IoT Based Computer Vision System for Nutrition Management

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Abstract

As people around the globe are becoming conscious about their weight, consume healthy and low calorie food and keep away from obesity, it's an urge to establish a reliable system with high accuracy and efficiency for calorie and nutrition measurement in fruit/vegetable. The proposed model is developed to assist patients and dieticians to compute daily intake of calories. In this approach, 5 different machine learning models are used to predict classification accuracy. Our system includes camera and intelligent mat to capture the picture of the fruit/vegetable, in order to calculate the consumption of calorie. The proposed model achieves 88% accuracy with different testing-training cross validation dataset.

Key Words: Image Segmentations, Image Classification, Neural Networks.

1. Introduction

Obesity in children and adults has almost doubled since 1980, and is considered to be fifth primary risks for the worldwide deaths. The main reason of obesity is consumption of high calorie foods and absence of physical activities. In 2008, one-tenth of the world's population was obese and figure is increased to one-sixth in 2012. According to the 1996 report by United Nation World Health Organization (WHO), in developing countries instead of obesity, starvation is a more challenging task as a big section of the people are below poverty line and cannot afford meals [1]. WHO evaluates that approximately 1.7 million or 2.8% of deaths are due to consumption of too few fruits and vegetables. Further, it estimates that inadequate use of fruits and vegetables in daily diet causes approximately 11% of ischemic heart diseases deaths, 14% gastrointestinal cancer death and 9% of stroke deaths [2]. The Health Behavior in School-aged Children (HBSC) study 2001/2002, which was organized in 33 European and North American countries for the students between the ages of 13 to 15, reported that less than 50% of all young people taking vegetables and fruits in their daily diet [3]. Deficiency of nutrients in diet results in raised chance of various diseases; such as, cardiovascular disease, obesity, scurvy, diabetes or osteoporosis in addition to behavioral and psychological problems.

Research has shown that eating fruits and vegetables reduces the risk of obesity thus lowering the risk of insulin resistance and diabetes as well as make people satisfy with low fat food [4]. Experts have advised to take at least 600g of fruits and vegetables daily [5]. Therefore, development of an intelligent automatic measurement system is required that not only measures the daily amount of calories and nutrition but also intimates if we are lagging behind.

In the present manuscript, we present a system that helps in calculating the amount of nutrients, we get from fruits and vegetables in daily diet through IoT based intelligent calorie measure. Our system uses image processing and classification methods to recognize the food and measures calories and intimates the user about daily/weekly/monthly deficiencies.

The work illustrated in this paper is divided into 6 sections. Section 2 gives a brief review of literature. Section 3 represents the material and method including feature extraction technique. Classification algorithm is represented in Section 4. A proposed measurement technique for fruits and vegetables is discussed in Section 5. Experimental results are introduced in Section 6. Conclusion and discussion is described in Section 7.

2. Literature Review

For measuring calories in daily food intake number of method have been proposed. The fundamental approach for all these methods is similar including image acquisition, enhancement and feature extraction followed by classification. The selection of the image-processing technique and classification strategies are important for the successful implementation of any computer vision system. A survey on latest research during last few years on classification and calorie measurement is summarized in Tab. 1.

Food Item	Method	Feature	Classifier	Accuracy	Author
Rice, Chicken, Vegetables etc.	Calorie and nutrition measurement from food image	Color, Size, Shape, Texture	SVM	90% (using all features) 92% (using 10-fold cross validation)	Parisa Pouladzadeh *et al.* [6]
Bread, Omelet, Vegetables etc.	Calorie and nutrition measurement by using SVM classifier	Size, Shape, Color, Texture	SVM	93.97% (using all features) 92.348 (using 10-fold cross validation)	D.Seles Ponrani *et al.* [7]
Vegetables, Fruits etc.	SVM Based Food Recognition Method	Size, Shape, Color, Texture	SVM	97%	Parisa Pouladzadeh *et al.* [8]
Fish, Corn, Pasta, Vegetables, Fruits etc.	Semi-automatic System For Calorie Measurement	Size, Shape, Color, Texture	SVM	92.21% (using all features) 90.41 (using 10-fold cross validation)	S.Anushadevi [9]
Fruits	Identification and Classification of Fruit Using ANN	Color and Texture	BPNN	92.8%	Dayanand Savakar [10]
Passion Fruit	Computer Vision System for volume estimation	Size, Shape, Color, Texture	ANN	80%	J.Bonilla *et al.* [11]
Fruits and Vegetables etc.	Assistive Calorie Measurement System using Deep Neural Network	Size, Shape, Color, Texture	Deep Learning Neural Network	99%	Parisa Pouladzadeh *et al.* [12]
Fruits, Cakes, Breads and	Mobile Cloud-Based Food	Size, Shape, Color, Texture	Cloud SVM	98.98%	Parisa Pouladzadeh

Vegetables	Calorie Measurement System				*et al.* [13]
Fruits, Cakes, Breads and Vegetables	Calorie Measurement using Distance Estimation	Shape, Size, Texture	Deep Learning Neural Network	95%	Pallavi Kuhad *et al.* [14]
Fruits, Vegetables etc.	Image processing approach for calorie measurement	Size, color, shape	SVM	87%	Gregorio Villalobos *et al.* [15]

Table 1: Literature review

3. Proposed Methodology

The schematic diagram of our system is shown in Fig. 1. As the figure represents the intelligent camera connected with roof and an intelligent mat with calibration hole is placed under it. To calculate the calories in fruit/vegetable it is kept over the mat.

