# An Approach for Image Segmentation based on Region Connectivity

[1]Shruti S. Kulkarni, [2]Nileshsingh V. Thakur

[1,2]PRM College of Engg. & Mgmt, Badnera, India

**Abstract— In image classification, the image segmentation is the fundamental step. Different techniques are available to perform the image segmentation, but the prominent one from image classification point of view is the watershed transform, as presented work concern with the approach based on graph kernels. To develop the graph kernel, it is necessary to have the identification of the different regions of the image. To get the different regions from the image, the watershed transformation based image segmentation is performed. Later, for image classification, the Support Vector Machine (SVM) is selected as the classifier. In view of the image classification, firstly, the image database of different classes is referred, to generate the attributes of the images in particular and that of the classes in general. These attributes consist of the feature based on the graph kernel which is obtained after performing the image segmentation using watershed transformation and the features for the whole image. In this way, the feature database for the particular classes is developed. Later, to identify the belongingness of the query image, once again the same attributes are extracted for the query image and then, query image feature and the feature database for the various classes is referred to classify the given query image. For this purpose the confusion matrix is evaluated through the SVM classifier. Experimentations are carried out with the five classes of images. Every class consists of 100 images. Obtained results are encouraging and motivating.**

**Index Terms— Image features, Image segmentation, Image transformation, Region growing**

## I. INTRODUCTION

This section describes the basics associated with the image segmentation and the terminologies used in view of image classification.

### A. Image Segmentation and Image Classification

An image may be defined as a two dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, is a digital image. Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two dimensional signal and applying standard signal processing techniques to it. Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Marker-controlled watershed segmentation follows this basic procedure:

- Compute a segmentation function.
- Compute foreground markers.
- Compute background markers.
- Modify the segmentation function so that it only has minima at the foreground and background marker locations.

Image classification as a machine learning task enjoys numerous applications, such as image retrieval or object recognition. Images are naturally high-dimensional data, which demands mandatory pre-processing targeted towards dimensionality reduction. Most techniques require a preprocessing step, which can be global as in color histogram binning or local through feature extraction. Classification includes a broad range of decision-theoretic approaches to the identification of images (or parts thereof). All classification algorithms are based on features and that each of these features belongs to one of several distinct and exclusive classes. The classes may be specified a priori by an analyst (as in supervised classification) or automatically clustered (as in unsupervised classification) into sets of prototype classes, where the analyst merely specifies the number of desired categories. Image classification analyzes the numerical properties of various image features and organizes data into categories.

B. Graph Kernels and Support Vector Machine (SVM)

Graph kernel is a kernel function that computes an inner product on graphs. Graph kernels can be intuitively understood as functions measuring the similarity of pairs of graphs. They allow kernelized learning algorithms such as support vector machines to work directly on graphs, without having to do feature extraction to transform them to fixed-length, real-valued feature vectors. They find applications in bioinformatics, in chemo informatics and in social network analysis. A scalar can be modeled as a graph with one single node labeled by the value of this scalar. Vectors and matrices can be modeled as graphs, with one node per entry and edges between consecutive components within a vector and matrix, respectively.

SVMs are a class of algorithms that use only key vectors from the training set to determine the decision boundary. These vectors are called support vectors. The idea behind using only a subset of the training set to contribute to the decision boundary is to limit the number of computations between the training vectors and the testing vectors. In its basic form, a Support Vector Machine (SVM) classifier uses two sets of discriminative examples for training; these examples belong to a vector space endowed with a dot product.

The main advantage of this classifier is the fact that it minimizes the classification error while maximizing the distance from the training examples to the separating hyper-plane. It also allows the definition of a soft margin to prevent the mislabeled examples from perturbing too much the classification. Although SVMs have been originally designed as linear classifiers, they have been extended to perform nonlinear discrimination by using a 'kernel trick', which replaces the dot product needed in computation by a non-linear positive definite kernel function. Measuring graph similarity can be addressed by considering kernels function on graphs. This function can be interpreted as an inner product on two graphs, obtained by comparing edges and vertices that have been crossed during random walks on the graphs. Then a major particularity of this kernel is the use of kernels between vertices and edges. It means that labels can be complex structures, like vectors, histograms or set of histograms, instead of a single real value, which is the case for most of graph matching algorithms.

C. Contribution and Organization of Paper

In view of image classification, the image segmentation approach is developed. Based on this the features are evaluated for the graph. For this purpose the graph kernels are used. Other features are evaluated through the wavelet transform and histograms. Obtained results are satisfactory from the image classification point of view. Different features are used, namely, the regional features, color features, and the moments for the image based on wavelet transform. For image classification, the SVM classifier is used, based on the confusion matrix, the results are obtained.

The paper is organized as follows: Section II presents the analysis of studied research papers. Section III describes the details of problem formulation and section IV gives the details of the proposed approach. Section V provides the summary of experimental setup which is used to obtain the results. It also provides the obtained results and discussion. Section VI presents the conclusion and future scope followed by the references.

## II. LITERATURE REVIEW

This section presents the analysis of studied literature which is categorized into three parts, namely image segmentation related work, image classification related work, and graph kernel related work.

A. Image Segmentation Related Work

Anju Bala [1] discussed watershed transformation based segmentation. This approach includes image enhancement and noise removal techniques with Prewitt's edge detection operator which detects the edges instead of Sobel Operator as in existing marker controlled watershed transformation. This approach reduces the over segmentation effect and achieve good segmentation. This approach uses preprocessing methods to reduce the noise of image and adjust the image intensity. Athira Devi and Venugopal [3] introduced a multi region graph cut image partitioning through kernel mapping of the image data. The approach uses two terms: an original kernel-induced term which evaluates the deviation of the mapped image data within each region from the piecewise constant model and a regularization term expressed as a function of the region indices. Using a common kernel function, the objective functional minimization is carried out by iterations of two consecutive steps: minimization with respect to the image segmentation by graph cuts and minimization with respect to the regions parameters via fixed point computation. Change in kernel function, in such a way that can improve optimization process is first step in medical analysis. Leibe and Schiele [5] explained approach for object recognition at level where a large number of previously seen and known objects can be identified. In this paper, the authors analyzed the performance of several state-of-the-art appearance and contour-based recognition methods for the more general task of multi-class object categorization. Later, the authors used the multiple cue decision tree. In this paper, the authors explored the two approaches to find segmented regions. Fowlkes et al. [6] explained the Spectral graph theoretic approach for the problem of image segmentation. However, due to the computational demands of these type of approaches, applications to large problems such as spatio temporal data and high resolution imagery have been slow to appear. The approach presented in this paper reduces the computational requirements of grouping algorithms based on spectral partitioning making and it can be applied to very large grouping problems. This approach is based on a technique for the numerical solution of eigen function problems known as Nystrom method. In this paper, authors have presented a technique for the approximate solution of spectral partitioning for image and video segmentation based on the Nystrom extension. Gomila and Meyer [7] discussed about graphs and graphs offer a compact representation of 2D or 3D images, as each node represents a region with its attributes and the edges convey the neighborhood relations between adjacent regions. Such graphs may be used in the analysis of video sequences and the tracking of objects of interest. Each image of a sequence is segmented and represented as region adjacency graph. Object tracking becomes a particular graph-matching problem, in which the nodes representing the same object are to be matched. The intrinsic complexity of graph matching is greatly reduced by coupling it with the segmentation. In this paper, object tracking is formulated as a joint problem of segmentation and matching.

