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Food Recognition and Calorie Estimation Using Multi-Class SVM Classifier

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Abstract: In this study, an automatic food recognition system using multi class support vector machine classifier is presented. For classification of the food item, four features are considered viz. Size, shape, color and texture. In the works carried out previously, only single food item types were considered but in this study mixed foods are also taken into account. To detect mixed foods, Region Of Interest (ROI) method is used. Since, four important features are considered for classification, this system provides high accuracy. The system is built for food image processing and uses nutritional fact Table for calorie measurement. Three techniques are adopted to extract features. They are: Scale Invariant Feature Transformation (SIFT) method-extracts shape of images. Gabor method-extracts the texture feature. Color histogram-extracts color features of an image. After extracting these features, the image is classified using multiclass SVM to identify the class of provided food image. By finding, the area and volume of the food samples, calorie values are calculated. The multiclass SVM methods like “one-against-one” and “one-against-all” methods are compared with binary SVM against the food samples. Furthermore, the results show that the proposed methods become favorable as the number of classes are increased.

Key words: Food recognition, image classification, feature extraction, segmentation, calorie measurement

INTRODUCTION

The recent results on classification algorithms show that the Support Vector Machine (SVM) classifiers often have higher recognition rates when compared to other classification methods. But, the SVM was originally developed for binary decision problems. Extending it to multiclass problems is not a straight forward approach. Moreover, extending it to solve multiclass classification problem is still a challenging research issue. However, SVMs can be applied to multiclass problems by decomposing it into several two-class problems and can be directly addressed by several SVMs.

Now a days, the number of diabetic patients are increasing worldwide. But there is an inability to access their diet accurately raised the development of this system. Diabetes is a long-term condition that produces high blood sugar levels. Three types of diabetics are identified in the literature (Fei-Fei and Pietro, 2005). The first type is called as type 1 diabetes which is not a hereditary disease type and is mostly found in children. In this type the body doesn’t produce insulin. Approximately 10% of the patients belongs to type 1 diabetic’s cases. In type 2 diabetes, the body doesn’t produce enough insulin for proper function. Approximately 90% of diabetic worldwide are of this type. The third type namely gestational diabetes affects only females during pregnancy. The mostly diabetes symptoms include frequent urination, intense thirst and hunger, weight increase, unusual weight reduction, cuts and bruises that do not heal, men sexual dysfunction, numbness and tingling in hands leg and feet (Kong and Tan, 2012).

Type 1 diabetes: In this case, the quantity of insulin produced is very little. The type 1 diabetes develop for humans before their 40 years of age, often in early adulthood or teenage. Approximately 10% of all diabetes cases are of this type. They can do regular blood tests and follow diet in order to maintain and ensure the required insulin level (Kong and Tan, 2012).

Type 2 diabetes: The body cannot use the insulin it makes or the cells in the body do not react to insulin (insulin resistance). Approximately 90% of all cases of diabetes worldwide are of this type. By measuring the blood glucose level, some people may be able to control their type 2 diabetes symptoms like weight loose. One can control this disease by taking healthy diet, doing required of exercise and monitoring their blood glucose levels.

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However, type 2 diabetes is typical a hereditary and progressive disease it gradually gets worse and the patient will probably end up have to take insulin, usually in the form of tablets. People found overweight and obese in nature have a much higher risk of developing type 2 diabetes compared to those with a healthy body weight (Kong and Tan, 2012).

Gestational diabetes: This type affects females at the time of pregnancy. Some women have very high glucose levels in their blood. Their bodies are unable to produce required insulin to transport all the glucose into the cells which will result in progressive rise in levels of glucose. Diagnosis of gestational diabetic is made during pregnancy period. Most of the gestational diabetes patients can control their diabetes with exercise and diet. In-between 10-30% of them will need to take some kind of blood-glucose-controlling medications.

Proposed work: Intaking food in appropriate calorie is an important health issue for humans. By providing the image of food items, calculation of calorie is an important task in food recommendation system. In this study, an image of a food item is given as input to the system. Then, the image is processed using feature extraction algorithm. On feeding these extracted features to a classifier, it classifies and recognizes the type of the given food item followed by the calorie estimation of the same.

It is observed that various studies make several contributions in the food recognition field. A visual dataset of 120 color images was created in this research. This image dataset contains 6 classes of food image. Based on the above said dataset, we conducted the experiments on the proposed system in order to recognize and estimate the calorie value of the food item.

