Fruit Classification using Global and Local Descriptors

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We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Computer Engineering.

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ABSTRACT

Recognizing different kinds of food such as vegetables and fruits is a recurrent task in supermarkets where the cashier must be able to point out not only the species of a particular fruit but also its variety which will determine its price. The use of barcodes has mostly ended this problem for packaged products but given that consumers want to pick their produce, they cannot be packaged, and thus must be weighted. A common solution to this problem is issuing codes for each kind of fruit/vegetable; which have problems given that the memorization is hard, leading to errors in pricing. In view of this, attention for classification and matching of these foods were carried out using global and local descriptors.

In this thesis, global descriptors such as Principal Component Analysis (PCA), Histograms of Oriented Gradients (HOG) and local descriptors such as Local Binary Patterns (LBP), Binarized Statistical Image Features (BSIF) are implemented in order to classify fruits. Experiments are conducted on two datasets from Fruits_360 database and TropicalFruits database. Experimental results obtained with global and local descriptors are presented as a comparative analysis on fruit classification on the aforementioned datasets. Among all descriptors, BSIF results are better than the other algorithms employed with 70.06% and 75.00% on the aforementioned datasets, respectively. On the other hand, LBP algorithm achieved 61.11% and 75.00% recognition rate while HOG results are 37.96% and 58.33% and PCA results are 42.90% and 45.83% on both datasets, respectively. The results show that local descriptors achieve better performance compared to the performance of the global descriptors for fruit classification.

Keywords: Fruit classification, Global Descriptors, Local Descriptors, PCA, HOG, LBP, BSIF.

ÖZ

Meyve ve sebze gibi besinlerin süpermarketlerde sınıflandırılması tekrarlanan bir işlemdir. Ürünlerin fiyatlarının belirlenmesi için kasiyerlerin belirli bir meyvenin hem cinsini hem de çeşidini işaretlemesi gerekir. Bu problemin çözümü için paketlenmiş ürünlerde barkod kullanılır. Ancak müşterinin paketlenmemiş meyve almak istediği durumlarda, meyvenin tartılıp fiyatlandırılması gerekir. Meyve ve sebze sınıflandırma probleminin genel çözümü her çeşit meyve/sebze için bir kod belirlemektir. Fakat bu kodun ezberlenmesi zor olduğu için fiyatlandırmada hatalar oluşabilir. Bu durumda ürünlerin sınıflandırılması ve eşleştirilmesi için evrensel ve yerel yöntemlere başvurulur.

Bu tezde meyve sınıflandırması için evrensel yöntemlerden Ana Bileşenler Analizi (PCA) ve Gradientlere Yönelik Histogramlar (HOG); yerel yöntemlerden de Yerel İkili Örüntü (LBP) ve İkili İstatistiksel Görüntü Öznitelikleri (BSIF) kullanılmıştır. Deneyler, Fruits_360 ve TropicalFruits veritabanları üzerinde yapılmıştır. Bu veritabanları üzerinde yapılan karşılaştırmalı sınıflandırma analizlerinin sonuçları, evrensel ve yerel yöntemler kullanılarak elde edilmiştir. Kullanılan yöntemler arasında diğerlerine göre en iyi sonuçları bahsedilen veritabanları üzerinde %70.06 ve %75.00 olarak veren BSIF yöntemidir. Öte yandan, LBP yöntemi ile %61.11 ve %75.00 tanıma oranları, HOG yöntemiyle %37.96 ve %58.33, PCA yöntemiyle de %42.90 ve %45.83 tanıma oranları bahsedilen iki veritabanı üzerinde sırasıyla elde edilmiştir. Meyve sınıflandırması için elde edilen sonuçlar, yerel yöntemlerin evrensel yöntemlere göre daha başarılı olduğunu göstermiştir.

Anahtar kelimeler: Meyve sınıflandırma, evrensel tanımlayıcılar, yerel tanımlayıcılar, PCA, HOG, LBP, BSIF.

DEDICATION

This work is dedicated to all supermarket world-wide in order to help in recognition of fruit and vegetable.

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LIST OF ABBREVATIONS

BSIF	Binarized Statistical Image Features
CCLBP	Color Completed Local Binary Pattern
HOG	Histogram of Oriented Gradients
LBP	Local Binary Pattern
PCA	Principal Component Analysis
RAM	Random Access Memory
RGB	Red Green Blue

Chapter 1

INTRODUCTION

An intelligent fruit and vegetable recognition system expresses a lot of information by utilizing image recognition it can accurately identify fruits and vegetables of different kinds to help improve efficiency in supermarket and market sales.

Recognizing different kinds of vegetables and fruits is a recurrent task in supermarkets, where the cashier must be able to point out not only the species of a particular fruit (i.e., orange, apple, and pear) but also its variety, which will determine its price. The use of barcodes has mostly ended this problem for packaged products but given that consumers want to pick their produce, they cannot be packaged and weighted to know the prices. A common solution to this problem is issuing codes for each kind of fruit/vegetable; which has problems given that the memorization is hard, leading to errors in pricing [1] [2].

In order to represent the texture feature of fruit and vegetable images better and improve the intelligent fruit and vegetable system recognition, feature extraction algorithms such as global and local descriptors are used [1] [2]. Fruit/vegetable classification is a study in computer vision. In this thesis, global descriptors such as Principal Component Analysis and local descriptors such as Local Binary Patterns is implemented in order to classify fruits [2]. Experiments on the aforementioned descriptors are performed on fruits image databases such as Tropical Fruits and Fruit-

360 databases. Results obtained with global and local descriptors are presented as a comparative analysis on fruits classification.

Different sets of fruits are used in the training and testing the methods accuracy to determine their performance. Progressively the methods are built to achieve satisfying performance and the highest possible accuracy. This thesis compares the performance of the approach and established fruit recognition and matching using different global and local descriptors for fruit recognition on Tropical Fruits and Fruit-360 datasets. These datasets are high quality online datasets of images containing fruits. The datasets comprises of 71125 fruits images, which is minimized to 96 for the Tropical Fruits and 648 for Fruit-360 datasets. The datasets consist of different fruits with various specification. Some of the fruits studied in this thesis are agata potato, asterix potato, cashew, diamond peach, fuji apple, granny smith apple, honeydew melon, kiwi, nectarine, onion, orange, plum, spanish pear, taiti lime and watermelon.

The rest of the thesis is organized as follows Chapter 2 gives a summary of the literature review related to fruit/vegetable classification. Chapter 3 gives information about global and local approaches, the methods implemented as global and local approaches for feature extraction are explained in Chapter 4. Experimental analysis and results are presented in Chapter 5. Finally, Chapter 6 concludes the thesis with the conclusion drawn and recommendations for future work.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

This section gives summary of previous work done in the literature of fruit/vegetable classification with different methods and algorithms carried out previously to get results.