Malik et al. [15] explained an algorithm for partitioning grayscale images into disjoint regions of coherent brightness and texture. Natural images contain both textured and untextured regions, so the cues of contour and texture differences are exploited simultaneously. Contours are treated in the intervening contour framework, while texture is analyzed using textons. Each of these cues has a domain of applicability, so to facilitate cue combination introduced a gating operator based on the texturedness of the neighborhood at a pixel. The spectral graph theoretic framework of normalized cuts is used to find partitions of the image into regions of coherent texture and brightness. Yi et al. [19] described the approach for multiscale segmentation which is always needed to extract semantic meaningful objects for object-based remote sensing image analysis. This paper discusses a simple scale-synthesis approach which is highly flexible to be adjusted to meet the segmentation requirements of varying image-analysis tasks. In this approach, the whole image is divided into multiple regions where each region consisted of ground objects that have similar optimal segmentation scale. Then, synthesize of the suboptimal segmentations of each region is carried out to get the final segmentation result. The result is the combination of sub optimal scales of objects. This is a simple scale-synthesis approach for High Spatial Resolution Remote Sensing image (HSRI) segmentation. This approach simplifies image segmentation by dividing the segmentation task into multiple subtasks of different land-cover categories. An edge-embedded marker-based watershed (EEMW) algorithm has been first implemented to get an initial over segmentation result. Then, a bottom-up region-merging method has been implemented with a MumFord-Shah segmentation model to establish linking hierarchy multi scale segmentation network. The final segmentation result has been generated by synthesizing the selected segmentation results together. Farmer and Jain [24] explained framework for segmentation and classification that follows the wrapper methods of feature selection. This approach wraps the segmentation and classification together, and uses the classification accuracy as the metric to determine the best segmentation. By using shape as the classification feature, authors explained segmentation algorithm that relaxes the requirement that the object of interest to be segmented must be homogeneous in some low-level image parameter, such as texture, color, or grayscale.

### B. Image Classification Related Work

Morales-Gonzalez et al. [2] described about graph-based data representation is an important research topic due to the suitability of this kind of data structure to model entities and the complex relations among them. In computer vision, graphs have been used to model images in order to add some high level information (relations) to the low-level representation of individual parts. In this paper, authors proposed combined graph-based image representation and frequent approximate subgraph (FAS) mining algorithm in order to classify images. Here, FASs is used as features which are used in a classification framework. The FASs are obtained by means of FAS miners. Elsayed et al. [4] explained an approach to classify magnetic resonance (MR) image data. A variation of the spectral segmentation with multi-scale graph decomposition mechanism is introduced. Aldea et al. [8] proposed an image classification technique based on kernel methods and graphs. This work explores the possibility of applying marginalized kernels to image processing. This work consists of two distinct parts. In the first one, authors described a model to represent the images by graphs to be able to represent their structural properties and inherent attributes. In the second one, authors used kernel functions to project the graphs in a mathematical space that allows the use of performant classification algorithms. Huang and Cun [11] explained an approach for the detection and recognition of generic object categories with invariance to viewpoint, illumination, and clutter. They presented a hybrid system where a convolutional network is trained to detect and recognize generic objects, and a Gaussian-kernel SVM is trained from the features learned by the convolutional network. Here, convolutional nets and SVM are investigated with results on a generic object categorization dataset which includes two step learning process.

Perronnin et al. [12] explained several objective functions for large-scale image classification by comparing one-vs-rest, multiclass, ranking and weighted average ranking SVMs. Suard et al. [13] presented an approach for object categorization which is based on two complementary descriptions of an object. First, described its shape through labeled graphs. This graph is obtained from morphological skeleton, extracted from the binary mask of the object image. The second description uses histograms of oriented gradients which is aimed at capturing objects appearance. The histogram descriptor is obtained by computing local histograms over the complete image of the object. These two descriptions are combined using a kernel product. Cuturi et al. [21] discussed positive definite kernels on measures, characterized by the fact that the value of the kernel between two measures is a function of their sum. These kernels can be used to derive kernels on structured objects, such as images and texts, by representing these objects as sets of components, such as pixels or words, or more generally as measures on the space of components. It is observed that the computational complexity is high for the k-IGV kernel.

C. Graph Kernels Related Work

Bach et al. [9] discussed classical kernel-based classifiers which are based on a single kernel, in practice it is often desirable to base classifiers on combinations of multiple kernels. They considered conic combinations of kernel matrices for the support vector machine (SVM), and showed that the optimization of the coefficients of such a combination reduces to a convex optimization problem known as a quadratically -constrained quadratic program (QCQP). Bach et al. [10] explained the problem of learning a sparse conic combination of kernel functions or kernel matrices for classification or regression which is achieved via the regularization by a block 1-norm. They presented an algorithm that computes the entire regularization path for these problems. The path is obtained by using numerical continuation techniques and involves a running time complexity that is a constant times the complexity of solving the problem for one value of the regularization parameter. They explained effect of the block 1-norm regularization differs notably from the non-block 1-norm regularization commonly used for variable selection and that the regularization path is of particular value in the block case and also presented an algorithm to compute entire regularization paths for the problem of multiple kernel learning.