Literature review: There are many research carried out in the literature on image processing and on food recommendation system. Vailaya *et al.* (1999), Mindru *et al.* (2004) and Almaghrabi *et al.* (2012) proposed a system which captures food item fed to SVM classifier and measured calorie and nutrition of the food. This system uses a calibration card as a reference; this card is placed next to the food while capturing the image, so that the dimensions of the food are known. However, this card must always be present in the photo when the user wants to use the system. The drawback is that the system will not work without this card, which means that in the case of misplacement or in absence of the card, the system does not work.

Wenyan proposed a Light Emitting Diode (LED) which is positioned besides the camera at a fixed distance with its optical axis the camera. The oblique angle distance to the object plane is calculated and the spotlight pattern based on the deformation of the projected image is obtained. The primary drawback of this system is that the algorithm is only suitable for estimating the size of foods that have a planar or nearly planar surface for the for the food items that have a certain known shapes. In each image, the center position and dissimilarity of the spotlight pattern were extracted after binarization by a threshold to make a final decision.

Image segmentation using contour algorithm and food recognition using SVM classifier was used by Villalobos *et al.* (2012). In this system, the user must capture the photo in a special tray (calibration measure purpose). A Personal Digital Assistive (PDA) system is used to capture the food image where patients use the PDA to record their daily food intake information on a mobile phone. But, it has been shown that the result of the portion estimation has significant error and also it takes a long time for the user to record the information. A main drawback of this system is that it does not focus on classification with support vector machines. Moreover, only limited numbers of features were considered for feature extraction and special tray method is not possible to measure calorie value.

Anthimopoulos *et al.* (2014) proposed a dense SIFT which is used to extract key points and feature vector from an image. K-means clustering algorithm is used to cluster similar group of images. The SVM classifier classifies the food class and displays the carbohydrate levels. For a given test image, this system displays the carbohydrate level and also displays the type of food class it belongs to. The main disadvantage of this system is that the mass of food taken is not been considered. Moreover, dense SIFT method considers only less amount of features. Another disadvantage of this system is it only considers single food image to measure the carbohydrate level in the food.

Joutou and Yanai (2009) introduced a real time mobile food recognition application. The recognition accuracy achieved is 81.55% using support vector machine classifier. In their model, support vector machines and Chi square techniques were used in image classification where a user draws bounding boxes over food items appearing in the screen. The bounding boxes are adjusted automatically to the food regions. Estimating the expected food region is not effective and classifier accuracy is not good for practical use. Dataset size used by the researcher s is 50. For some food items which are not able to be recognized, it took longer time to find food names using food recognition.

Puri *et al.* (2009) proposed a pair wise classification framework that takes advantage of the user's speech input to enhance the process of food recognition.