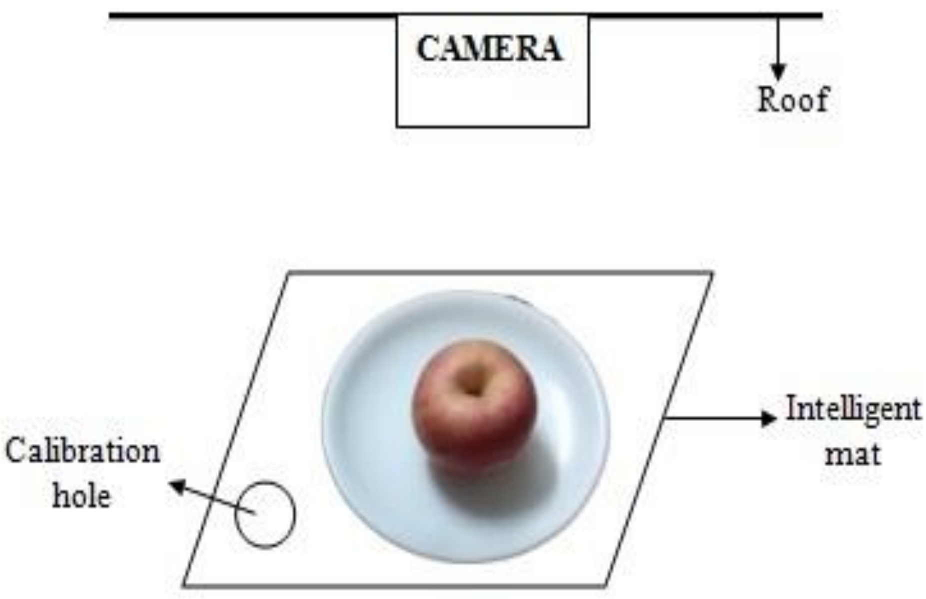


Figure 1: Schematic diagram

The proposed method is divided into several stages as discussed in following subsections, starting with capturing images to final classification. Fig. 2 demonstrates the overall system consisting of five main parts: dataset collection, pre-processing, feature extraction, classification, calorie measurement and intimate through application.

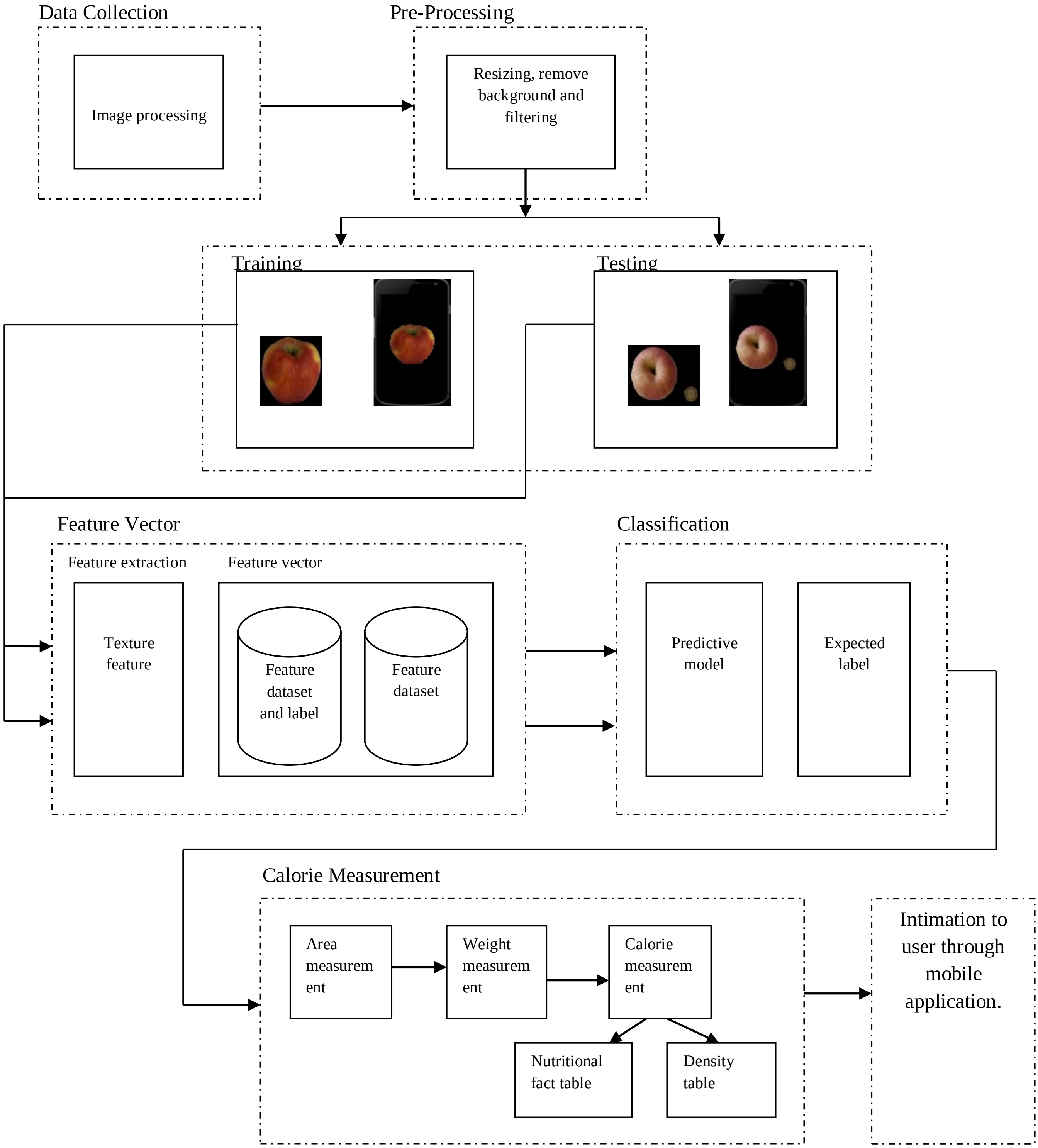


Figure 2: Proposed methodology

3.1. Data set collection and pre-processing

In the proposed work dataset consisting of 450 image of 9 types of fruits and vegetables; such as, apple (i.e. Akane apple, Alkmene apple), orange (i.e. tangerines**,** Mediterranean mandarin), guava (peru), pomegranate, chiku, watermelon, tomato, capsicum, and cucumber is developed. These images are collected from fruit vendors. All original fruit images are obtained in RGB format. The images are captured using 13 mega pixel rear mobile phone camera having resolution 4128 x 3096 pixels under proper lightening condition at different angles and distances to avoid fruit and vegetable image virulent effect of illumination. They are resized to 160×150 with black background. Fig. 3 represents some of captured images.