A rapid improvement and development have been gained in the field of fruit and vegetable classification. Previous approaches considered patterns in color, edge, shape and texture properties ; low- and middle-level features to distinguish broad classes of images. In addition, Rocha and Hauagge [1] presented an approach to establish image categories automatically using histograms, colors and shape descriptors with an unsupervised learning method. To represent texture feature of fruit and vegetable images better and to improve the intelligent fruit and vegetable system recognition rate, a novel texture feature extraction algorithms called Color Completed Local Binary Pattern (CCLBP) was proposed. By extracting different kinds of color channels completed by a Local Binary Pattern (CLBP) texture feature, a new texture extraction algorithm was constructed by CCLBP. The fruit and vegetable recognition system model uses CCLBP to extract an image texture feature, and uses a HSV color histogram and Border/interior pixel classification (BIC) color histogram to extract image color features. Then it uses a matching score fusion algorithm to fuse color and texture features, and finally, a Nearest Neighbor (NN) classifier is used to realize fruit and vegetable recognition [1] [3].

Rocha and Hauagge in 2008 [1] [22] considered spatial constraints using a generative constellation model. The algorithm copes with occlusion in a very elegant manner, albeit very costly (exponential in the number of parts). Fei-Fei et al, made further development in 2006 [25] introducing prior knowledge into the estimation of the distribution; the number of training examples were reduced to around 10 images while preserving a good recognition rate. Even with this improvement, the problem of exponential growth with the number of parts persists, which makes it unpractical for the problem where speed is required for on-line operation [2][3].

Rocha and Hauagge in 2010 [22] proposed another interesting technique. In that work, feature points are found in a gradient image. A joining path connects these points and if the found contour is similar enough to the one in the database, a match is signalized. A serious drawback of this method for classification is that a nonlinear optimization step is required to find the best contour; besides that it relies too heavily on the silhouette cues, which are not very informative feature for fruits like oranges, lemons and melons [1].

A new descriptor for the image categorization is the progressive randomization (PR), which was introduced in the literature by Rocha and Goldenstein in 2007 [22] that uses perturbations on the values of the least significant bits (LSB) of images. The methodology captures the changing dynamics of the artefacts inserted as a perturbation process in each of the broad-image classes. Major drawback of using PR is that only LSB of the images, which lacks the information contained in the most significant bits

(MSB) of the images, is used. Generally, the fruit and vegetable recognition problem can be seen as an object's categorization instance. Turk and Pentland in 1991 [23] implemented Principal Component Analysis (PCA) to obtain the reconstruction error of projecting the whole image to a subspace then returning to the original image space. However, it depends on pose, shape and illumination consideration.

2.2 Pre-processing

This section describes existing preprocessing techniques based on the identification system created. The main techniques are de-noising and enhancement. Enhancement involves an increase or improvement in quality, contrast, value, or extent of an image applying filtering techniques and histogram equalization. De-noising is the reduction of noise in an image using wavelet thresholds to scale down unwanted features in an image. Cropping is another pre-processing technique which is used to increase localization of the important features and remove less needed part of an image [5].

The pre-processing method used in this thesis to expose region of interest of images is cropping to be able to remove background regions and unwanted shadows. Fruits come in different shapes and size; standard process is needed to extract relevant features from the images and resize images to a common scale. In addition, the conversion of these images to grayscale is needed in HOG, LBP and PCA approaches for proper implementation of these algorithms.

2.3 Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Basic principle of machine learning approach is to create algorithms that input data/images to extract patterns and features from the learnt data, Updating and prediction of the outputs are automatically done as new data is added as the output becomes available without being programmed. Classification of machine learning algorithms are done as unsupervised learning, Reinforcement learning and supervised learning.

During supervised learning, algorithms train data set containing examples associated with correct labels to facilitate accurate conclusion if new set of data is given. Therefore, labelling of dataset in unsupervised learning is not done. Patterns and relationships are found to the given unlabeled and uncategorized data without any training. On the other hand reinforcement learning expose systems to an environment where training is made continually using trial and error to make specific decisions. Learning from experience tries to make it possible to achieve the best predictions. Some applications of machine learning in daily activities include speech recognition, medical field application, prediction and image recognition.

A general overview of machine learning system is shown in Figure 2.1.

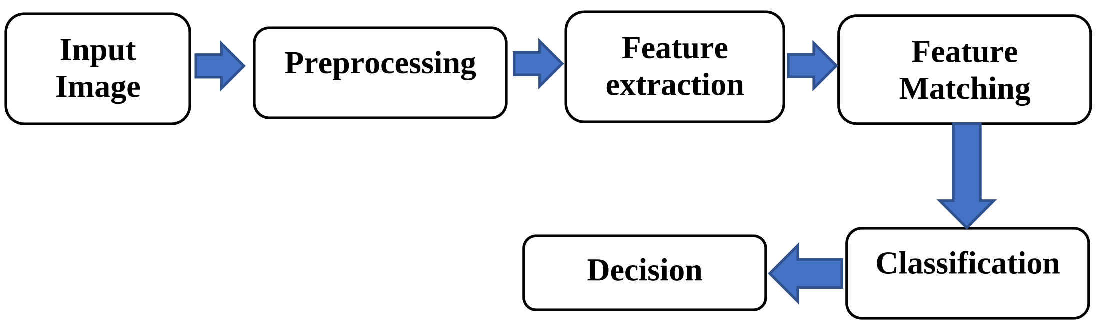


Figure 2.1: General Overview of a Machine Learning System

2.4 Different Features Extracted from Fruit Images

In the literature, many studies on fruit classification use different types of features. The most common features extracted from fruit images are texture, color and shape features. These features are explained below.

2.4.1 Texture

Texture can be defined as a function of spatial variation of the brightness intensity of the pixels. The most commonly used filter found to be appropriate for texture representation and discrimination is Gabor filter. It is a Kernel function in Gaussian modulated by a sinusoidal plane wave. The function is defined in 2-D as

$$G2D(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{1}$$

where σ satisfies the width of the Gaussian kernel. Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale. Filters with Gaussian transfer functions when viewed on the logarithmic frequency scale have a better code on natural images. Texture is a feature used to partition images into regions of interest and to classify those regions, which provides information in the spatial arrangement of colors or intensities in an image [7].

2.4.2 Color

Another most important feature is color in visual feature case. Color is explored with color stimuli: Red, Green and Blue by humans, which are color models specified as RGB color model. These are the primary color components of an image as monitoring these three individual color component can modify an image color outcome. HSV is another color space that consists of three components: Hue, Saturation and Value [7].