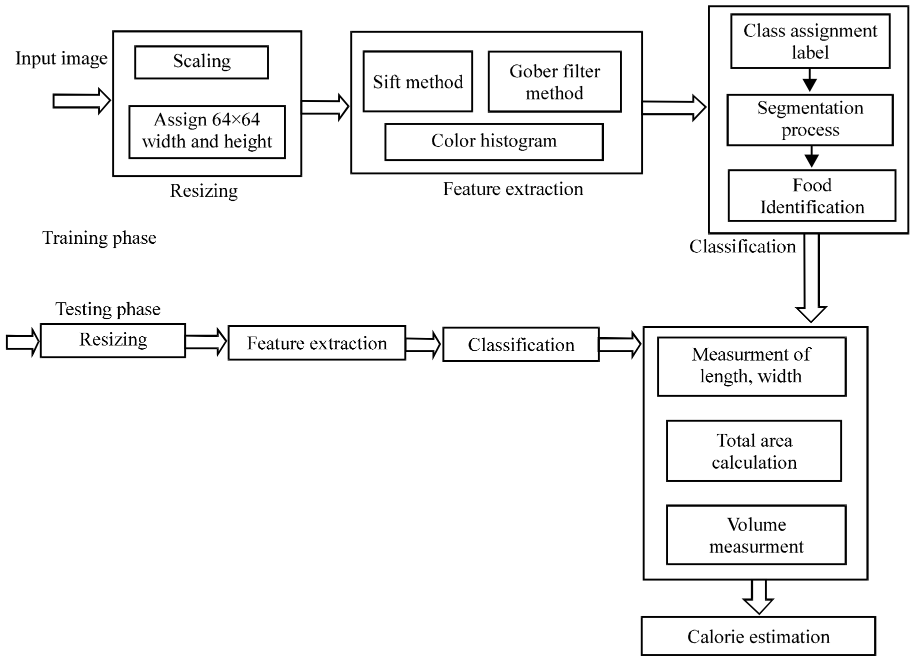

Fig. 1: System architecture

Recognition process is based on the combined use color neighborhood and maximum response feature in a Texton histogram model. The selection of features was done using Adaboost and SVM classifiers. Texton histograms resemble Bag of Feature (BoF) model which uses simple descriptors, such that histograms of all possible feature vector can be used. In this way, the feature vector clustering procedure can be omitted. However, this model considers less information which might not be able to deal with high visual variation. Moreover, the proposed system requires a colored checker-board captured within the image in order to deal with varying lighting conditions. In an independently collected dataset, the system achieved accuracies from 95-80%, as the number of food categories increases from 2-20.

A database of fast-food images and videos was created and used by Chen *et al.* (2009) for benchmarking of the problem of food recognition. Two image description methods were evaluated comparatively based on color histograms and bag of SIFT features for a seven fast-food classes problem. The mean classification accuracy using an SVM classifier was 47% for the color histogram based approach and 56% for the SIFT-based approach. However, the used patches are sampled with the SIFT detector which is generally not a good choice for image classification problems and describe the standard gray scale SIFT that ignores the color information.

The combined use of bag of SIFT, gabor filter and color histograms features in a Multiple Kernel Learning (MKL) approach was proposed by Kong and Tan (2012) for recognizing Japanese food images. However, the BoF model uses the conventional scheme of fixed-size SIFT features clustered with standard k-means algorithm while the additional color and texture features are global and are not included in the BoF architecture. For the problem of 50 food classes, a mean recognition rate of 61% was reported.

A set of color (pixel intensities and color components) and texture (Gabor filter responses) features was used by Zhu *et al.* (2010) together with a Support Vector Machine (SVM) classifier, for recognizing 19 food classes, results in the recognition rate of 94% for food replicas and 58% for real food items. Kong and Tan (2012) proposed the use SIFT features clustered into visual features and fed to a simple Bayesian probabilistic classifier that matches the food items to a food database containing fast-food item images homemade food images and fruits. A recognition performance of 92% was reported given that the number of references per food class in the database is 50 and the number of food items to be recognized is less than six.

In spite of the presence of all these methods, the classification accuracy is not upto the level of suggesting accurate recommendations. Hence, the feature selection and classification techniques must be improved so that better classification accuracy can be achieved.

Hence in this study, multiclass SVM based food image classification is proposed.

MATERIALS AND METHODS

Proposed system architecure: The proposed system architecture consists of five important modules namely, resizing, feature selection, classification, volume measurement and calorie estimation modules as shown in Fig. 1 A photo of the food image is taken with the built-in camera of a smart phone. More specifically, an image of the food is captured and stored with its measurements in the first usage time. This unique method will lead to relatively accurate results without the difficulties of other methods. Food images will be taken with the two food items making it easy to segment the size of the portions. We then apply image processing and classification techniques to find the food portions, their volume and their nutritional facts.

Implementation details

Resizing: First, the input food image is fed to resizingstage. This module resizes image based on width and height. The resizing is done such that the image should have 64 pixels and then all images were rescaled so that their greatest side is assigned as 64×64 pixels which measures the size feature of food image as shown in Fig. 2.

Feature extraction: This module extracts different features of the given image using three algorithms namely SIFT, gabor filter and color histogram method.

Sift method: Scale Invariant Feature Transform (SIFT) algorithm detects and describes local features of an image. Resized image is given as input to feature extraction module. This phase extracts key points and feature vector from a dense grid on the image as shown in Fig. 3 SIFT algorithm is used to extract key points and feature vector. This algorithm consists of four steps (Madival and Vishwanath, 2012).

Scale-space extrema detection: This step searches the overall image locations in order to extract the key points using difference of Gaussian function (Eq. 1) The extracted key points are invariant to scale and orientation.

$$L(x,y,\sigma) = G(x,y,\sigma) \times I(x,y) \qquad (1)$$

Where:

G (x, y, σ) = A Gaussian function

I(x,y) = An input image and L(x,y) is a scale-space function

Key point localization: This step is used to eliminate the low contrast key points from the extracted key points.