Suard et al. [14] presented an approach for pedestrian detection with stereovision and graph comparison. Images are segmented by the NCut method applied on a single image, and the disparity is computed from a pair of images. This segmentation keep only shapes of potential obstacles, by eliminating the background. The comparison between two graphs is accomplished with an inner product for graph, and then the recognition stage is performed. Learning is done among several pedestrian and non-pedestrian graphs with SVM method. Shi and Malik [16] explained image segmentation as a graph partitioning problem, the normalized cut, for segmenting the graph. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups. A computational technique based on a generalized eigen value problem is used to optimize this criterion and approach to segment static images, as well as motion sequences. Normalized cut is an unbiased measure of disassociation between subgroups of a graph and minimized normalized cut leads directly to maximizing the normalized association, which is an unbiased measure for total association within the subgroups. A computational method based on this idea has been developed and applied to segmentation of brightness, color, and texture images. Shawe-Taylor and Cristianini [17] described the concepts about the pattern analysis, clustering, kernel methods, kernel matrix, and different types of kernels. Wu and Rehg [18] presented common visual codebook generation approach used in a Bag of Visual words model, e.g. k-means or Gaussian Mixture Model. Histogram Intersection Kernel (HIK) is used in place of the Euclidean distance to generate the codebooks. In this paper, author demonstrated that HIK is used in an unsupervised manner to generate the visual codebooks. Authors claimed that the HIK codebook has higher recognition accuracy over k-means codebooks.

Zhang et al. [20] discussed an approach for object classification based on multi-view segment graphs. For given set of multi-view images for an object, each of them is segmented in terms of its color intensity distribution. Inter and intra-view segment graphs are constructed to describe the spatial relations of the segments between and within view images respectively. Then, these two types of graphs are integrated into a multi-view segment graph Kernel between objects which is computed by accumulating all matching of walk structures between their corresponding multi-view segment graphs. Singha and Hemachandran [22] described content based image retrieval approach where the texture and color features are extracted through wavelet transformation and color histogram. Nilsback and Zisserman [23] described an approach for automatically segmenting flowers in color photographs. This approach consist of two models- a color model for foreground and background, and a light generic shape model for the petal structure. The segmentations are produced using MRF cost function optimized using graph cut. Farmer and Jain [24] presented a framework for segmentation and classification that follows the wrapper methods of feature selection. This approach wraps the segmentation and classification together, and uses the classification accuracy as the metric to determine the best segmentation. By using shape as the classification feature, authors explained segmentation algorithm that relaxes the requirement that the object of interest to be segmented must be homogeneous in some low-level image parameter, such as texture, color, or grayscale.

Demirci et al. [25] explained matching configurations of image features, represented as attributed graphs. Noisy segmentation of images and imprecise feature detection may lead to graphs that represent visually similar configurations that do not admit an injective matching. The framework utilized a low distortion embedding function to map the nodes of the graphs into point sets in a vector space. The Earth Movers Distance (EMD) algorithm is then used to match the resulting points, with the computed flows specifying the many-to-many vertex correspondences between the input graphs. Hein and Bousquet [26] investigated the problem of defining Hilbertian metrics and positive definite kernels on probability measures. They also discussed about the structural kernel which is independent of the dominating measure.

Neuhaus and Bunke [27] discussed an approach in structural pattern classification to define a dissimilarity measure on patterns and then apply a distance-based nearest-neighbor classifier. They have elaborated he approach for classification using kernel functions based on edit distance. This approach is applicable to both string and graph representations of patterns. By means of the kernel functions introduced in this paper, string and graph classification can be performed in an implicit vector space. Kernel functions described in this paper provided direct link between the structural pattern space and the kernel space in that the Euclidean distance in the kernel space is identical to the edit distance in the pattern space. Salman [28] discussed combination of K-means, watershed segmentation method, and Difference In Strength (DIS) map which is used to perform image segmentation and edge detection tasks. An initial segmentation is obtained which is based on K-means clustering technique. Authors used two techniques; the first is watershed technique with merging procedure based on mean intensity value to segment the image regions and to detect their boundaries. The second is edge strength technique to obtain edge maps of images without using watershed method. Acosta-Mendoza et al. [29] discussed the use of approximate graph matching for frequent subgraph mining. In this paper, an approach for mining frequent connected subgraphs over undirected and labeled graph collections VEAM -Vertex and Edge Approximate graph Miner is presented. Slight variations of the data, keeping the topology of the graphs, are allowed in this approach. Approximate matching in existing algorithm (APGM) is only performed on vertex label set. In VEAM, the approximate matching between edge labels set in frequent sub graph mining is included in the mining process. Also, a framework for graph-based image classification is introduced. This approach identifies the frequent patterns in collections of images allowing slight angular differences between the positions of image segments.

Guan et al. [30] explained gradient approach for solving non-negative matrix factorization and its variants. Nesterov’s gradient approach is used to alternatively optimize one factor with another fixed. In particular, at each iteration round, the matrix factor is updated by using the PG method performed on a smartly chosen search point, where the step size is determined by the Lipschitz constant. Authors presented a nonnegative matrix factorization solver NeNMF, which sequentially optimizes one matrix factor with another fixed by using Nesterov’s method. Tsuda et al. [31] explained an approach where each image is represented as a graph where nodes correspond to local image features and edges encode geometric relations between features. In this paper author proposed a way to bridge the gap between high prediction performance and interpretability.

Chapelle and Zien [32] discussed three semi-supervised algorithms where first one is deriving graph-based distances that emphasize low density regions between clusters, followed by training a standard SVM, second one is optimizing the transductive SVM objective function, which places the decision boundary in low density regions, by gradient descent and third is combining the first two to make maximum use of the cluster assumption. These algorithms are based on two different principles: the regularization by margin maximization on the labeled points, and the cluster assumption by margin maximization on the unlabeled points. Poorani et al. [33] presented features extraction mechanism which is used for retrieving the images. These features include color, shape and texture. These features are extracted by different techniques. Color feature is extracted by Color Histogram and Color Descriptor. Shape feature is extracted by Hu Moment and Edge detection Mechanism.

## III. PROBLEM FORMULATION

The presented work is related to the classification of query image. Main aim in this work is to classify the given image correctly i.e. to find the class to which it belongs. From this point of view, the concerned problem is formulated as follows:

- Do the collection of different images for the typical class

- To develop an approach to correlate all these images of same class

- For this, Graph kernel based feature extraction and complete image feature extraction have to be developed

- To have the Graph Kernel based feature extraction, the segmentation of the given image have to be done

- Therefore, to develop the image segmentation mechanism in view of graph kernel based feature extraction

- To develop an approach for the complete image feature extraction

- To develop the approach for the image classification. This approach will be based on the support vector machine

- For SVM classifier, the feature of query image and feature database of different classes will act as input

Mathematically, this problem can be formulated as follows. Consider the image as variable 'X'.

- For this variable 'X', different partitions have to be developed i.e. 'X' will be divided into different parts ($X_1, X_2, X_3, \ldots\ldots\ldots\ldots X_n$).

- Being $X_1, X_2, X_3, \ldots\ldots\ldots\ldots X_n$ are the different parts of the 'X', all these parts are connected with each other by some means.

