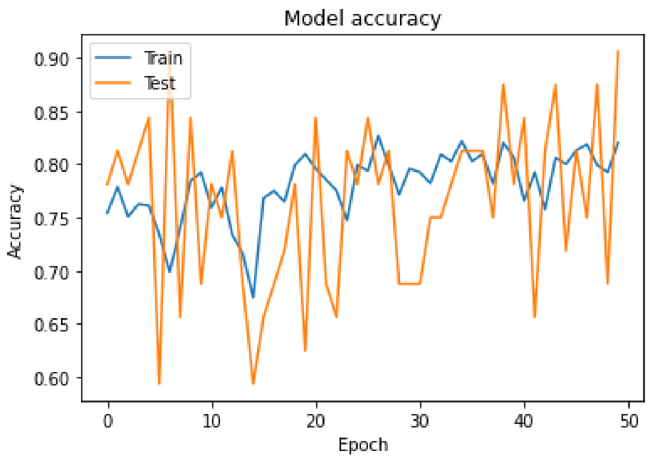


Fig. 14. Random Forest Model accuracy

Training and Testing accuracy plot for random forest as shown in fig 14, we can observe that classification rate is high for random forest compared to LDA and SVM models. Classification accuracy predicts a output class label based on dividing dataset into different and distinct classes based on different dry and semi-dry chilli unseen parameters and new are put to one of output labels.

B Chilli ripening stages identification

The overall performance of SVM classifier for four chilli ripening stages with HOG features visualization of chilli ripening stages of chilli with different cell size as in Fig 14. Confusion matrixes for chilli ripening stages are shown in Table 4. It is observed from the table that the feature set {COLOR, HOG, SURF, LBP} combined feature set has yielded best classification accuracy of 94.54%. For the feature set {COLOR, SURF, LBP} has the accuracy of 90.56%. is obtained. From Table 5, it is observed that HOG accuracy compared to LBP and HOG + LBP feature is less.

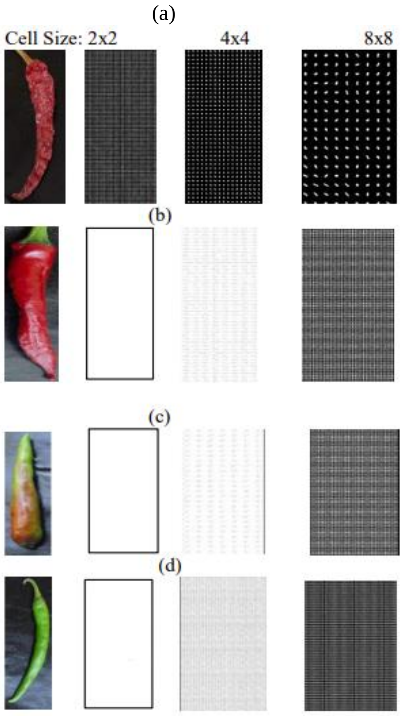


Fig. 15. HOG features visualization of chilli ripening stages of chilli with different cell size, (a) Dry-red stage chilli, (b)Red stage chilli (c)Breaker turning stage, (d)Freshgreen Stage.

The Hog descriptor made of M*N cells covering subimage in a grid. Each cell represented as HOG's, which is number of edge orientation parameters. The histogram cell visualized as a 'star' as in Fig 15(a), reflecting strength of edge orientations in histogram, as specific orientation is stronger, the more relative to others neighbors. Local normalization schemes applied were the cells are normalized with respect to neighbors only.

Table 4. Confusion matrix for chilli ripening for SVM

Chilli Ripening Stages	Fresh Green Stage	Breaker Turning Stage	Red Stage	Dry Red Stage
Fresh Green Stage	430	28	0	0
Breaker Turning Stage	20	419	19	0
Red Stage	0	12	428	01
Dry Red Stage	0	0	03	433

By observing Table 4. chilli ripening stages classified by SVM classifier model and for testing case we considered around 400 images that are unseen by models and the classification was around 95%. For each particular label considered 100 images for testing, Various chilli ripening stages accuracies are Fresh-green stage with 93.54%, Breaker stage with 91.48%, Red mature stage with 97.05 and dry-red chilli with 99.31%. Breaker stage and Red mature stage chilli are overlapping as model confused among label 2 (breaker stage) and label 3 (red stage) detection for few test images. Other classes were predicted correctly as in Table 4.

Table 5. Accuracy, precision and recall based on different chill features set with SVM classifier.

Features	Accuracy %	Precision	Recall
Color	82%	0.827	0.94
HOG	83%	0.83	0.95
SURF	89.56%	0.89	0.95
LBP	82.56%	0.82	0.94
Color+HOG	85%	0.85	0.96
Color+SURF	88%	0.88	0.96
Color+LBP	85.08%	0.858	0.94
HOG+SURF	86.48%	0.864	0.95
HOG+LBP	84.78%	0.847	0.945
SURF+LBP	87.48	0.87	0.945
Color+HOG+SURF	91.6%	0.849	0.947
Color+HOG+LBP	89.5%	0.825	0.943
Color+ SURF +LBP	90.56%	0.845	0.943
HOG+SURF+LBP	90.04	0.847	0.945
Color+HOG+SURF +LBP	94.54	0.88	0.967

4. Conclusion

Chilli dryness and chilli ripening stages work takes two step process to complete the task. In the first step, chilli dryness identification by extracting color and HOG features using ML algorithms LDA, Random Forest and SVM. To identify the chilli ripening stages analyzed Color, HOG, SURF and LBP chilli features using SVM algorithms in step two. The findings of study are:

1) Above study experimented color, edge and textures features of chilli, to identify chilli dryness and chilli ripening stages and results indicates the potentiality for chilli quality assessment of the proposed work.

(2) Chilli HOG feature extraction separates regions of interest from the chilli image. Random forest and SVM classifier were efficient to classify

(3) The CIE La*b* components like a* and b* were used to discriminate four chilli ripening stages: Green Stage, Breaker stage, Red mature stage and Dry red stage.

(4) Analyzed the model performance with different ML algorithms with respect classification performance. Random forest outperformed with 85.3% of accuracy for chilli dryness classification. SVM classifier yielded excellent average accuracy of 94.54% for chilli ripening stages with combined feature set of Color+HOG+SURF+LBP.

The future work to improve dataset and accuracies and to consider above models for chilli and chilli powder classification/grading and in development of android application. Chilli tool can be used by farmers, traders, institutes, exporters and food processing industries to determine and analyze the chilli quality In future work to consider the above model for chilli powder classification and adulteration issues.

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