Orientation assignment: This step assigns the orientations for each key point locations based on image gradient directions. As a result, the image has been transformed relative to the assigned orientation, scale and location for each feature is used for further operations. The invariance of these transformations is as in Eq. 2:

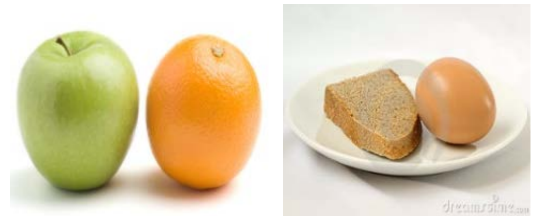

Fig. 2: Resized image

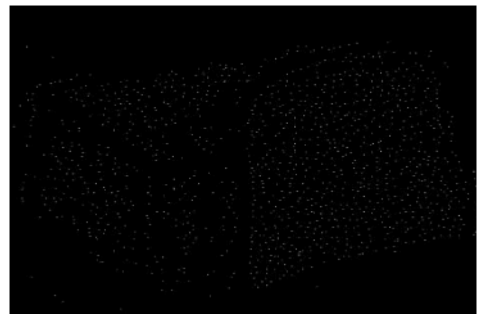

Fig. 3: Extracted shape features

$$\theta(x,y) = \tan -1\left(\frac{L(x,y+1) - L(x,y-1)}{\left(L(x+1,y)\right) - L(x-1,y)}\right) \qquad (2)$$

Where:

L (x, y) = A scale space

θ (x, y) = The pre computed using pixel difference

I (x, y) = An input image

L(x, y, σ)= A scale-space function

Key point descriptor: This step is used to extract feature vector by using key points. Each key point is extracted as 16×16 pixel region and is further divided into 4×4 sub regions using SIFT algorithm. Each sub region has 4×4 array of histogram with 8 orientation points.

Gabor filter method: The feature extraction stage takes resized image as an input. It uses Gabor filter bank method (Madival and Vishwanath, 2012) to extract feature vector. Gabor function is used to extract feature vector based on texture of image. Gabor filter method is used to segment the image based on texture features as shown in Fig 4. This algorithm consists of three steps.

Filtering: Gabor filter is suitable for images where the texture features are contained by subjecting each image to Gabor filtering operation oneach pixel around window. Then, the mean and the standard deviation of the energy of the filtered image is measured. The size of the block is proportional to the size of the segment:

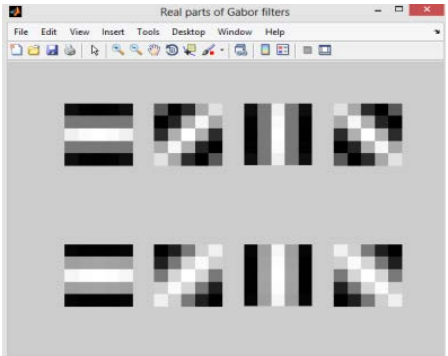

Fig. 4: Extracted texture feature of food image

$$G(x, y, \theta, u, \sigma) = 1/2\pi\sigma^2 \exp\left\{-x^2 + \frac{y^2}{2\sigma^2}\right\} \exp\left\{2\pi^i (u \times \cos\theta + u y \sin\theta)\right. \quad (3)$$

Where:
σ = Standard deviation
θ = Orientation and u is frequency of sinusoidal wave

Smoothing: This step eliminates low contrast points using Gaussian function.

Image segmentation: Each image is divided into 4×4 blocks and each block is convolved with Gabor filter. Six orientations and five scale Gabor filter is used and the mean and variance of the Gabor sizes are calculated for each block.

Color histogram method: Resized food images are given as input to color histogram method. The color histogram of an image defines the image color distribution. Color histograms the color space and hold the count of pixels for each color zone. For gray level images, the gray level histogram is built similarly (Bottou *et al.*, 1994).

Image I: Quantized colors: c1, c1 ... cm, Distance b/w two pixels: |p1-p2| = Maxi(|x1-x2|, |y1-y2| Pixel set with color c: Ic = p| I(p) = c Given distance:k.

Multiclass SVM classification method overview: Even though, SVMs is originally designed for binary classification problems, approaches that address a multi-class problem as a single "all-together" optimization problem exist (Vapnik, 1999). But, it is computationally more expensive than solving several binary problems. Several techniques for decomposition of the multi-class problem into several binary problems using SVM as a binary classifier have been proposed, the generally used two techniques are discussed in this study.