2.4.3 Shape

Another attribute component for fruit recognition is shape. The motivation behind shape analysis component is that different fruits may have identical color or shape but possibilities of same value in both attributes (color and shape) are rare [16]. The main stages involved in finding shape feature is area and perimeter calculation.

Calculation of the shape features for fruit image, feature extraction is performed in the following formula:

$$\text{Shape} = 4\pi * \left(\frac{\text{Area}}{\text{perimeter}^2}\right) \tag{2}$$

Therefore, shape features, as well as color and texture features, help to extract useful features from fruit images.

Chapter 3

GLOBAL AND LOCAL APPROACHES

3.1 Introduction

Global features extracted from images are described as a whole to generalize the entire object whereas the local features describe the image in patches (key points or partitions in the image) of an object. Global features include shape descriptors, contour representations and texture features and local features represent the texture in an image patch. Shape Matrices, Invariant Moments (Hu, Zernike), and appearance based approaches are some examples of global descriptors. SIFT, SURF, LBP, BRISK, MSER and FREAK are some examples of local descriptors. Generally, global features are used for low-level applications such as object detection and classification and for higher-level applications such as object recognition, local features are used. Combination of global and local features improves recognition accuracy with side effect of computational overheads [14].

3.2 Feature Extraction Using Global and Local Approaches

The extraction ability of distinctive characteristics from an image in such a way that those characteristic features represent the information in that image in a highly descriptive and lower-dimensional form are called feature extraction. These features can be local and or global characteristics of the image such as edges, entropy, color, shapes or regions and combination of these. The main idea of a fruit recognition system is to extract features common among images belonging to the same class consequently indexing them. The features are categorized into two: local descriptors and global features. Local features or texture-based properties of a fruit image are obtained from each patch of the image separately and then they are concatenated to make a feature vector. On the other hand, global features describe universalism specification which consider the fruit images as a whole to obtain a single feature vector.

3.2.1 Global Approach

Another stage employed for making the feature vector depending on generic characteristics of a fruit is the extraction of global features. Feature extraction is required to represent high dimensional image data into low feature vectors of low dimension. In general, there are two approaches to feature extraction, global method is one of the feature extraction approach which describe the image as a whole to generalize the entire object [14]. The most common among the global approach is Principal Component Analysis (PCA). PCA for recognition is known as a global method due to the extraction of fruit features using the bases which describe a whole fruit image. The bases are eigenvectors of the covariance matrix of fruit images. Projecting of fruit image onto the eigenspace, the weights of linear combination for Eigen space are calculated. The details related to PCA are explained in Chapter 4.

3.2.2 Local Approach

Feature descriptors are an important component of many computer vision algorithms. Local features and their descriptors, which are compact vector representations of a local neighborhood are the building blocks of many computer vision algorithms. Their applications include image registration, object detection and classification, tracking, and motion estimation. Using local features enables these algorithms to better handle scale changes, rotation, and occlusion. SIFT, SURF, HOG, BSIF, LBP, BRISK, MSER and FREAK are some examples of local descriptors; LBP, HOG and BSIF are used in this thesis. Generally, for higher-level applications such as object recognition, local features are used. Local features let you find image correspondences regardless of occlusion, changes in viewing conditions, or the presence of clutter. The details related to local methods used in this thesis are given in Chapter 4.

Chapter 4

METHODOLOGY

4.1 Introduction

This chapter presents algorithms and methodology adopted in this thesis regarding classification and matching of fruits. Four algorithms are used to extract features from images selected from Tropical Fruit database and fruit_360 database and these algorithms are involved to train and test the system. Algorithms used to extract features from fruit images are PCA, HOG, LBP and BSIF. The following sections give details about the employed algorithms.

4.2 Global Approaches Implemented

4.2.1 Principal Component Analysis (PCA)

A strategy is necessary to reduce the number of features used in classification. PCA is defined as the orthogonal projection of the data onto a lower dimensional linear subspace, known as the principal subspace, such that the variance of the projected samples is maximized. In addition, it is defined as the mean squared distance between the data points and their projections minimized. It is also an efficient tool to reduce the dimensionality of a data set consisting of a large number of interrelated variables while retaining the most significant variations, that is done by transforming the dataset to new set of ordered variables according to their degree of variance or importance. The three PCA effects are (1) orthogonolization is done to the component of the input vectors so that they are uncorrelated with each other, (2) orthogonal component results are ordered so that those with the largest variation comes first, (3) elimination to the components in the data set that the least variation is done. In addition, input vectors should be normalized in order to have zero mean and unit variance before performing PCA since the normalization is a standard procedure. Details about PCA algorithm are given in the following steps.

Step 1: Dataset description/acquisition: Separate data set into Y and X. Y will be the validation set and X will be the training set. In simple terms, X is used for study and Y is used to check correctness. Let $\{x_i|i=1,...,N\}$ be a set of M-dimensional vectors, which are training samples for PCA.

Step 2: Normalization/standardization: the data is normalized to obtain better performance from PCA. Mean is subtracted from each training sample for standardization. Standardization is all about scaling your data in such a way that all the variables and their values lie within a similar range, missing standardization will probably result in a biased outcome. Equation 3 shows how standardization is calculated.

$$z = \frac{\text{Variable value} - \text{mean}}{\text{Standard deviation}} \tag{3}$$

Step 3: Covariance matrix computation: PCA provide identification of correlation and dependencies among the features in a data set. A covariance matrix expresses the correlation between the different variables in the data set. Identification of heavily dependent variables is necessary because they contain biased and redundant information, which plays a role in the overall performance of the model. Mathematically, a covariance matrix is a p × p matrix, where p represents the dimensions of the data set as shown in equation 4.

$$matrix(covariance) = \begin{bmatrix} \mathrm{Var[X1]} & \mathrm{Cov[X1, X2]} \\ \mathrm{Cov[X2, X1]} & \mathrm{Var[X2]} \end{bmatrix} \tag{4}$$

It should be noted that $\mathrm{Var}[X_1] = \mathrm{Cov}[X_1,X_1]$ and vice versa.

Step 4: Eigenvalues and Eigenvectors**:** computing eigenvalues and eigenvectors is the next step for covariance matrix. λ is an eigenvalue for a matrix ***A*** if it is a solution of the equation:

$$\det(\lambda I - A) = 0 \tag{5}$$

where, **I** is the identity matrix of the same dimension as **A** which is a required condition for the matrix subtraction as well in this case and **'det'** is the determinant of the matrix. For each eigenvalue λ, a corresponding eigenvector ***v*** can be found by solving:

$$(\lambda I - A)v = 0 \tag{6}$$

Eigenvectors and eigenvalues are the mathematical constructs that must be computed from the covariance matrix in order to determine the principal components of the data set, for every eigenvector there is an eigenvalue. The dimensions in the data determine the number of eigenvectors that is calculated.