- The connectivity representation of these parts forms the graph with different nodes (i.e. n) with different edges (i.e. e).

- The graph 'G' will be formed with 'n' nodes and 'e' edges (edges depends on the adjacency of $X_1, X_2, X_3, \ldots\ldots\ldots\ldots X_n$ parts).

- For every region and adjacent regions or parts, the features have to be evaluated as feature matrix or vector- e.g.

$\overrightarrow{X_1}$ : For $X_1$: Features are centroids, area, ……….etc.

$\overrightarrow{X_2}$ : For $X_2$: Features are centroids, area, ……….etc.

...

...

$\overrightarrow{X_n}$ : For $X_n$: Features are centroids, area, ………, etc.

- To find the complete features for 'X', e.g.

For X: Features are shape, texture, color, ………, etc.

- Collectively, for the image variable 'X', the Feature Vector will become the collection of features for different parts and for whole image i.e.

$$\overrightarrow{Feature} = Features\ for\ X_1, X_1, \ldots, X_n \cup Features\ for\ X$$

- Image classification becomes the problem of set matching

That is, matching of the sets $\overrightarrow{Feature}$ with $\overrightarrow{Feature_{query\,image}}$ (extracted features of query image which are extracted in same similar way as that of $\overrightarrow{Feature}$).

- Here, the aim is to get intersection of these two sets. It should not be NULL, i.e.

$$\{\downarrow\} = \{\overrightarrow{Feature}\} \cap \{\overrightarrow{Feature_{query\,image}}\}$$

$\{\downarrow\}$ : If the Intersection set is NULL then no match and no classification will be there.

## IV. PROPOSED APPROACH

In image classification, the image segmentation is the fundamental step. Main key issue, here, is the choice of the methodology for the image segmentation. Different techniques are available to perform the image segmentation, but the prominent one from image classification point of view is the watershed transform, as presented work concern with the approach based on graph kernels. To develop the graph kernel, it is necessary to have the identification of the different regions of the image. To get the different regions from the image, the watershed transformation based image segmentation have to be performed. Later the next important thing is that the image classification. For this purpose the Support Vector Machine (SVM) is selected as the classifier. In view of the image classification, firstly, the image database of different classes is referred, to generate the attributes of the images in particular and that of the classes in general. These attributes consist of the feature based on the graph kernel which is obtained after performing the image segmentation using watershed transformation and the features for the whole image. In this way, the feature database for the particular classes is developed. Later, to identify the belongingness of the query image, once again the same attributes are extracted for the query image and then, query image feature and the feature database for the various classes is referred to classify the given query image. For this purpose the confusion matrix is evaluated through the SVM classifier. The block schematic for the proposed approach is depicted in Figure 1.

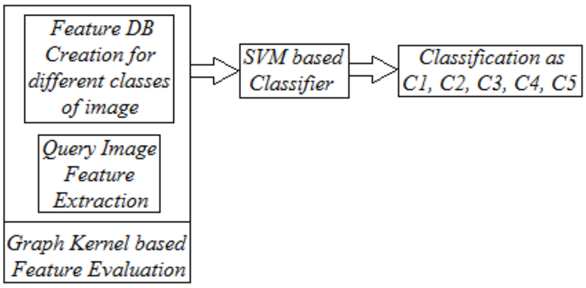


Figure 1: Block schematic of proposed approach

A. Feature Database Creation

Feature database for the different image classes is created by using the concept of graph kernel. The images are segmented to get the different regions, based on these regions the various features for the regions are evaluated and the whole image features are also evaluated. Five image classes are identified and for every class, 100 images are collected. The process of feature extraction is repeated for the every image of every class. Combined feature vector for every image of every class is recorded in the feature database. The complete process of the feature database creation is depicted through the block schematic given in Figure 2.

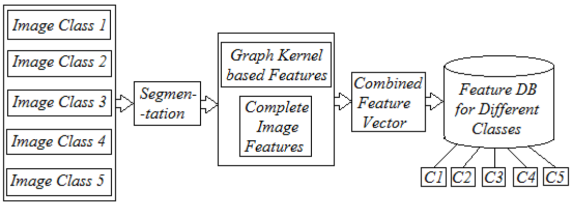


Figure 2: Block schematic for feature database creation

B. An Approach for the Feature Extraction of an Image

Block schematic of the approach for the feature extraction of an image is shown in Figure 3. Procedure for the same is described as follows:

Input: Color or Gray Image

Output: Feature Vector for image

Procedure: Step by step representation

Step 1: Read or refer the given image (from image database or query image)

Step 2: Perform the watershed segmentation

Step 3: Obtain the features for different regions based on graph kernel

Step 4: Obtain the features for complete image

Step 5: Form the feature vector for the given image

Step 6: Store the feature vector

Step 7: If feature database creation

Then

Repeat the Step 1 through Step 5

Else

Stop.

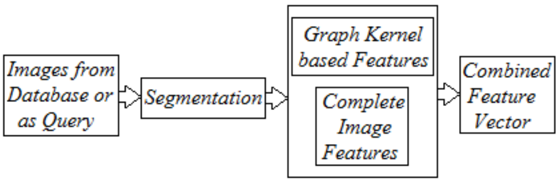


Figure 3: Block schematic of the approach for the feature extraction of an image

Step 2 in Approach for the Feature Extraction of Image (Watershed Segmentation):

Input: Color or Gray Image

Output: Segmented Image

Step 1: Read the Color Image and Convert it to Grayscale

Step 2: Use the Gradient Magnitude as the Segmentation Function

Step 3: Mark the Foreground Objects

Step 4: Compute Background Markers

Step 5: Compute the Watershed Transform of the Segmentation Function

Step 6: Visualize the Result

Step 7: Mark the centroids in the segmented region

Stop.

Step 3 in Approach for the Feature Extraction of Image (Graph kernel based features)

Input: Segmented Image

Output: Region Features

Step 1: Read the Segmented Image

Step 2: Mark the Region as the Nodes

Step 3: Connect the Adjacent Regions

Step 4: Find the Attributes of the Nodes

Step 5: Record the Attributes of the Nodes

Step 6: Form the Feature Vector

Stop.