One-against-all (O v A): The earliest used implementation for SVM multiclass classification is probably the one-against-all method (Friedman, 1997.) It constructs k SVM models where kis the number of classes. For the N-class problems (N>2), N two-class SVM classifiers are constructed (Xu and Chan, 2003). The ith SVM is trained while labeling the examples in the ith class with positive labels and all others are labelled asnegative. The labeling is done according to the maximum output among N classifiers. Each of N classifiers are trained using all available samples.

One-against-one (O v O): This algorithm constructs N(N-1)/2 two-class classifiers by considering all the binary pair-wise combinations of the N classes. Each classifier is trained with the samples of the first class as positive examples and the samples of the second class as negative examples. Forcombining the result of these classifiers, the MaxWins algorithm is adopted. The algorithm finds the resultant class by choosing the class voted by the majority of the classifiers (Xu and Chan, 2003). Since, the number of samples used for training each one of the OvO classifiers is smaller, only samples from two of all N classes are selected. The lower the number of samplesselected causes smaller nonlinearity which results in shorter training time. The drawback of this method is that every test sample has to be presented to large number of N(N-1)/2 classifiers. This results in reduced testing performance, especially when the number of the classes in the problem is big (Nowak *et al.*, 2006).

Extracted feature vector is given as input to Multiclass SVM classifier. SVM classifier technique is most popular for data classification. This classification involves two data such as training and testing data. One class label for several features is used for more accuracy. Radial Basis Function (RBF) is used for mapping samples into higher dimensional space (Anthimopoulos *et al.*, 2014). RBF assigns class labels using:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (4)$$

Segmentation process is used to segment the food image features to identify portions of food. The main goal of multiclass SVM is to produce more than two class, in order to predict target value of data instances in the testing set which are given only by their attributes. SVM module determines each food portion type. The system can interact with the user to verify the kind of food portions. Segmentation process is used to provide boundary of food image.

Measurement of volume: Identified food portion is given as input for measuring volume of food. This stage

Table 1: True positive values for recall

	True Positive (TP)	
Class	SVM	MSVM
Apple	5	7
Banana	8	10
Bread	9	10
Guava	5	6
Pizza	6	8
Pomegranate	5	7

measuresthe size of the food by taking two pictures: one from the top and one from the side view. Top view is used to measure length and width and side view is used to measure height and depth. The calculation of the area of food item is given in Eq. 5:

$$A = \sum_{i=1}^{n} Ti \quad (5)$$

Where:
A = Area
Ti = Total subarea

Finally, volume of food portion is measured using total area and depth of food item using (Eq. 6):

$$V = A \times T \quad (6)$$

where, T is food thickness Food portions that happens to be regular shapes such as square, circle, triangle and so on, we can use geometric formulas to calculate their area, instead of using a grid.

Measuring calorie of food: The calculated volume of food is taken to measure calorie. This stage calculates the mass of food item using mathematical (Eq. 7):

$$M = pV \quad (7)$$

Where:
M = Mass of food portion
p = Density of food and
V = Volume of food

Finally, calorie of the food item is estimated using mass of food item and calorie value from the Table 1 by Eq. 8:

$$\text{Estimated calorie} = \text{Calorie from table} \times \text{volume} \quad (8)$$

Dataset description: An image dataset of 120 color images were created fromthe web. This image dataset consists of 6 food image classes. The number denotes the number of images considered per class: apple (20), bread (20), banana (20), pomegranate (20), guava (20) and pizza (20). The downloaded images were filteredsuch that it should have at least one side >64 pixels.

RESULTS AND DISCUSSION

All experiments were carried out in MATLAB environment on a machine and windows 8 plus 4GB RAM. We have carried out the image classification for 6 kinds of food images to evaluate the proposed system performance. First, the set of input images are resized based on the width and height. Then, the resized images have been fed to the feature extraction module. This module extracts three features from the image: color, shape and texture feature using color histogram, SIFT and Gabor filter.

The calorie estimation step takes two kinds of input viz. singleand mixed food. For the case of single food input, the classifier is directly invoked and it identifies the given food type. After that area and volume are measured for the food item and using that, calorie value is calculated by table look-up. If mixed food is given as input, segmentation needs to be done to separately identify the food items. After that, each food item is labeled using the classifier. Then, area and volume measurement is done for each food item and the overall calorie value is calculated. The overall accuracy for food image classification achieved by the proposed system is 93% (Fig. 5).