Step 5: Forming a feature vector and choosing a component: Eigenvalues are ordered from largest to smallest so that it gives components in order of significance. Dimensionality reduction is done by constructing a dataset with *n* eigenvalues and eigenvectors. It turns out that the eigenvector corresponding to the highest eigenvalue is the principal component of the dataset and it depends on how many eigenvalues are chosen to proceed with the analysis. Next a feature vector is formed which is a matrix of vectors, in our case, the eigenvectors, as shown in equation 7.

$$\text{Feature Vector} = (\mathrm{eig}_1, \mathrm{eig}_{2, \dots}) \tag{7}$$

Step 6: Computing the Principal Component: The principal components are constructed using the feature vector and scaled data. The transpose of the feature vector is multiplied with the transpose of scaled version of original dataset, as given in equation 8.

$$\text{NewData} = \text{FeatureVector}^{T} \times \text{ScaledData}^{T} \tag{8}$$

Here, the matrix consisting of the principal components is the NewData, Feature Vector is the matrix formed using the eigenvectors to keep, and Scaled Data is the scaled version of original dataset where 'T' in the superscript denotes transpose of a matrix which is formed by interchanging the rows to columns and vice versa.

4.3 Local Approaches Implemented

4.3.1 Local Binary Patterns (LBP)

Local Binary Patterns is a simple yet very efficient texture operator, which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to variations and distortion that can have a significant influence in machine learning tasks which will be insignificant to recognition, LBP algorithm was developed to be able to resist these variations and distortions. It extracts texture features combining the features from each cell of images divided initially. Then the features extracted are concatenated (making it a single vector) to form a feature vector representing the image used to train the recognition model. LBP operator can be extended as an arbitrary number of bilinear interpolated pixels on a circle with arbitrary size used as neighbor pixels. Instead of its 3×3 neighborhood, the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings [11]. Details about Local Binary Patterns (LBP) algorithm are as follows.

Step 1: Convert an image to grayscale and obtain the feature vector that is created from the image pixels.

Step 2: Binary operation: 3 by 3 pixel for each partition is considered in the grayscale image and neighborhood of size r is selected. In this study for each pixel's 3 by 3 neighbor, the center pixel value and its neighbor pixel values are compared. If the neighbor pixel values are greater than center pixel, the value 1 is recorded, otherwise the value 0 is recorded.

Step 3: Improvement from the second step, radius r is circular with the neighborhood taken with the number of pixels P. Different P neighbors are taken, and range of radius R is used for feature calculation. Figure 4.1 shows an example Uniform LBP for demonstration.

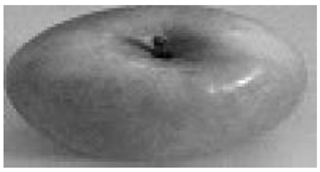
Step 4: Further Implementation: Uniform patterns with extracted binary numbers are considered uniform if they have at most a bit transition from 0 to 1 or vice versa which is called a circular pattern. A representation is shown in Figure 4.1, where a white circle represents a value smaller than the center pixel value and a dark circle represents a value greater than the center pixel value. Figure 4.2 shows an image pixel values and its LBP binary output. Figure 4.3 (a) shows a gray image sample before extraction of LBP features. Figure 4.3 (b) shows the extracted features from the sample images.

An algorithm for classification and matching processes can be used to obtain the final decision of the system.

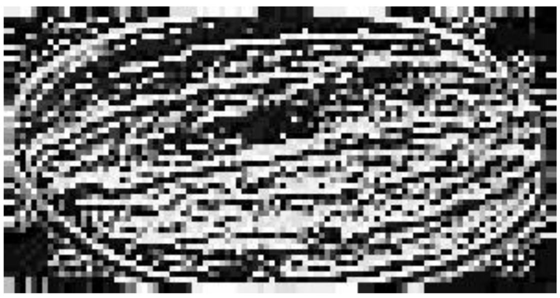
Figure 4.1: Uniform LBP (R, P)

(a) (b)

Figure 4.2: (a) A threshold Center pixel. (b) Binarized LBP Output



(a)



(b)

Figure 4.3: (a) A Grayscale Image before Extraction. (b) Extracted Local Binary Pattern

4.3.2 Histogram of Oriented Gradients

HOG is a feature descriptor used for object detection in computer vision, which counts frequencies of oriented gradients in localized part of an image. The image is divided into smaller connected regions called cells. It is invariant to geometric transformations since it works on local cells. Cells of an image are equally spaced and formed while histogram gradient over the pixels is counted for each cells. The histograms are concatenated to form a feature descriptor after applying overlapping contrast normalization, which is the calculation of intensity of a larger region of cells called blocks and using the calculated value to normalize the individual cells within the image to improve the feature invariance to shadowing and illumination [24]. The algorithm is described using the following steps.

Step 1: Pre-processing: Typically, patches at multiple scales are analyzed at many image locations. An image of RGB colored is inputted to the feature extractor. Comparable performance is achieved by any of the above image forms.

Step 2: Computing gradient images: To calculate a HOG descriptor, first calculate the horizontal and vertical gradients using Gaussian smoothing and discrete derivational mask of [-1, 0, 1]. This is easily achieved by filtering the image with the Gaussian kernels that is for color images.

Step3: Binning: Using orientation binning of $0^o – 180^o$ for unsigned weighted votes and $0^o – 360^o$ for signed, weighted votes from each pixels are collected over spatial regions (‘cells’) for edge orientation histogram. Nonlinearity to the image feature is introduced.

Step 4: Blocks Normalization: Normalization of the histogram is performed for the blocks in that step so they are not affected by lighting variations. Normalization by grouping cells together to form a larger block and contrast normalization of the individual cells improve the efficiency of the descriptors.

Step 5: Training: This steps leads to accurate descriptors, which can be used to train a machine-learning model for recognition and matching.

An example of original grayscale image and its histogram are demonstrated in Figure 4.4

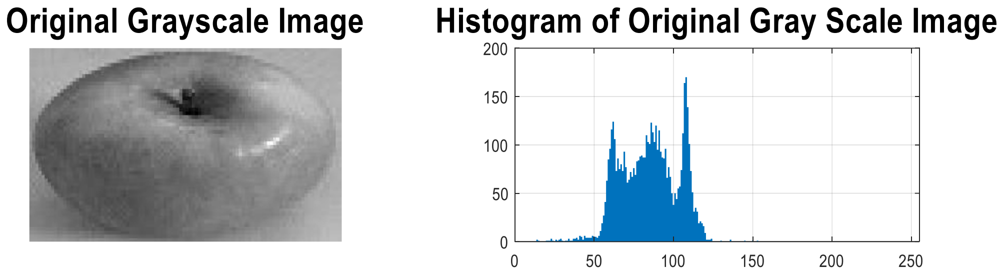


Figure 4.4: Oringinal Grayscale Fruit Image and Histogram of the Image

4.3.3 Binarized Statistical Image Features Algorithm

BSIF is a novel binary local image descriptor which is based on LBP. It is used for description of local features in image. The technique employs Independent Component Analysis (ICA) and efficient scalar quantization scheme. Pixel values in each neighborhood of an image give output of binary strings; and different codes give different filters. The code output of an image is binary and it is used as a descriptor [10].