Every region in the segmented image is marked as the node and all adjacent regions are connected through the edges. Adjacency matrix is created from the graph. Apart from this, different attribute values are obtained for the different nodes and edges of the graph. These attributes are- Area- the actual number of pixels in the region; BoundingBox- The smallest rectangle containing the region; Centroid- Specifies the center of mass of the region; ConvexHull- Specifies the smallest convex polygon that can contain the region; ConvexImage- Binary image (logical) that specifies the convex hull, with all pixels within the hull filled in (i.e., set to on). (For pixels that the boundary of the hull passes through.) The image is the size of the bounding box of the region; ConvexArea- Specifies the number of pixels in 'ConvexImage'; Eccentricity- Specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment); EquivDiameter- Specifies the diameter of a circle with the same area as the region, computed as sqrt(4*Area/pi); EulerNumber- Specifies the number of objects in the region minus the number of holes in those objects. 8-connectivity is used to compute the EulerNumber; Extent- Specifies the ratio of pixels in the region to pixels in the total bounding box, computed as the Area divided by the area of the bounding box; Extrema- 8-by-2 matrix that specifies the extrema points in the region. Each row of the matrix contains the x- and y-coordinates of one of the points; FilledArea- Specifying the number of on pixels in FilledImage; FilledImage- Binary image (logical) of the same size as the bounding box of the region. The on pixels correspond to the region, with all holes filled in; Image- Binary image (logical) of the same size as the bounding box of the region; the on pixels correspond to the region, and all other pixels are off; MajorAxisLength- Specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region; MinorAxisLength- Specifying the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region; Orientation- Specifying the angle (in degrees ranging from -90 to 90 degrees) between the x-axis and the major axis of the ellipse; and Perimeter- Specifying the distance around the boundary of the region. It is calculated by using the distance between each adjoining pair of pixels around the border of the region. These attribute forms the feature vector based on the graph kernel.

Step- 4 in Approach for the Feature Extraction of Image (Feature of the complete image)

Input: Color or Gray Image

Output: Complete Image Features

Step 1: Read or refer the given image (from database or query image)

Step 2: Color Features and Wavelet Transform of the Image

Step 3: Obtain the Features

Step 4: Record the Features

Step 5: Form the Feature Vector

Stop.

After taking the Wavelet transform of the image, various features like HSV histogram, color autocorrelation, color moments, mean amplitude, msenergy, and wavelet moments are obtained to form the feature vector for the complete image. Finally the features obtained through graph kernel and through Wavelet are combined together to form th final main feature vector for the image.

C. Image Classification

For the given image the corresponding image class is identified by using the SVM classifier. For the query image, the same procedure is adopted as that one which is used for the feature database formation. Through the evaluation of the confusion matrix and error, the corresponding class of the query image is identified and accordingly the result is generated. Block schematic for query image classification based on SVM classifier is shown in Figure 4.

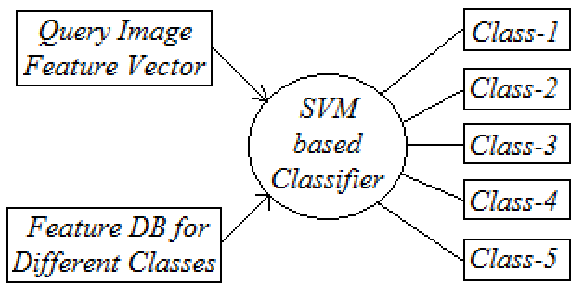


Figure 4: Block schematic for query image classification

SVM based Image Classification approach is described as follows:

Input: Color or Gray Image (Query)

Output: Feature Vector for image and Class of the image

Procedure: Step by step representation

Step 1: Load the Feature database for different classes of Image

Step 2: Obtain the Feature Vector for Query Image

Step 3: Record the Query Image Feature Vector

Step 4: Evaluate the Confusion Matrix

Step 5: SVM based Classification of Query Image using Step 1 through Step 4

Stop.

# V. EXPERIMENTAL SETUP, RESULTS AND DISCUSSION

The approach is implemented using (MATLAB 7.10.0.499) (R2010a). The experiments are carried out on Intel (R) Core (TM) i5-4200U CPU @ 1.60GHz 2.30 GHz processor, RAM 4GB and HD 500GB. The operating system is Windows. The experiments are carried out on different images taken for the five image classes. There are five different types of classes of images, namely, Horses, Roses, Cars, Parrots, and Pandas. Each class contains 100 images. Each image having different poses, different backgrounds. That means 100 images with 100 poses and 100 different backgrounds. The scope is there to add new class images for the feature database creation. For every image of respective class, the feature database is created based on the graph kernel and the wavelet transforms which includes HSV histogram, color autocorrelation, color moments, mean amplitude, msenergy, and wavelet moments.

## A. Watershed Segmentation and Graph Kernel based Features

For every image of the image classes, the watershed segmentation is carried out. Firstly, the color image is converted to grey level image. Then the gradient magnitude is used as the segmentation function. Foreground objects are marked and the background markers are computed. Later, the watershed transform of the segmentation function is computed. Regions are evaluated and centroids are marked to form the adjacency graph. For these regions and adjacent graph, the features are evaluated.

Watershed segmentation intermediate results for sample image are shown in Figure 5 (a) and Figure 5 (b). Graph formation for sample image based on segmented regions to get the graph kernel based features is shown in Figure 6. Different feature values for the graph are shown in Table I (a) and Table I (b). Centroids of the nodes and Adjacency matrix for the graph are shown in Table II.

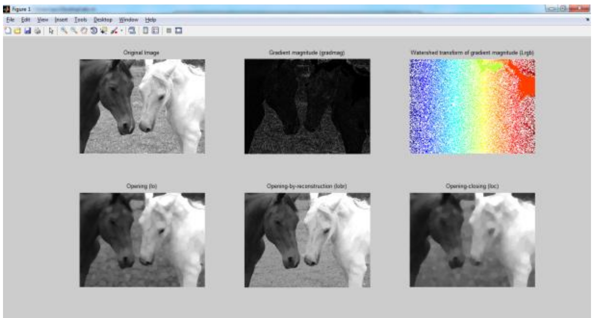

Figure 5 (a): Watershed segmentation intermediate results for image

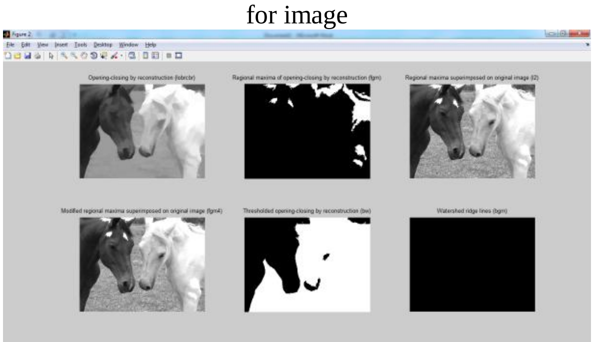

Figure 5 (b): Watershed segmentation intermediate results for image

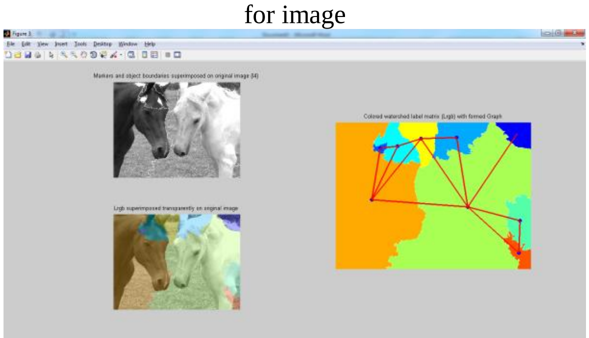

Figure 6: Graph formation for image based on segmented regions to get the graph kernel based features