Evaluation: The evaluation is done on the food classes mentioned. Table 2 and 3 show the true positive and false positive values obtained using SVM and Multiclass SVM algorithms respectively for the considered food classes. From these tables it can be seen that the Multiclass SVM provides better true positive results and lesser false positive results.

Figure 6 and 7 shows the results of food classes and their classification accuracies. From these results, it is observed that the proposed algorithm provides better classification accuracy. This is due to the fact that the use of multiclass SVM increases the classification accuracy when it is compared with SVM.

Table 4 shows the precision values using SVM and Multiclass SVM classifiers, respectively. From the Table 4, it is observed that the proposed algorithm provides higher precision rates which is very useful for the classification of food items into classes.

Figure 8 shows the precision results for the algorithms. From the Fig. 8, it is observed that multiclass SVM algorithm provides higher precision values when compared to SVM.

Table 4 and 5 gives the values which can be used for the calculation of recall. From these Table 4 and 5 also it can be seen that the proposed algorithm provides better results when it is compared to SVM.

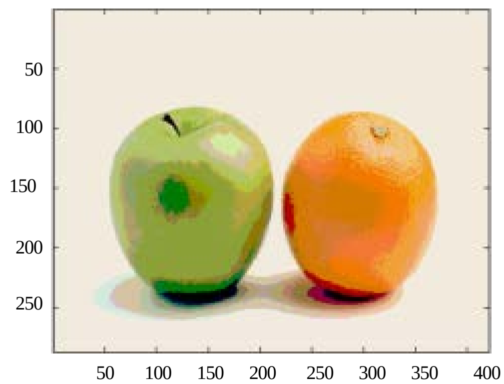

Fig. 5: Image segmentation process

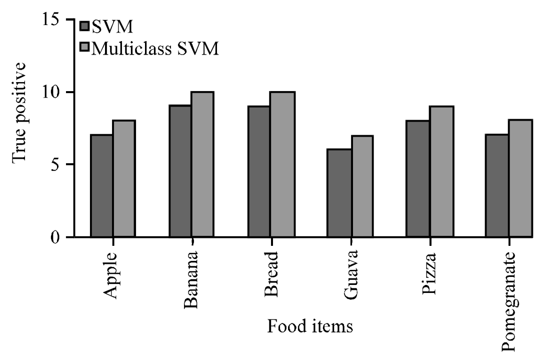

Fig. 6: True positive results

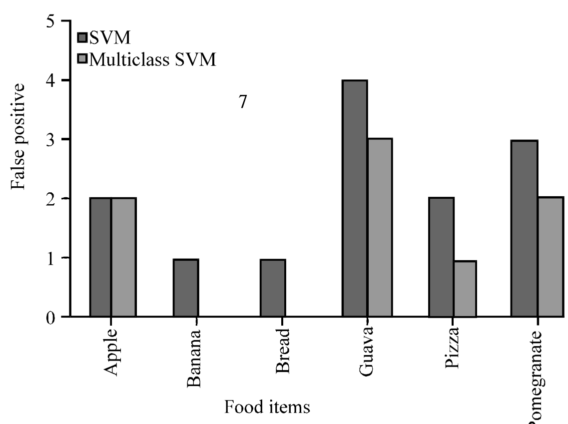

Fig. 7: False positive results

Table 2: True positive values for precision

Class	True Positive (TP) SVM	MSVM
Apple	7	8
Banana	9	10
Bread	9	10
Guava	6	7
Pizza	8	9
Pomegranate	7	8

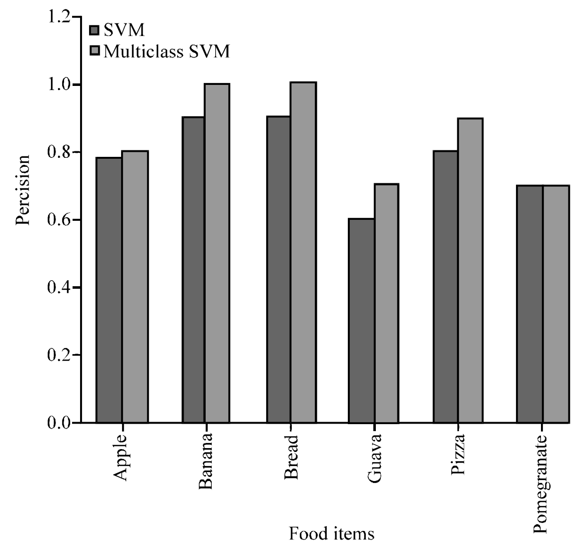

Fig. 8: Precision for SVM and MSVM

Table 3. False positive values for precision

Class	ClassFalse Positive (FP) SVM	MSVM
Apple	2	2
Banana	1	0
Bread	1	0
Guava	4	3
Pizza	2	1
Pomegranate	3	2