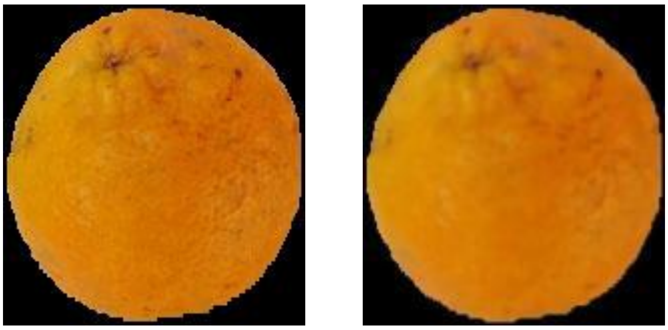
Figure 3: Images of fruits and vegetables with black background

Out of 450 images 356 are used for training and independent set of 94 images are used as testing set to estimate the performance of different classifiers.

Data set (fruits and vegetables)	Number of original images	Number of training images	Number of testing images
Apple	66	51	15
Guava	40	30	10
Pomegranate	55	45	10
Chikoo	40	30	10
Orange	52	40	12
Capsicum	60	45	15
Tomato	52	40	12
Watermelon	40	30	10
Cucumber	45	45	10

Table 2: Dataset specification

The aim of pre-processing is to remove unwanted disturbances and enhance visual aspects of an image. We use nonlinear median filter to eliminate noise from the image while preserving edges [16], refer Fig. 4.



(a) (b)

Figure 4: (a) Original image (b) Image after enhancement

3.2. Feature Extraction

3.2.1. Texture Features

A feature is distinct information, which differentiates one entity from another and differentiates redundant data from the informative data [17].

We use Gray Level Co-occurrence Matrix (GLCM) [18] for extracting texture information. It generates a square matrix of size equal to the maximum intensity and created with frequency of the distinct intensities of grey in the stack. The process is strongly influenced by the direction and pitch of the pixel. Element P(i, j, d, θ) in matrix represents probability of concurrence between two pixels with intensities i and j, respectively. Pixel pattern can exist in four orientations of θ; i.e., horizontal (0°), vertical (90°) and two diagonal directions (45°, 135°) for specified d where d is gap between the pixels of interest. Texture in an image is unequally distributed among its RGB components; therefore, the prominence of features is different in different RGB planes. In the proposed work, 21 texture features are extracted using GLCM for red, green and blue planes, respectively. An example of four configurations of GLCM matrices with d=0 is demonstrated in Fig. 5.

3	2	0	0
1	0	2	3
3	1	0	2
3	0	1	2

(a)

#	0	1	2	3
0	1	1	2	0
1	2	0	1	0
2	1	0	0	0
3	1	1	1	1

(b)

#	0	1	2	3
0	2	0	0	0
1	0	0	3	0
2	1	0	0	0
3	1	1	0	0

(c)

#	0	1	2	3
0	0	0	1	0
1	2	0	0	1
2	1	0	1	1
3	1	1	0	1

(d)

#	0	1	2	3
0	1	0	0	2
1	0	2	0	0
2	0	0	2	0
3	1	0	0	0

(e)

Figure 5: GLCM formation based on a (a) test image along four possible directions (b) 0^0 (c) 45^0 (d) 90^0 (e) 135^0 with a distance d=0.

The GLCM can find up to 14 distinct features, however those calculated in the manuscript for are:

Angular Second Moment, explaining the consistence of an image, given by (1).

$$\text{ASM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i,j)\}^2 \tag{1}$$

Contrast, evaluating the local uniformity in the image, defined by (2).

$$\text{CONTRAST} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)\right\} \tag{2}$$

Inverse Difference Moment, computing the consistency of the image, represented by (3).

$$\text{IDM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \tag{3}$$

Correlation, describing the relation between the pixels and its neighbors; it can be positive or negative, given by (4).

$$\text{CORRELATION} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \tag{4}$$

Inertia, calculates the intensity contrast between the pixels and its neighbor for the entire image, defined by (5).

$$\text{INERTIA} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i-j\}^2 \times P(i,j) \tag{5}$$

Cluster Shade, calculates the skewness of the matrix, defined by (6).

$$\text{SHADE} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i+j-\mu_x-\mu_y\}^3 \times P(i,j) \tag{6}$$

Cluster Prominence, measure the irregularity, defined by (7).

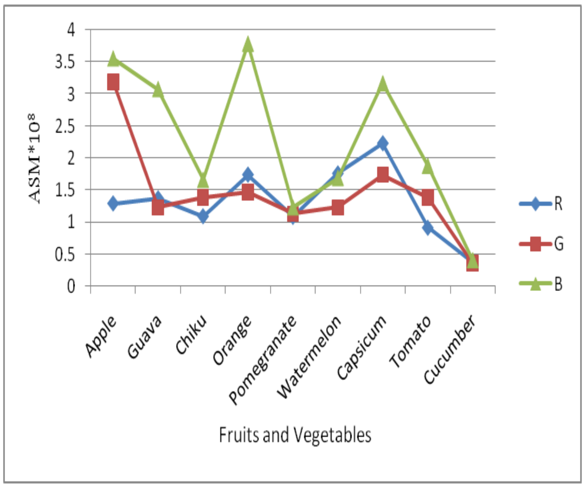
$$\text{PROM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i+j-\mu_x-\mu_y\}^4 \times P(i,j) \tag{7}$$

Features → Fruits and Vegetables		Asm*10^8	Con*10^4	Idm*10^3	-Corr* 10^{-10}	Inertia	-Shade* 10^{16}	Prom*10^{21}
Apple	R	1.29	34.72	23.73	5.37	2582	1590	1380
	G	3.19	34.72	23.83	147	2096	11.1	1.83
	B	3.56	34.72	23.87	246	2042	5.15	0.656
Guava	R	1.37	35.16	23.99	3.42	5468	3180	3440
	G	1.23	35.16	23.86	2.90	5880	4060	4770
	B	3.08	35.16	23.98	77.6	4468	29.5	6.69
Chiku	R	1.09	33.37	22.83	2.88	5368	3910	4610
	G	1.39	33.37	22.89	5.40	4336	1520	1310
	B	1.66	33.37	22.81	11.9	3820	465	26.9
Orange	R	1.74	32.94	22.67	0.80	9050	26300	5870
	G	1.47	32.94	22.49	4.38	5204	2050	1960
	B	3.79	32.94	22.55	460	4132	1.92	0.17