BSIF is an improvement of LBP and Local Phase Quantization (LPQ). Images are represented as pixels of histogram in binary code. Analyzing and binarizing the coordinates in the image by thresholding like in LBP generate the binary code. In BSIF, generated filters are from small number of images used to binarize pixel neighbours of an image. Different algorithms use different filters and different length of bit string features. The outputs represent the features of the candidate image produced by the pattern intensity of the neighbors [10]. The following algorithm shows how BSIF works.

Step1: Image patch X of size lxl pixels is given with same size linear filter w_i, b$_i$ as the binarized feature. The responded filter s_i is obtained from equation 9 as

$$s_i = \sum_{u,v} w_i(u,v) \times (u,v) = w_i^t x \tag{9}$$

where w_i and x_i are vectors, the features are obtained in binary form if $s_i > 0$ equates 1 and 0 otherwise for b_i.

To obtain filters at high performance, statistical output from equation 9 is maintained by image restoration application.

Step 2: Dimensionality reduction of the filters is done through using PCA, where the principal components are taken and divided by their standard deviation to obtain a whitened data sample.

Step 3: Obtaining of final filter is conducted by the application of principal component analysis to the whitened sample data to obtain the orthogonal matrix, which is used as the filter for descriptors extraction in BSIF [12].

Step 4: Feature descriptors extraction is done from an image using the filters in step 1, 2 and 3 for texture extraction.

4.4 Architecture of the Implemented Systems

The general system architecture is presented in Figure 4.5 that presents the approaches employed in preprocessing of the images, which involves, preprocessing, global and local descriptors, matching, classification and decision. Each descriptor contains a feature extraction algorithm either global or local approach, namely HOG, PCA, LBP and BSIF.

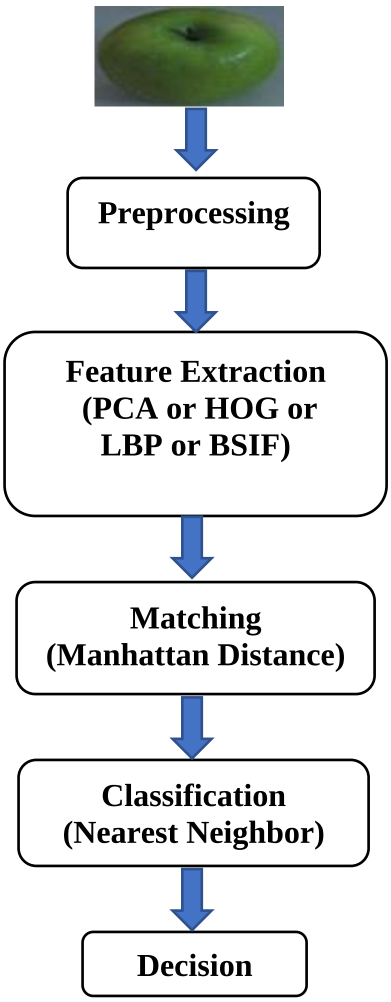


Figure 4.5: Architecture of the Implemented System.

Chapter 5

EXPERIMENTAL ANALYSIS

5.1 Experimental Setup

This thesis conducts several experiments for fruits classification using different descriptors. The experimental setup adopted in this thesis comprises of 746 image from 81 different fruits, which comprises of two databases namely TropicalFruits and Fruit_360. The datasets are divided into training and testing parts for both databases separately. Four images are used for training and the remaining 4 images are used for testing. TropicalFruit dataset is represented with twelve classes (each fruit is a class). Four images are used training and the remaining four are used for testing. Therefore, there exist 50% training images and 50% testing samples, totaling 48 training and 48 testing images from each data sample summing up to 97 images for TropicalFruit dataset and vice versa for Fruit_360 dataset. Fruit_360 dataset contains 81 subjects, categorized into training and testing, which has eight samples like the TropicalFruit dataset. Four train and 4 test images are used for each fuit class, totally 648 images.

After training and testing of both datasets, a database is created for 5 subjects with intersection, that includes the subjects that exist in both databases. The experiment analysis is carried out for tropical fruit dataset with a scenario of 25% training and 75% testing sample that is 2 training samples and 6 testing samples for each subject to obtain better performance evaluation. Same scenario is performed for Fruit_360 dataset but the subjects or classes used is 5 subjects in place of 81 subjects.

Additionally a scenario was performed with high training samples (75%) and less testing samples (25%), that is 6 training and 2 testing samples for both TropicalFruit and Fruit_360 dataset. The experimental analysis is carried out on intersection samples of both datasets. Therefore, we comprehensively investigate the effect of different percentage for training and testing to find a good performance with the implemented algorithms. The breakdown of each experimental analysis is shown in Table 5.1 to 5.6.

Table 5.1: Tropical Fruit Dataset: 12 Subject/Class Training and Testing Samples

#Class	Fruits	Training Samples	Testing Samples
1	agata_potato	4	4
2	diamond_peach	4	4
3	fuji_apple	4	4
4	granny_smith_apple	4	4
5	honneydew_melon	4	4
6	kiwi	4	4
7	nectarine	4	4
8	orange	4	4
9	plum	4	4
10	spanish_pear	4	4
11	taiti_lime	4	4
12	watermelon	4	4
Total		48	48

Table 5.2: Fruit_360 Dataset: 81 Subject/Class Training and Testing Samples

#Class	Name of fruits	Training Samples	Testing Samples
1	Apple Braeburn	4	4
2	Apple Golden 1	4	4
3	Apple Golden 2	4	4
4	Apple Golden 3	4	4
5	Apple Granny Smith	4	4
6	Apple Red 1	4	4
7	Apple Red 2	4	4
8	Apple Red 3	4	4

Table 5.2 (Continued)