Table I (a): Feature values for the graph of sample image

| | R-1 | R-2 | R-3 | R-4 |
|---|---|---|---|---|
| Area | 668016 | 6314 | 68646 | 68712 |
| MajorAxisLength | 1259.7709 | 123.23678 | 397.47999 | 392.94906 |
| MinorAxisLength | 741.30715 | 78.54576 | 271.53955 | 256.60863 |
| Eccentricity | 0.8085365 | 0.7705691 | 0.7302755 | 0.7573296 |
| Orientation | -84.812141 | 10.888218 | -61.658534 | -45.078756 |
| ConvexArea | 768811 | 8963 | 81772 | 86852 |
| FilledArea | 668016 | 6314 | 68646 | 68712 |
| EulerNumber | 1 | 1 | 1 | 1 |
| EquivDiameter | 922.24963 | 89.661778 | 295.63965 | 295.78174 |
| Solidity | 0.868895 | 0.7044516 | 0.8394805 | 0.7911389 |
| Extent | 0.7522703 | 0.5317053 | 0.5558201 | 0.5309718 |
| Perimeter | 4869.5475 | 519.50462 | 1434.0631 | 1868.2195 |

Table I (b): Feature values for the graph of sample image

| | R-5 | R-6 | R-7 | R-8 | R-9 |
|---|---|---|---|---|---|
| Area | 90653 | 864754 | 30726 | 70000 | 42657 |
| MajorAxisLength | 475.878 | 1358.81 | 346.802 | 456.111 | 303.348 |

| | | | | | |
|---|---|---|---|---|---|
| MinorAxisLength | 275.7065 | 900.342 | 133.779 | 208.963 | 198.96 |
| Eccentricity | 0.815069 | 0.74898 | 0.9226 | 0.88888 | 0.75486 |
| Orientation | 23.78704 | 57.4646 | -54.692 | -84.23 | -31.572 |
| ConvexArea | 110456 | 1051211 | 42603 | 78978 | 45812 |
| FilledArea | 90653 | 864754 | 30726 | 70000 | 42657 |
| EulerNumber | 1 | 1 | 1 | 1 | 1 |
| EquivDiameter | 339.7396 | 1049.3 | 197.792 | 298.541 | 233.051 |
| Solidity | 0.820716 | 0.82263 | 0.72122 | 0.88632 | 0.93113 |
| Extent | 0.612984 | 0.60813 | 0.42782 | 0.72723 | 0.68099 |
| Perimeter | 2093.568 | 6691.76 | 1477.6 | 1881.77 | 1050.22 |

Table II: Centroids of the nodes and adjacency matrix for the graph of sample image

| | | | Edge Connectivity | | | |
|---|---|---|---|---|---|---|
| Nodes | Centroids | | SN | DN | SN | DN |
| R-1 (Node-1) | 296.811 | 632.395 | 1 | 2 | 3 | 6 |
| R-2 (Node-2) | 367.101 | 210.711 | 1 | 3 | 5 | 6 |
| R-3 (Node-3) | 701.327 | 132.295 | 1 | 4 | 6 | 7 |
| R-4 (Node-4) | 508.725 | 193.183 | 1 | 6 | 6 | 8 |
| R-5 (Node-5) | 993.73 | 123.296 | 2 | 4 | 6 | 9 |
| R-6 (Node-6) | 1085.2 | 691.432 | 3 | 4 | 7 | 8 |
| R-7 (Node-7) | 1504.58 | 1068.61 | 3 | 5 | | |
| R-8 (Node-8) | 1514.08 | 804.229 | SN- Source Node | | | |
| R-9 (Node-9) | 1491.53 | 89.475 | DN- Destination Node | | | |

B. Complete Image Features and SVM based Classification

Complete image features for sample image: HSV histogram, color autocorrelation, color moments, mean amplitude, msenergy, and wavelet moments are summarized in Table III. SVM based classification of Query Image is carried out. Intermediate results and query image classification result are shown in Figure 7 (a) through Figure 7(r).

Table III: Complete Image feature values for the sample image

| Features | Feature Values | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| hsvHist | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 0.25 | 0.01 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 0.05 | 0.4 | 0 | 0.06 | 0.1 | 0 | 0 | 0 |
| | 0.03 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 |
| autoCorrelogram | 0.01 | 0 | 0 | 0.03 | 0 | 0 | 0.06 | 0 |
| | 0.01 | 0.01 | 0 | 0.01 | 0 | 0.05 | 0.02 | 0 |
| | 0.11 | 0.05 | 0 | 0.06 | 0 | 0 | 0.24 | 0.03 |
| | 0.05 | 0.01 | 0.1 | 0.01 | 0.1 | 0 | 0.04 | 0.05 |
| | 0 | 0.17 | 0 | 0.1 | 0.1 | 0.2 | 0.11 | 0.14 |
| | 0.27 | 0.04 | 0 | 0.13 | 0 | 0.08 | 0 | 0.04 |
| | 0.66 | 0 | 0.2 | 0 | 0 | 0 | 0.08 | 0.04 |
| | 0 | 0.03 | 0 | 0.15 | 0 | 0 | 0.08 | 0.21 |
| color_moments | 156 | 59.9 | 145 | 74.3 | 119 | 81 | | |
| meanAmplitude | 25.9 | 63.3 | 124 | 249 | 13 | 27.4 | 50.5 | 113 |
| | 7.15 | 12.3 | 17 | 41 | 8 | 13.7 | 17.6 | 27.9 |
| | 6.83 | 12 | 19 | 34.4 | 13 | 28.8 | 56.1 | 108 |
| msEnergy | 0.01 | 0.02 | 0 | 0.04 | 0 | 0.01 | 0.02 | 0.03 |
| | 0.01 | 0.01 | 0 | 0.01 | 0 | 0.01 | 0.01 | 0.01 |
| | 0.01 | 0.01 | 0 | 0.01 | 0 | 0.01 | 0.02 | 0.03 |
| wavelet_moments | 7.16 | 7.16 | 7.3 | 8.54 | 9.3 | 9.33 | 9.01 | 8.99 |
| | 8.61 | 8.36 | 8.4 | 8.49 | 8.5 | 8.2 | 7.82 | 8.7 |
| | 8.92 | 8.97 | 8.8 | 8.79 | 4 | 3.99 | 3.85 | 4.81 |
| | 5.31 | 5.34 | 5.5 | 5.66 | 5.6 | 5.38 | 4.94 | 4.59 |
| | 4.16 | 3.91 | 3.7 | 3.34 | 2.8 | 2.52 | 2.57 | 2.55 |