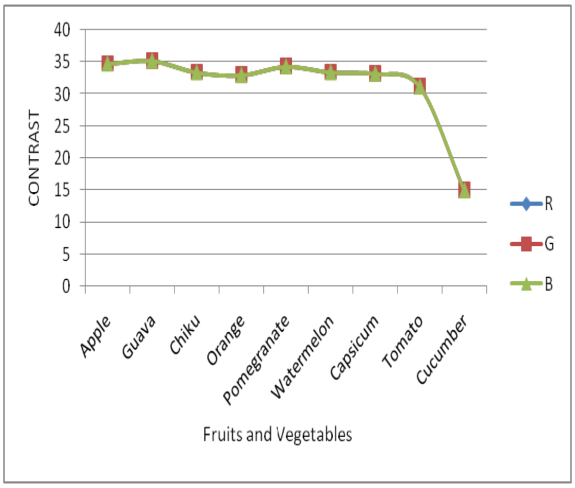
Pomegranate	R	1.08	34.28	23.10	1.12	9794	16600	3140
	G	1.13	34.28	22.97	6.67	6332	1140	881
	B	1.23	34.28	22.83	10.0	6296	617	390
Watermelon	R	1.76	33.39	23.07	8.88	2090	720.96	483.86
	G	1.23	33.39	22.94	3.73	2664	2641.0	2732.4
	B	1.69	33.39	23.05	7.21	2464	985.03	733.56
Capsicum	R	2.23	33.15	22.97	31.10	1538	109	39.1
	G	1.74	33.15	22.84	12.10	1906	452	261
	B	3.17	33.15	22.90	218.0	1606	5.89	0.798
Tomato	R	0.91	31.13	21.42	1.82	3084	7234.2	10719
	G	1.39	31.13	21.76	13.35	1252	364.63	199.57
	B	1.88	31.13	21.640	51.86	1416	47.68	13.24
Cucumber	R	0.37	14.91	10.29	91.22	1126	9.79	2.0522
	G	0.359	14.91	10.29	56.82	1094	19.91	5.28
	B	0.404	14.91	10.32	125.06	944	6.104	1.0923

Table 3: Different texture features values for individual fruits and vegetables

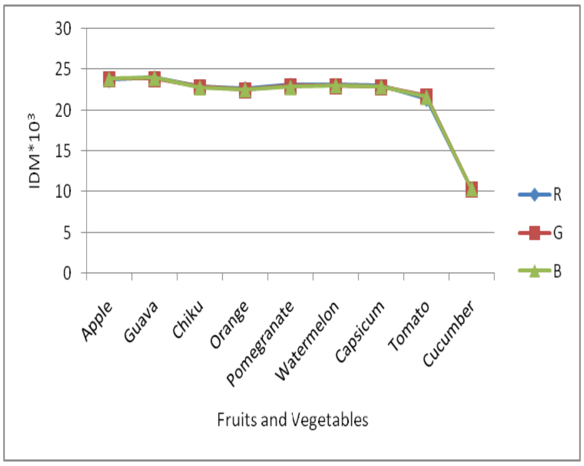
Graphical, representation of Tab. 3. is shown in Fig. 6 in which (a) represents the variation in value of ASM for RGB component of each fruit and vegetables, (b) represents the CONTRAST value which is same for RGB component of particular fruit and vegetable, (c) represents the variation in value of IDM for RGB component of each fruit and vegetables, (d) represents the variation in CORR value for RGB component of each fruit and vegetables, (e) represents the variation in value of INERTIA for RGB component of each fruit and vegetables, (f) represents the variation in value of SHADE for RGB component of each fruit and vegetables, (g) represents the variation in value of PROMINANCE for RGB component of each fruit and vegetables.



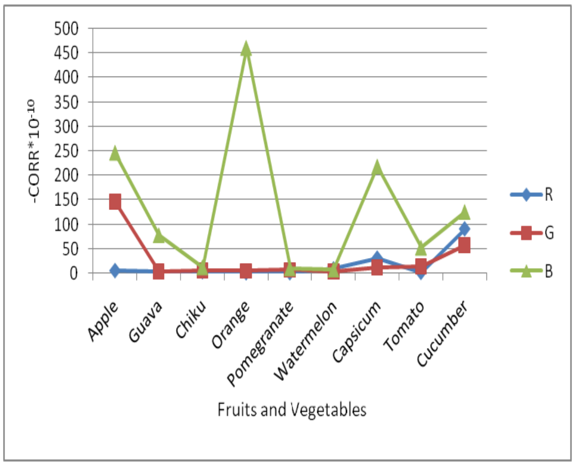
(a)



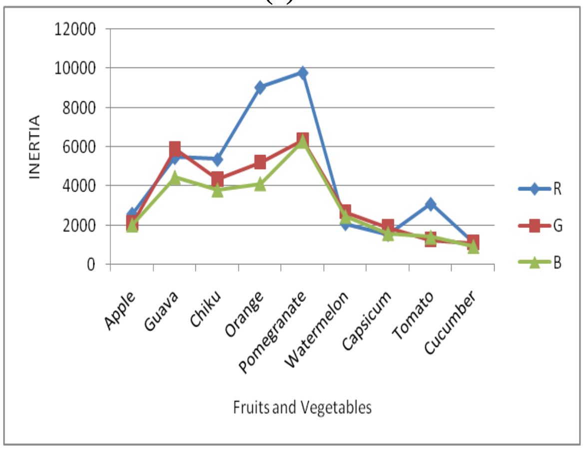
(b)



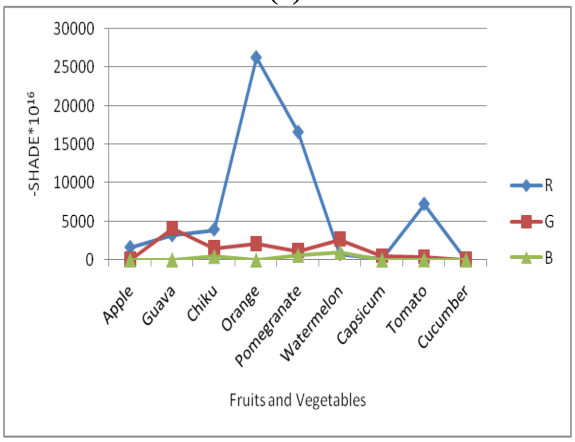
(c)