Table 4: Calculation of Precision (p) values

Class	Precision p = tp/(tp + fp) SVM	MSVM
Apple	0.8	0.8
Banana	0.9	1.0
Bread	0.9	1.0
Guava	0.6	0.7
Pizza	0.8	0.9
Pomegranate	0.7	0.8

Table 5: False negative values for recall Class

Class	False Negative (FN) SVM	MSVM
Apple	2	3
Banana	1	0
Bread	1	0
Guava	3	4
Pizza	1	2
Pomegranate	2	3

Table 6: Calculation of recall (r) values

Class	Recall r = tp/(tp+fn) SVM	MSVM
Apple	0.7	0.7
Banana	0.9	1.0
Bread	0.9	1.0
Guava	0.6	0.6
Pizza	0.9	0.8
Pomegranate	0.7	0.7

Table 7: Calculation of F-measure

Class	Precision SVM	Precision MSVM	Recall SVM	Recall SVM	SVMF = 2(p×r/p+r)	Multiclass SVMF = 2(p×r/p+r)
Apple	0.8	0.8	0.7	0.7	0.75	0.75
Banana	0.9	1.0	0.9	1.0	0.90	1.00
Bread	0.9	1.0	0.9	1.0	0.90	1.00
Guava	0.6	0.7	0.6	0.6	0.60	0.65
Pizza	0.8	0.9	0.9	0.8	0.85	0.85
Pomegranate	0.7	0.8	0.7	0.7	0.70	0.75

Table 8: Estimated calorie vales of food items

Food class	Reference calorie value (100 g)	Estimated calorie using SVM	Estimated calorie using multiclass SVM
Apple	52	61	57
Pomegranate	23.75	29	25
Pizza	75	83	81
Banana	89	78	75
Bread	81.3	88	83
Guava	21.6	27	23

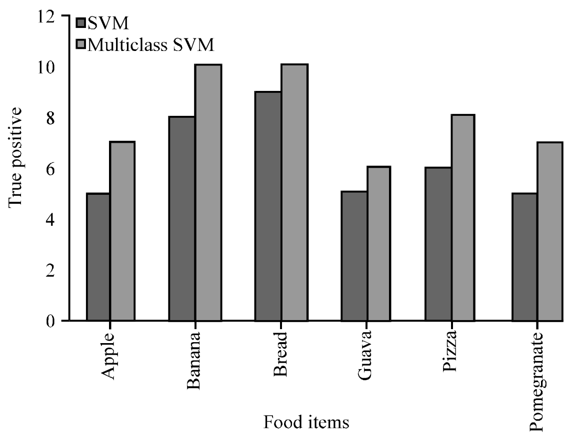

Fig. 9: True positives for SVM and multiclass SVM

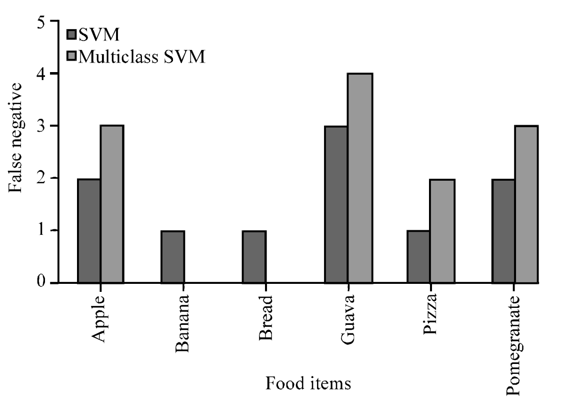

Fig. 10: False negativefor SVM and Multiclass SVM

Figure 9 and 10 illustrate the comparison of classification true positive and false negatives values for SVM and Multiclass SVM and it is observe that Multiclass SVM provides better classification accuracy when compared to SVM.

Table 6 provides therecall values calculated for food classes using SVM and multiclass SVM and the same is represented in Fig. 11.