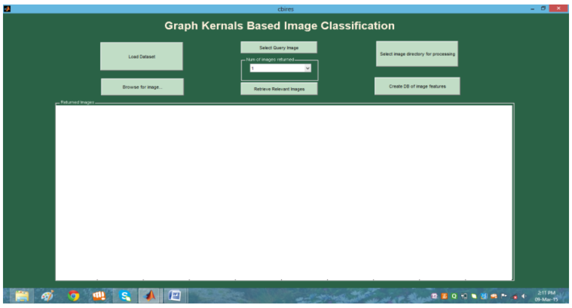

Figure 7 (a): Intermediate results for SVM based classification

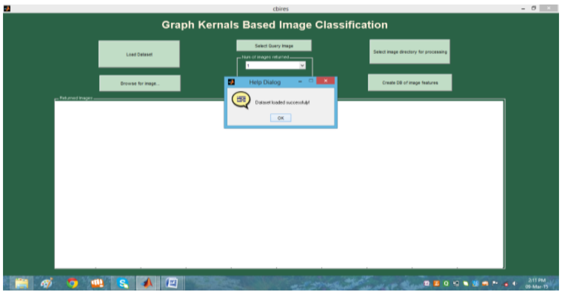

Figure 7 (b): Intermediate results for SVM based classification

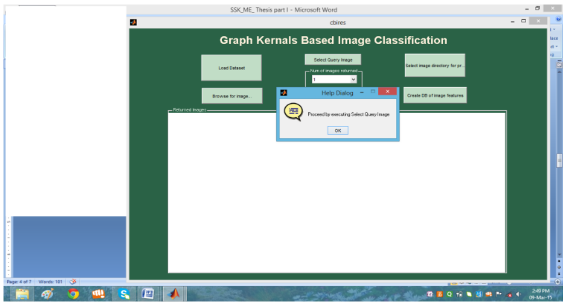

Figure 7 (c): Intermediate results for SVM based classification

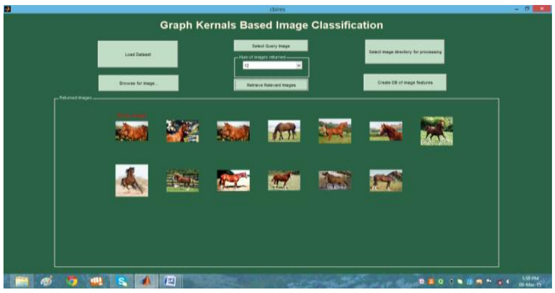

Figure 7 (d): Intermediate results for SVM based classification

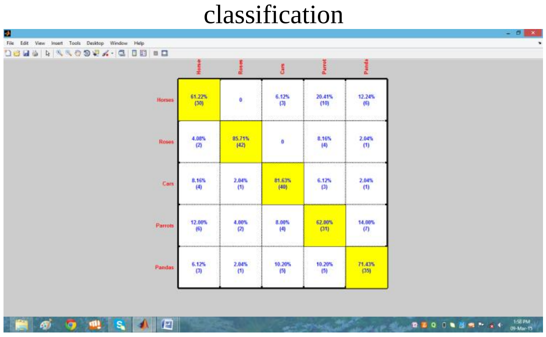
Figure 7 (e): Intermediate results for SVM based classification