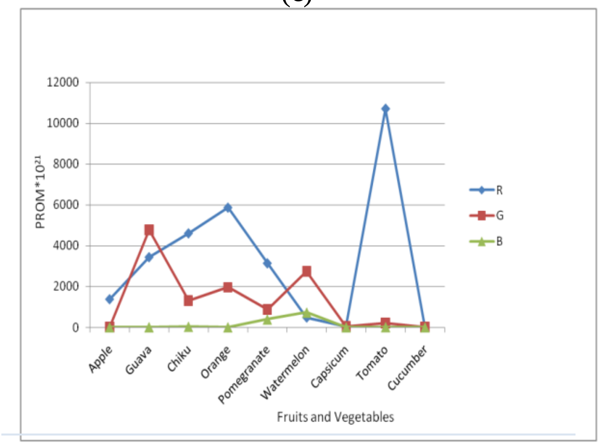
(d)



(e)



(f)



(g)

Figure 6: Illustrate the plot between the GLCM features (a) ASM (b) Contrast (c) IDM (d) Correlation (e) Inertia (f) Shade (g) Prom versus fruits and vegetables.

3.2.2. Color Features

Color is one of the most significant features of fruit and vegetable; it not only identifies a fruit and vegetable but also defines its quality and type. A specific color model or space is used to extract the color feature [19]. In proposed work color moments are calculated with equations (8) and (9)

$$\text{Mean} = \sum_{i=1}^{i=n} \sum_{j=1}^{j=m} x_{ij} / mn \quad (8)$$

Standard deviation = $\sqrt{\frac{1}{mn}\sum_{i=1}^{i=m}\sum_{j=1}^{j=m}(x_{ij}-mean)^2}$ (9)

Where,
x_{ij} is pixel value of i^{th} row and j^{th} column.

Fruits and Vegetables	meanR	stdR	meanG	stdG	meanB	stdB
Orange	126.95	80.53629	44.21364	29.96962	4.921069	12.08431
Apple	67.13089	47.57889	22.08442	20.42097	20.04058	17.71358
Guava	79.73331	57.79211	85.11535	62.81757	23.80249	28.71638
Chiku	90.08063	64.17347	68.17142	48.30125	50.64092	35.45427
Pomegranate	135.6643	97.6562	61.48945	46.6062	51.99663	40.40788
Capsicum	35.40206	27.67329	48.37374	36.46482	21.29362	20.10348
Tomato	112.0463	84.49108	62.225	49.96769	36.46163	30.10033
Watermelon	54.45363	64.71448	79.48808	80.96927	59.40817	64.17226
Cucumber	39.12938	48.98193	47.57528	56.16836	34.74226	44.01197

Table 4: Different mean and standard deviation values for individual fruits and vegetables

Graphical, representation of Tab. 4. is shown in Fig. 7 in which represents the variation in mean and standard deviation values in R, G and B channel for different fruits and vegetables.

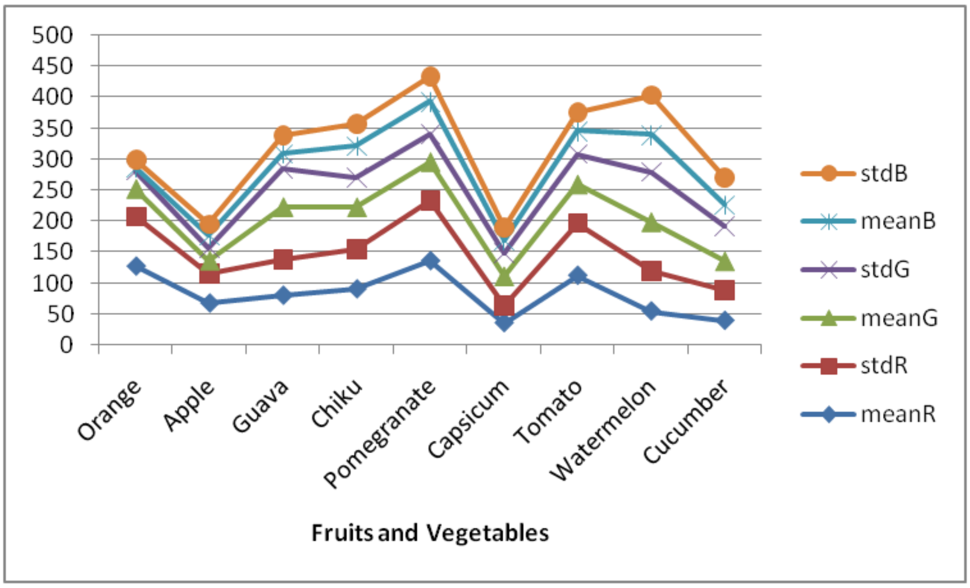


Figure 7: mean and standard deviation R, G and B component of fruits and vegetables.