9	Apple Red Delicious	4	4
10	Apple Red Yellow	4	4
11	Apricot	4	4
12	Avocado	4	4
13	Avocado ripe	4	4
14	Banana	4	4
15	Banana Red	4	4
16	Cactus fruit	4	4
17	Cantaloupe 1	4	4
18	Cantaloupe 2	4	4
19	Carambula	4	4
20	Cherry 1	4	4
21	Cherry 2	4	4
22	Cherry Rainier	4	4
23	Cherry Wax Black	4	4
24	Cherry Wax Red	4	4
25	Cherry Wax Yellow	4	4
26	Clementine	4	4
27	Cocos	4	4
28	Dates	4	4
29	Granadilla	4	4
30	Grape Pink	4	4
31	Grape White	4	4
32	Grape White 2	4	4
33	Grapefruit Pink	4	4
34	Grapefruit White	4	4
35	Guava	4	4
36	Huckleberry	4	4
37	Kaki	4	4
38	Kiwi	4	4
39	Kumquats	4	4
40	Lemon	4	4
41	Lemon Meyer	4	4
42	Limes	4	4
43	Lychee	4	4
44	Mandarine	4	4
45	Mango	4	4
46	Maracuja	4	4

Table 5.2 (Continued)

47	Melon Piel de Sapo	4	4
48	Mulberry	4	4
49	Nectarine	4	4
50	Orange	4	4
51	Papaya	4	4
52	Passion Fruit	4	4
53	Peach	4	4
54	Peach Flat	4	4
55	Pear	4	4
56	Pear Abate	4	4
57	Pear Monster	4	4
58	Pear Williams	4	4
59	Pepino	4	4
60	Physalis	4	4
61	Physalis with Husk	4	4
62	Pineapple	4	4
63	Pineapple Mini	4	4
64	Pitahaya Red	4	4
65	Plum	4	4
66	Pomegranate	4	4
67	Quince	4	4
68	Rambutan	4	4
69	Raspberry	4	4
70	Salak	4	4
71	Strawberry	4	4
72	Strawberry Wedge	4	4
73	Tamarillo	4	4
74	Tangelo	4	4
75	Tomato 1	4	4
76	Tomato 2	4	4
77	Tomato 3	4	4
78	Tomato 4	4	4
79	Tomato Cherry Red	4	4
80	Tomato Maroon	4	4
81	Walnut	4	4
Total		324	324

Table 5.3: Tropical Fruit Dataset: 5 Subjects with 25% Training and 75% Testing Samples

Classes	Fruits	Training Samples	Testing Samples
1	granny_smith_apple	2	6
2	kiwi	2	6
3	nectarine	2	6
4	orange	2	6
5	plum	2	6
Total	5	10	30

Table 5.4: Fruit_360 Dataset: 5 Subjects with 25% Training and 75% Testing Samples

Classes	Fruits	Training Samples	Testing Samples
1	granny_smith_apple	6	2
2	kiwi	6	2
3	nectarine	6	2
4	orange	6	2
5	plum	6	2
Total	5	30	10

Table 5.5: Tropical Fruit Dataset: 5 Subjects with 75% Training and 25% Testing Samples

Classes	Fruits	Training Samples	Testing Samples
1	granny_smith_apple	2	6
2	kiwi	2	6
3	nectarine	2	6
4	orange	2	6
5	plum	2	6
Total	5	10	30

Table 5.6: Fruit_360 Dataset: 5 Subjects with 75% Training and 25% Testing Samples

Classes	Fruits	Training Samples	Testing Samples
1	granny_smith_apple	6	2
2	kiwi	6	2
3	nectarine	6	2

Table 5.6 (Continued)

4	orange	6	2
5	plum	6	2
Total	5	30	10

The experiments are conducted using four feature extraction algorithms applied on the aforementioned datasets. These algorithms are PCA, HOG, LBP, and BSIF. The way of implementation of these algorithms are given below.

Experiment with Principal Component Analysis use images that were converted to grayscale. Normalization of the data is done where the maximum variance is identified and the contribution of each variable to a component is based on the magnitude of the variance to avoid distortion of relative comparison of variance across features. The mean is computed to be able to create a covariance matrix for eigen decomposition to present relation with the dataset. The optimal number of features are selected for training.

Experiments using Histogram of Oriented Gradients are applied on training dataset with the extraction of features after grayscale image creation. HOG algorithm is carried out over cells and blocks, with pixel values of the images. Gradients of X and Y directions from the pixels are taken with sigma = 0.5 Gaussian filter and at angles between the range 0^0 and 180^0. Histogram of Oriented Gradients descriptors are computed over image pixels and binned using bilinear interpolation. Block features are reshaped to meet the testing feature dimension where L1-norm is used and L2-norm normalizes the whole feature vector [24].

Local Binary Patterns algorithm starts with the conversion of images to grayscale; both the training and testing images are divided into cells of 12 by 12 pixels which proves better result. Each of the blocks is iterated to the Local Binary Patterns algorithm to enumerate the algorithms using circular symmetric pattern for each pixel using (P, R) neighborhood. The neighbors employed in carrying out this experiment are using pixels with P = 4 and radius R = 1, i.e $LBP_{4,1}^{u,2}$ is used in calculating the Local Binary Patterns descriptors.

Features length acquired from the descriptor depends on the size of each cell, and Local Binary Pattern approach uses its features for computation. Block features are summed to form the whole cells of the images in a single vector.

Experiment using Binarized Statistical Image Features algorithm were done using pre-defined filters. The experimental images were converted to grayscale firstly, then passed through a 7 by 7 ICA texture with 12 bits filter to generate the features from the images. The features are passed through a normalization process to normalize and give a feature vector of size 48x4096 for the images.

5.2 Fruit Databases

The databases used in this study include supermarket produce fruit images data consisting of two datasets. Tropical Fruit dataset consist of 12 subjects with 2535 sample images and Fruit_360 dataset includes 81 subjects and 55244 sample images. Totally, 57779 images are used for the experimental analysis which are divided into 50% training and testing sets. In this thesis, global descriptors such as Principal Component Analysis and local descriptors such as Histogram of Oriented Gradients is implemented in order to classify fruits. Experiments on the mentioned descriptors is performed on the datasets which contain the following fruits: Agata potato, asterix potato, cashew, diamond peach, fuji apple, granny smith apple, honeydew melon, kiwi, nectarine, onion, orange, plum, Spanish pear, taiti lime and watermelon. Each subject contains a number of images per sample in the database file. Details and images of the subjects, its minimum and maximum samples are shown in the tables (Table 5.7 and Table 5.8) and some sample images from both datasets are shown in Figure 5.1 and 5.2

Table 5.7: Tropical Fruit Dataset: Minimum and Maximum Number of Samples

Class	Name	Min. no of Samples	Max no of Samples
1	agata_potato	30	200
2	diamond_peach	30	182
3	fuji_apple	30	210
4	granny_smith_apple	30	211
5	honneydew_melon	30	212
6	kiwi	30	155
7	nectarine	30	145
8	orange	30	171
9	plum	30	247
10	spanish_pear	30	75
11	taiti_lime	30	103
12	watermelon	30	264
Total	Number of samples		2535