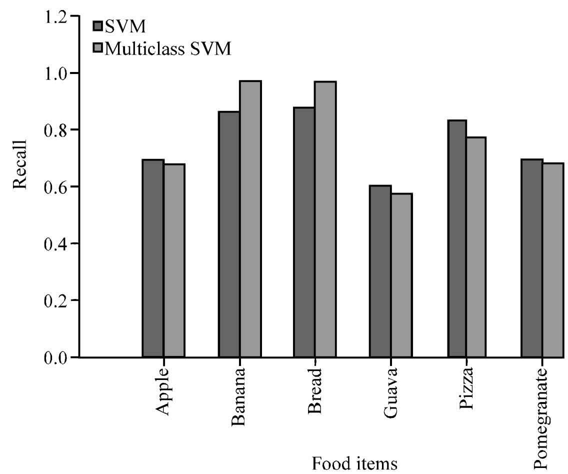

Fig. 11: Recall values using SVM and multiclass SVM

F-measure is used to test the accuracy. By taking the calculated precision and recall values of each class, F-measure is calculated as shown in Table 7.
The F-measure values in Table 7 shows that the proposed algorithm provides better classification results and hence, the calorie value is measured for the respective food item.

Figure 12 shows the graphical results of F-measure values against the precision and recall values. From the Figure, it is observed that the multiclass SVM provides the accurate result when compared to SVM algorithm.

Table 8 shows the reference calorie values and the estimated calorie values for the food classes using the SVM and Multiclass SVM algorithms. And also it is seen that Multiclass SVM provides the closer values to that of the reference values.

Figure 13 gives the comparison of accuracy of the calorie value estimation. From the above results it is observed that the multiclass SVM algorithm provides better classification accuracy which is an important factor in the process of food item identification and calorie estimation.

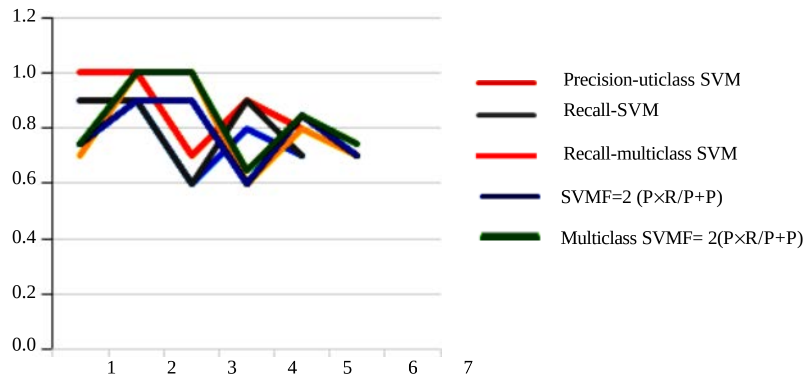

Fig.12: F- Measure Vs precision and recall

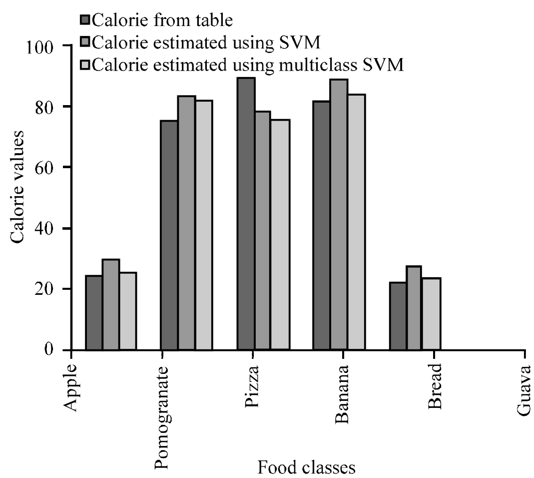

Fig. 13: Results comparison

CONCLUSION

In this research, we presented new image segmentation and classification methods for both single and mixed type of food images. This is useful for developing a portable application which canprovide dietary advice to diabetic patients through automatic calorie estimation. Five major steps have been carried out in this research formeasuring calorie values. Experiments were conducted on a newly constructed food image dataset with 120 images of fruits belonging to 6 different food classes and observed that it provides better accuracy.

RECOMMENDATIONS

This system can be furtherextended to incorporate calibration processto standardize input image that could be done using thumb, ATM cards, coins etc. and also to other types of food classes.

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