3.3. Classification

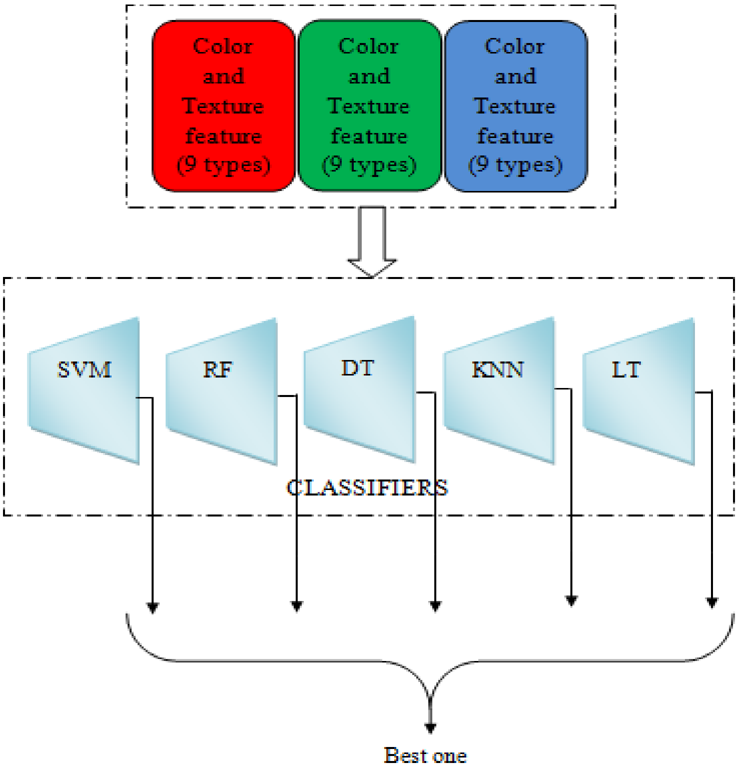


Figure 8: Classification Model

We use 5 classifiers refer Fig. 8, for statistical learning and to compare classifier accuracy. A brief outline of the classifier models used in the present work is:

3.3.1 Decision tree (DT)

It is a tree arrangement which classify input data into one of its probable classes. It is used to extract information by making decision rules from huge amount of available data. ID3 algorithm [20] is used to construct decision tree by calculating entropy and information which is represented by (10) and (11).

$$\text{Entropy(S)} = -\sum_i p_i \, log_2^{p_i} \tag{10}$$

Where, S is dataset, for which entropy is computed, i is set of classes, p_i is probability of number of elements in class i to the total number of elements in S.

$$\text{Gain(S)} = Entropy(S) - \sum_j p_j * I(j) \tag{11}$$

Where, $Entropy(S)$ is entropy of dataset, j is subset created by splitting S, p_j is probability of number of elements in class j to the total number of elements in S, $I(j)$ is entropy of subset j.

3.3.2. Support Vector Machine (SVM)

In SVM classification, data points belonging to different classes are separated by dividing planes. Classification is performed on the basis of margin between the separating planes. The testing data points are then mapped onto same space and prediction is performed on the basis of point cluster [21]. The two functions are used in SVM; i.e. linear and radial basis function (RBF) which is represented by (12) and (13).

$$k(x_i, x_j) = x_i^T x_j \tag{12}$$

$$k(x_i, x_j) = \exp\left(-\gamma \left\| \mathrm{x_i} - \mathrm{x_j} \right\|^2\right), \gamma > 0 \tag{13}$$

Where, x_i and x_j are feature vectors in input space, $\gamma = \frac{1}{2\sigma_2}$ where σ is free parameter.

3.3.3. Random Forest (RF)

Random forest is a grouping of decision tree. It is most popular ensemble technique where methods are not for achieving accuracy but for classification by ensemble of tree, where each tree grows according to random parameter. There is a generalization error in random forest which depends on the strength of each tree in the forest and the correlation between them [22]. Random forest is ensemble of classifiers $h_1(x)$, $h_2(x)$... $h_k(x)$ and training set is drawn from random distribution of the vector X, Y and margin function, defined by (14).

$$m_g(X,Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k\, I(h_k(X) = j) \tag{14}$$

Where, I (•) is indicator function. Margin function gies the extent to which average number of votes at X, Y for the right class is more than average for any other class. Higher margin produces better classification. The generalized error is given by (15).

$$PE^* = P_{X,Y}(m_g(X, Y) < 0) \tag{15}$$

Where, m_g is margin function and X, Y denote the probability over X, Y space.

3.3.4. K-means Nearest Neighbor (KNN)

The KNN algorithm is a process for classifying data based on nearby training examples in the feature pool. KNN is a kind of instance-based learning, or lazy learning where classification is performed on the basis of majority voting to label its k nearest neighbors [23]. KNN converts image into vector of fixed length with real values, we use Euclidean distance to find the distance by equation (16).

$$d(x, y) = \left\| x, y \right\| = \sqrt{(x-y).(x-y)}$$

$$= \left(\sum_{i=1}^{m}((x_i - y_i)^2)\right)^{1/2} \tag{16}$$

3.3.5. Linear Model (LM)

The Generalized Linear Models are expansion of linear modeling process. It expands the idea of regression analysis to a large class of complications concerning the relationship between a response and one or more descriptive variables. These models can be used for the systems which do not follow the normal distribution like chi square, binomial, Poisson, gamma and others. The link function is used when dependent variables is considered to be nonlinearly connected to the predictors [24]. In addition, these models can also be used to estimate the responses having non-continuous distribution and non-linearly related to the predictors for dependent variables. Generalized linear models equation for link linear relationship is defined by equation (17).

$$E(Y) = g(\mu) = \beta_0 + \beta_1 + \gamma + \beta_j x_j \tag{17}$$

Where, β is vector of regression coefficients, $g(\mu)$ is link function used to connect the random or stochastic components of the model.

4. Proposed Measurement Technique

The IoT based intelligent system then estimates the volume of fruit or vegetable and converts it to mass with the help of density tables, and afterwards uses the mass and nutritional fact table to get the overall calories in fruit or vegetable. The two components; i.e., volume measurement and calorie measurement are discussed in rest of present section.

4.1. Calibration and working of the system

In order to calculate the size of fruits and vegetables, a picture of fruit/vegetable placed on an intelligent mat is captured. On the top of Dining table an intelligent camera is connected as shown in Fig. 1. The camera will be connected to the mobile application through a Wi-Fi system. The camera works with a specific mat. The mat will contain small known size hole on it for calibration purpose. The hole will help in calculating the size of the fruit/vegetable. Since mats get spoiled and degrade quickly we have not attached any processing system with it. It will make sure that they are cheap and readily available. The camera will acquire images only when mat is present. The user has to place fruit or vegetable on the top of the mat before eating it. The pictures thus acquired will be transferred to the application where they will be processed and relevant information will be displayed through the application.

4.2. Measurement of Volume

In order to calculate the volume, a picture of fruit/vegetable kept on intelligent mat is captured from the top. The system already knows the area of hole on the mat and hence uses this information to calculate the area of fruit/vegetable. The height of minor axis gives us the depth of fruit/vegetable, which when multiplied by the obtained area gives us the volume of fruit/vegetable

4.3. Measurement of Calorie and Nutrition

The volume of fruits and vegetables measurement in section 4.2 is used to calculate mass of the fruits and vegetables, (equation 18). Once we get the mass, we can easily calculate the amount of calories by using the nutrition fact table [25] given by the health organization.