Table 5.8: Fruit_360 Dataset: Minimum and Maximum Number of Samples

#Class	Name of fruits	Min. number of Samples	Max. number of Samples
1	Apple Braeburn	150	492
2	Apple Golden 1	150	492
3	Apple Golden 2	150	492
4	Apple Golden 3	150	481
5	Apple Granny Smith	150	492
6	Apple Red 1	150	492
7	Apple Red 2	150	429
8	Apple Red 3	150	481
9	Apple Red Delicious	150	490
10	Apple Red Yellow	150	492
11	Apricot	150	492

Table 5.8 (Continued)

12	Avocado	150	427
13	Avocado ripe	150	491
14	Banana	150	490
15	Banana Red	150	490
16	Cactus fruit	150	490
17	Cantaloupe 1	150	492
18	Cantaloupe 2	150	492
19	Carambula	150	490
20	Cherry 1	150	492
21	Cherry 2	150	738
22	Cherry Rainier	150	738
23	Cherry Wax Black	150	492
24	Cherry Wax Red	150	492
25	Cherry Wax Yellow	150	492
26	Clementine	150	490
27	Cocos	150	490
28	Dates	150	490
29	Granadilla	150	490
30	Grape Pink	150	492
31	Grape White	150	490
32	Grape White 2	150	490
33	Grapefruit Pink	150	492
34	Grapefruit White	150	492
35	Guava	150	490
36	Huckleberry	150	490
37	Kaki	150	490
38	Kiwi	150	466
39	Kumquats	150	490
40	Lemon	150	492
41	Lemon Meyer	150	490
42	Limes	150	490
43	Lychee	150	490
44	Mandarine	150	490
45	Mango	150	490
46	Maracuja	150	490
47	Melon Piel de Sapo	150	738
48	Mulberry	150	492
49	Nectarine	150	478
50	Orange	150	479
51	Papaya	150	492
52	Passion Fruit	150	490
53	Peach	150	492
54	Peach Flat	150	492
55	Pear	150	492
56	Pear Abate	150	490
57	Pear Monster	150	490
58	Pear Williams	150	490

Table 5.8 (Continued)

59	Pepino	150	490
60	Physalis	150	492
61	Physalis with Husk	150	492
62	Pineapple	150	490
63	Pineapple Mini	150	493
64	Pitahaya Red	150	490
65	Plum	150	447
66	Pomegranate	150	492
67	Quince	150	490
68	Rambutan	150	492
69	Raspberry	150	490
70	Salak	150	490
71	Strawberry	150	492
72	Strawberry Wedge	150	738
73	Tamarillo	150	490
74	Tangelo	150	490
75	Tomato 1	150	738
76	Tomato 2	150	672
77	Tomato 3	150	738
78	Tomato 4	150	479
79	Tomato Cherry Red	150	492
80	Tomato Maroon	150	367
81	Walnut	150	735
Total	Number of samples	55244	

Figure 5.1: Samples from the Tropical Fruit Database.

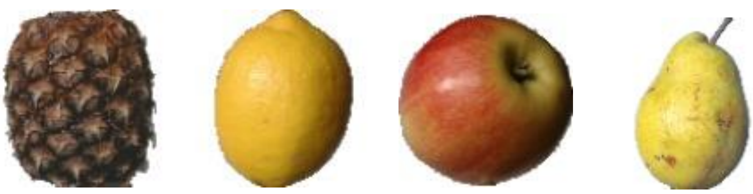


Figure 5.2: Samples from Fruit_360 Database.

5.3 Preliminary Experiments with the Same Type of Fruits

In this section, preliminary experiments are implemented with the same kind of fruits in both datasets using the global and local approaches to check the matching or recognition rate when looking at the same fruit and to help tell the accuracy and flaws of the approach used. 50% training and testing samples were used to carry out this purpose. Principal Component Analysis algorithm, Histogram of Oriented Gradients algorithm, Local Binary Patterns and Binarized Statistical Image Features are used for this experiment. Each subject was trained and tested with the same samples, Details of the carried out experiments are shown in Table 5.9 and 5.10.

Table 5.9: Tropical Fruit Dataset: Recognition Rate with the Same Kind of Fruit

Class #	Fruits	Recognition Rate (%)			
		PCA	HOG	LBP	BSIF
1	agata_potato	100	100	100	100
2	diamond_peach	75	100	75	100
3	fuji_apple	75	100	100	75
4	granny_smith_apple	50	100	100	100
5	honneydew_melon	0	0	0	25
6	kiwi	75	75	100	75
7	nectarine	0	25	100	25
8	orange	75	100	100	100
9	plum	0	100	100	100
10	spanish_pear	0	0	25	25
11	taiti_lime	75	0	75	100
12	watermelon	25	0	25	75

Table 5.10: Fruit_360 Dataset: Recognition Rate with the Same Kind of Fruit

#Class	Name of fruits	Recognition Rate (%)			
		PCA	HOG	LBP	BSIF
1	Apple Braeburn	25	100	50	25
2	Apple Golden 1	0	0	50	50
3	Apple Golden 2	0	0	0	0
4	Apple Golden 3	0	75	75	50
5	Apple Granny Smith	0	25	0	50
6	Apple Red 1	0	0	25	25
7	Apple Red 2	50	0	0	50

Table 5.10 (Continued)

8	Apple Red 3	0	0	25	0
9	Apple Red Delicious	50	50	75	100
10	Apple Red Yellow	0	0	0	0
11	Apricot	50	50	50	50
12	Avocado	0	0	25	25
13	Avocado ripe	50	0	50	50
14	Banana	0	50	50	100
15	Banana Red	75	0	25	25
16	Cactus fruit	25	25	25	25
17	Cantaloupe 1	50	50	100	100
18	Cantaloupe 2	50	25	50	25
19	Carambula	0	0	0	0
20	Cherry 1	0	50	100	75
21	Cherry 2	100	75	100	100
22	Cherry Rainier	0	0	0	0
23	Cherry Wax Black	75	100	100	100
24	Cherry Wax Red	0	75	75	100
25	Cherry Wax Yellow	0	0	0	100
26	Clementine	0	0	0	0
27	Cocos	0	0	25	75
28	Dates	100	100	100	100
29	Granadilla	0	0	0	100
30	Grape Pink	25	0	25	25
31	Grape White	50	0	50	50
32	Grape White 2	100	75	100	100
33	Grapefruit Pink	0	100	100	100
34	Grapefruit White	50	50	100	100
35	Guava	100	75	100	100
36	Huckleberry	0	0	50	25
37	Kaki	100	50	100	75
38	Kiwi	50	50	50	50
39	Kumquats	100	75	100	100
40	Lemon	50	50	50	50
41	Lemon Meyer	100	75	100	100
42	Limes	25	0	25	25
43	Lychee	50	25	100	100
44	Mandarine	25	25	25	100
45	Mango	25	25	100	100
46	Maracuja	0	0	75	100
47	Melon Piel de Sapo	50	50	50	100
48	Mulberry	50	25	50	100
49	Nectarine	50	50	50	75
50	Orange	100	50	100	100
51	Papaya	50	50	50	50
52	Passion Fruit	25	25	100	75
53	Peach	0	0	0	75