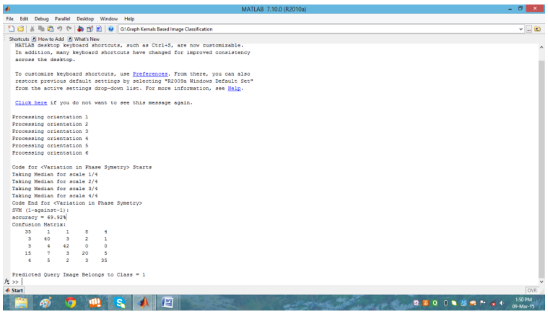

Figure 7 (f): Intermediate results for SVM based classification

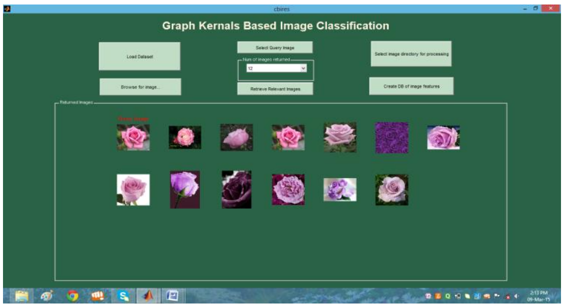


Figure 7 (g): Intermediate results for SVM based classification

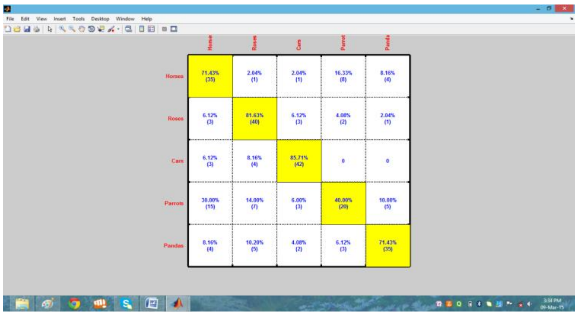

Figure 7 (h): Intermediate results for SVM based classification

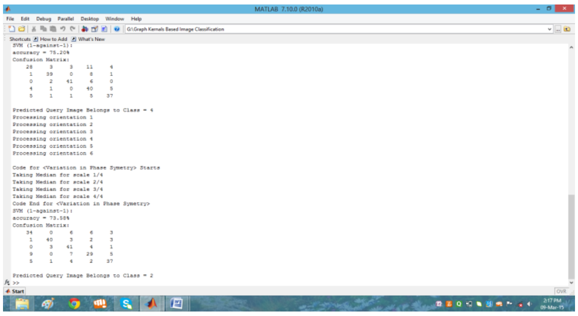

Figure 7 (i): Intermediate results for SVM based classification

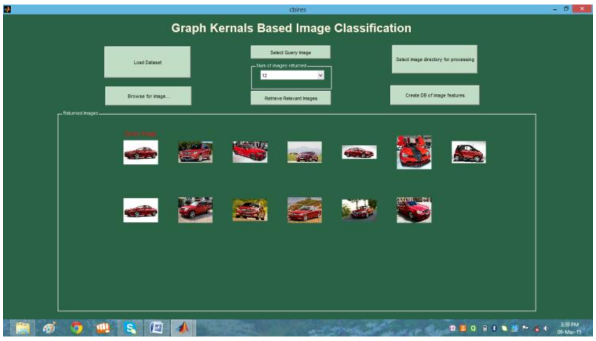


Figure 7 (j): Intermediate results for SVM based classification

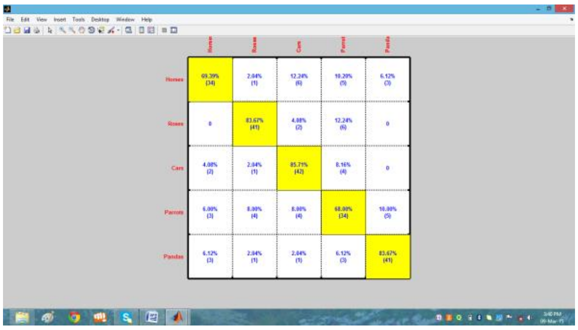

Figure 7 (k): Intermediate results for SVM based classification

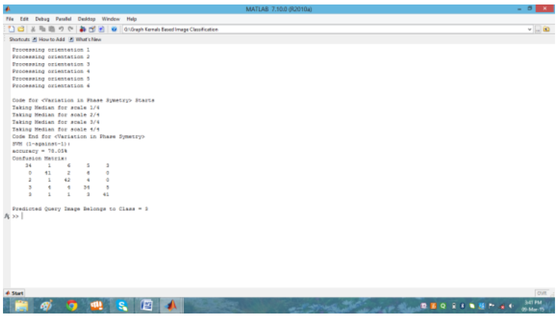

Figure 7 (l): Intermediate results for SVM based classification

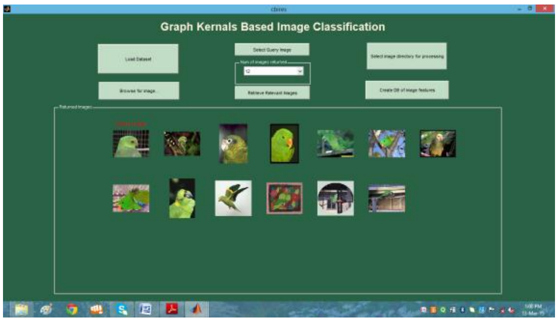


Figure 7 (m): Intermediate results for SVM based classification

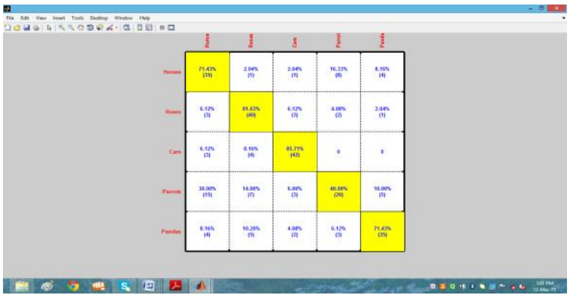

Figure 7 (n): Intermediate results for SVM based classification

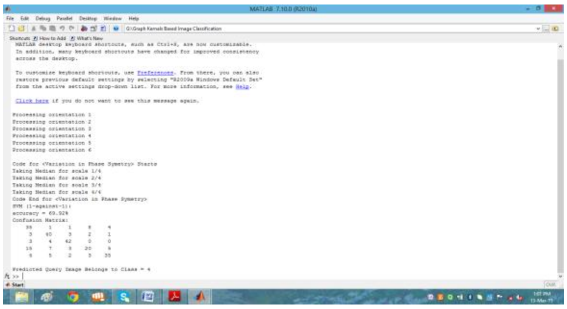

Figure 7 (o): Intermediate results for SVM based classification


Figure 7 (p): Intermediate results for SVM based classification

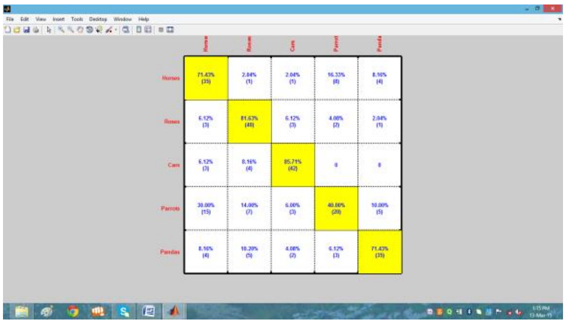

Figure 7 (q): Intermediate results for SVM based classification

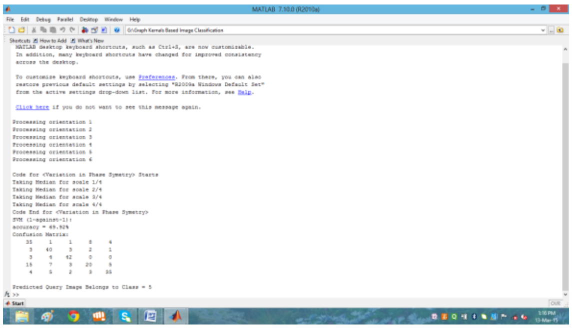

Figure 7 (r): Intermediate results for SVM based classification

## VI. CONCLUSION AND FUTURE SCOPE

Based on the implementation and obtained results, following conclusions are drawn: Image segmentation is the key step in any image classification approach; therefore, the results related to the segmentation leave the impact on the image classification results. In presented work, the image segmentation is carried out with the watershed transformation. Graph kernel based implementation provides, the insight of the given image, as the attributes are related to the different regions formed. Region node and the adjacency of the regions provided the first part of the features and the second part of the features is associated with the wavelet transform. Second part, also, includes the feature related to the hsv histogram and color correlation. Through extensive experimentation, it is observed that the classification accuracy of the presented approach is satisfactory. The obtained results are encouraging and motivating for the further optimization in number of features used.

Following are the future directions to extend the presented wok: The number of features used can be minimized by using the Principal Component Analysis. Artificial neural network implementation may be possible by using the selected features for training, validation and testing. Presented work is carried out for five image classes and this can be extended to more number of classes.

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