The mass of eatables, is given by

$$M = \rho V \tag{18}$$

Where, M is the mass of eatable, V is volume of food and ρ is the density of food. In the proposed work aqua-calc [26] is used to calculate the mass from estimated volume.

After calculating the mass of the food system will calculate the calories with equation (19)

$$\text{Calorie in picture} = \frac{\text{Calorie from table} \times \text{Mass in the picture}}{\text{Mass from tables}} \tag{19}$$

5. Experimental Results

5.1. Tools used

During our experiments, we use both Matlab (2015a) and R open (version 3.2.2) software tools on HP Core i3, 2.2-GHz platform.

5.2. Classification model evaluation metrics

Different evaluation parameters are used to measure the performance of the classification process, defined in equation (20), (21), (22) and (23).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \tag{20}$$

$$\text{Recall} = \frac{\text{TN}}{\text{TN+FP}} \tag{21}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}} \tag{22}$$

$$\text{Error} = \frac{\text{FP+FN}}{\text{TP+FN+TN+FP}} \tag{23}$$

Where, TP = True Positive, TN = True Negative, FP=False Positive, FN=False Negative

5.3. Result analysis, comparison and discussion

A classification performance of different machine learning approaches on fruits and vegetables dataset (1) Support Vector Machine (2) K Nearest Neighbor (3) Decision Tree (4) Linear Model (5) Random Forest using texture features shown in Fig. 9.

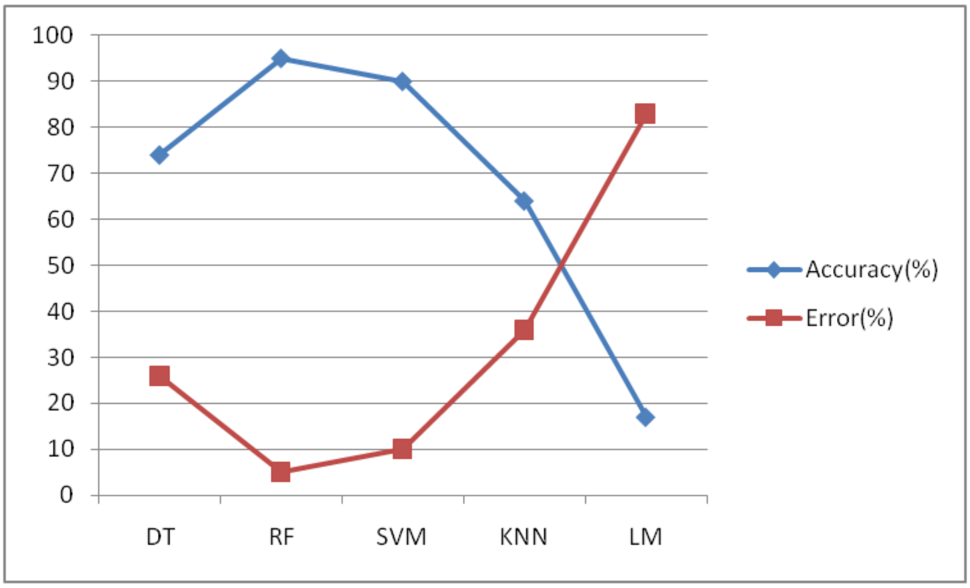


Figure 9: Accuracy and error rate of different classifiers

From Fig. 9 it becomes evident that random forest gives much better accuracy in comparison to Decision tree, Support vector machine, linear tree and K-means nearest neighbor.

Furthermore, the accuracy is calculated for training-testing partition of 50-50, 60-40, 70-30 and 80-20 respectively to verify its uniformity demonstrated in Tab. 5. It shows that random forest performs well in all training-testing patterns.

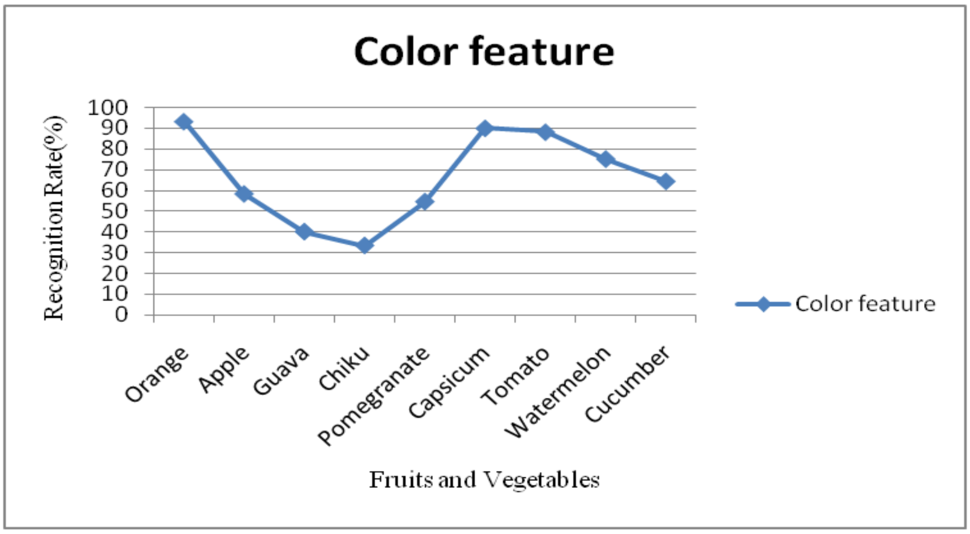
Models	Training and testing partition calculation			
	50-50%	60-40%	70-30%	80-20%
Random Forest	95%	94%	95%	92%

Table 5: Performance comparison on different testing-training partition.