Table 5.10 (Continued)

54	Peach Flat	75	75	0	75
55	Pear	50	50	0	50
56	Pear Abate	25	25	0	75
57	Pear Monster	0	25	0	0
58	Pear Williams	50	50	50	75
59	Pepino	50	50	0	75
60	Physalis	100	50	100	100
61	Physalis with Husk	75	50	75	75
62	Pineapple	25	25	25	25
63	Pineapple Mini	100	0	100	100
64	Pitahaya Red	100	0	100	75
65	Plum	50	50	50	50
66	Pomegranate	75	25	75	100
67	Quince	25	0	25	75
68	Rambutan	75	25	100	100
69	Raspberry	0	25	50	50
70	Salak	100	75	100	100
71	Strawberry	50	75	100	100
72	Strawberry Wedge	75	50	75	100
73	Tamarillo	50	100	100	100
74	Tangelo	25	75	100	100
75	Tomato 1	25	50	100	100
76	Tomato 2	75	100	100	100
77	Tomato 3	100	75	100	100
78	Tomato 4	75	75	100	100
79	Tomato Cherry Red	100	100	100	100
80	Tomato Maroon	50	50	100	100
81	Walnut	50	0	75	100

5.4 Experiments with All Fruits on Two Databases

In this section, experiments are implemented to compute the overall performance in both databases using the global and local approaches to check the recognition rate with all subjects, identifying each subject when paired with different fruits. High recognition rate emphasizes that it is mostly possible for the subject to be correctly recognized. Firstly, 50% training and testing samples were used to carry out this purpose, then 25% training samples and 75% testing samples were also carried out, including 75% training and 25% testing sample. This experiment is implemented to help tell the accuracy and flaws of the approach used and to identify better performance algorithms regardless of the samples provided in real world settings, Principal Component Analysis, Histogram of Oriented Gradients, Local Binary Patterns and Binarized Statistical Image Features are used for this experiment. Recognition rates of the carried out experiments are shown in Tables 5.11 and 5.12 below for both supermarket datasets.

Table 5.11: Tropical Fruit Dataset: Recognition Rates

		Recognition Rate (%)			
Implemented Approach		PCA	HOG	LBP	BSIF
All	12 subjects	45.83	58.33	75.00	75.00

Table 5.12: Fruit_360 Dataset: Recognition Rates

		Recognition Rate (%)			
Implemented Approach		PCA	HOG	LBP	BSIF
All	81 subject	42.90	37.96	61.11	70.06

5.5 Discussion on Experimental Results

Global and local feature extraction approaches are evaluated in this study based on their recognition rates on fruit classification problem. This is to investigate the efficiency of the approach used and get performance estimation in real-world settings, where matching and recognition of fruits will be carried out using the system. From the presented results, different algorithms execution performed comparatively better on different classes and samples presented on fruits. Physical features of fruits also have influence on the recognition rate.

For different approaches, the testing precision acquired after training and testing of the presented subject samples are averaged to give an overall accuracy rate. Experiments are conducted using PCA, HOG, LBP and BSIF algorithms. From the preliminary experiments with the same kind of fruits and experiments with all fruits, Tropical Fruit Dataset results show that BSIF and LBP recognition rates for each subject with the same fruit is 75% which are much better when compared with the other algorithms. Then, HOG and PCA obtain competitive recognition rates with each other. From experiments with all fruits, Fruit_360 dataset results show that BSIF provides better recognition rate as 70.06% which is more than LBP with 61.11% , HOG with 37.96% and PCA with 42.90%. The results in the experimental section show that BSIF attained the highest recognition rates as 75.00% and 70.06% in Tropical Fruit and Fruit_360 datasets, respectively which makes it the best method compared to other feature extractor algorithms, namely PCA, HOG and LBP. It is therefore concluded that Tropical Fruit dataset provides images that can be recognized better than Fruit_360 dataset images. BSIF emerged as the best algorithm for every case. BSIF algorithm on the presented datasets emerges as the most fitting algorithm for recognition and matching. Therefore, it can be stated that local approaches are better than global approaches for solving the fruit classification problem.

Furthermore, time for each employed algorithm is computed and shown in Table 5.13 for Tropical Fruit Dataset and in Table 5.14 for Fruit_360 Dataset. The time for training and testing each algorithm is indicated in seconds.

According to computation times, HOG runs least computation time for Tropical Fruit Dataset and LBP executes in the least time for Fruit 360 Dataset. Training the model varies with the computations of the required times by the algorithms. The trials were processed on a Windows 8 Operating System with 4GB RAM and Pentium dual core CPU @ 2.00GHz.

Table 5.13: Computation Time for Tropical Fruit Dataset

Algorithm	**Training time(sec)**	**Testing time (sec)**
HOG	0.541649	1.135006
LBP	0.062226	1.361997
BSIF	0.563538	1.162098
PCA	0.514359	1.647279

Table 5.14: Computation Time for Fruit 360 Dataset

Algorithm	**Training time(sec)**	**Testing time (sec)**
HOG	6.355306	16.337455
LBP	6.329495	12.142890
BSIF	4.879530	18.422306
PCA	9.006377	14.044324

Chapter 6

CONCLUSION

In this thesis, global and local feature extraction algorithms are implemented on fruit images for the extraction of features and development of a recognition system. Three local descriptors and a global descriptor are used to show that it is applicable to obtain a feature vector for fruit recognition system by covering important characteristics where each category of the features demonstrates a different aspect of fruit properties. The feature descriptors used are PCA, HOG, LBP and BSIF. BSIF achieved better results than other algorithms employed. Recognition rates with Principal Component Analysis, Histogram of Oriented Gradient, Local Binary Patterns and Binarized Statistical Image Features approaches are compared on two datasets, where BSIF seems to be more precise than other algorithms with higher recognition rates. We used several set of experiments with different number of subjects selected from two datasets. Evaluation on our experiment sets on images from Tropical Fruit Dataset and Fruit_360 Dataset involved 57779 images from both datasets that are used to train and test all descriptors separately. The use of computers in analyzing the images has considerable potential applications for recognition tasks. However, the variability of the supermarket produce makes it difficult to adapt the existing industrial algorithms to the fruit domain. In this thesis we compared four approaches and the experiment results shows that BSIF approach achieves the best recognition rates on both datasets used in this study. As a future work, color based feature extraction methods may be used for fruit classification to boost the performance of fruit classification systems.

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