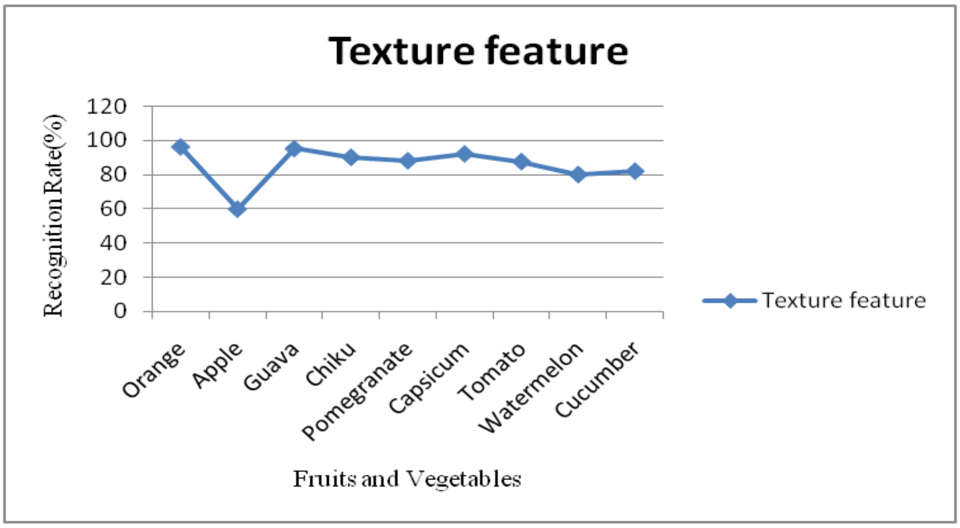
No.	Food items	Using Color Features	Using Texture Features	Using all Features
1.	Orange	93.33	96	98
2.	Apple	58.33	60	50
3.	Guava	40.01	95	95
4.	Chiku	33.33	90	88
5.	Pomegranate	54.54	88	66
6.	Capsicum	90.09	92	95
7.	Tomato	88.23	87.50	92
8.	Watermelon	75.22	80	82
9.	Cucumber	64.40	82	80
Total Average		66.38	85.61	82.88

Table 6: Results of Fruits and Vegetables Recognition Rate

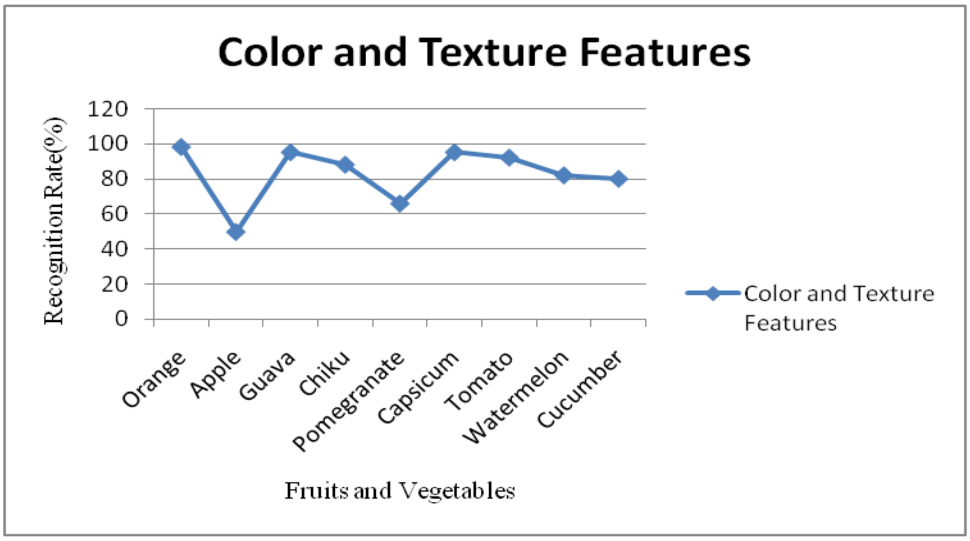
Graphical representation of Tab. 6 is shown in Fig. 10 in which (a) represents the recognition rate of each fruit and vegetable on the basis of color features, (b) represents the recognition rate of each fruit and vegetable on the basis of texture feature, (c) represents the recognition rate of each fruit and vegetable by combining both texture and color feature.



(a)



(b)



(c)

Figure 10: Recognition Rate of Fruits and Vegetables through (a) Color Features (b) Texture Features (c) Both Color and Texture Features

We have calculated the mass of variety of fruits and vegetables by using the proposed technique. Our experimental results, few of which are presented in Tab. 7, show that our mass measurement technique achieves an error of about 24% in the worst case, and less than 3% in the best case.

Items	Calculated Mass(grams)	Actual Mass(grams)	Error percentage
Apple	124	140	11.4%
Pomegranate	267	282	5.31%
Tomato	18.8	25	24.8%
Cucumber	68	70	2.85%
Capsicum	71	80	11.25%
Orange	233	240	2.91%

Table 7: The results of calculating the mass of different types of fruits and vegetables

In order to compute the accuracy of the proposed technique, we have presented two different scenarios. In the first scenarios, technique is applied on variety of fruits and vegetables, and volume are extracted and then by using density table [27] mass is evaluated. With the help of extracted mass, calories in fruits and vegetables are computed using table given by health Canada. In the second one, the real fruits and vegetables is weighted and its actual calories is computed by using table [25]. Finally, the extracted calories from two different scenarios are compared. Tab. 8 shows some of the results.

Items	Calculated Calorie	Actual Calorie	Absolute Accuracy (%)
Apple	70.85	80	88
Pomegranate	113.61	120	94
Tomato	12.03	16	75
Cucumber	20.40	21	95
Capsicum	28.40	32	88
Orange	120.30	124	90
Average Accuracy			88

Table 8: Accuracy of proposed technique in comparison with real values

6. Conclusions

In this paper, we built a measurement method that approximate the amount of calories from an image by computing the volume of the fruit or vegetable from the image and using nutrition facts tables to calculate the amount of calories in fruits and vegetables. As we argued, our system is constructed to help the obese or overweight people, even though normal people can also take advantage from our system by measuring their daily eating of fruits and vegetables without worrying about overeating. We focused on identifying fruits and vegetables in an image by using image processing techniques, classification, volume measurement, and calorie measurement based on identified fruit or vegetable mass and nutrition tables. Our results show reasonable accuracy of our technique in volume and calorie measurement.
An observable work for future is to cover more fruits and vegetables types from a variety of cuisines around the world. Also, more work is required for supporting liquid or mixed food, if possible.

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