An Approach for Image Classification

Shruti Kulkarni M.E. EEE SGBAU University Amravati India kulkarnishruti.first@gmail.com

Abstract- 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. Experimentations are carried out with the five classes of images. Every class consists of 100 images. Obtained results are encouraging and motivating.

Keywords— image processing, image segmentation, SVM, image classification

I. INTRODUCTION

1.1 Image and Image Processing

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 signalprocessing techniques to it.

1.2 Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). 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.

1.3 Image Classification

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.

1.4 Graph Kernels in Image Classification

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.

1.5 Support Vector Machine

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 hyperplane. 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'', that replaces the dot product needed in computation by a nonlinear 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.

1.6 Contribution

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.

II. LITERATURE SURVEY

A. Image Segmentation Related Work

Anju Bala (2012) [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 (2012) [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 (2003) [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 stateof-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. (2004) [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 (2003) [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. (2001) [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. (2012) [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 scalesynthesis 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 edgeembedded 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 (2005) [23] 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. The summary of image segmentation related work is given in Table 2.1 (a) and Table 2.1 (b).

Def	Deve	Det	T	A 41	0
Ref no, Autho rs, vear	Perfor mance para meter used	Data base used	lss ues Addre ssed	Authors Remark	Our Findings
[1] Anju Bala 2012	Noise, Intensi ty	Synthe tic image	Prewit t's operat or, gradie nt magnit ude	Image is segmente d accordin g to object, color, shape	To avoid over segmentatio n Prewitt's operator is used to detect the edges instead of Sobel operator
[3] A. Devi C P and A Venug opal 201 2	Seg mentat ion time, Pix el count and label, region param eters	Synthe tic image	image segme ntation by graph cuts and Kernel mappi ng	mini mization with respect to the image segmenta tion by graph cuts minimiza tion with respect to the regions paramete rs via fixed point computat ion	Kernel function is used to improve optimization process
[5] Bastia n Leibe, Bernt Schiel e, 2003	Conto ur, Color, texture ,global and local shape of image	COIL, RSOR T ETH - 80	high- resolut ion color image s	Object Categori zation Contour methods	Combinat ion of Different methods is used

Table 2.1 (a):Image segmentation related work

[6]	Texto	Sy	Spec	The	Color and
C.	ns,	ntheti	tral	specific	texture
Fowlk	histogr	с	groupin	applicati	segmentatio
es, S.	am,	imag	g of	on is	n,
Belong	eigen	e	images	classifica	spatio
ie, F.	vector		by	tion of	temporal
Chung	S		k-	MRI	segmentatio
, and J.			means	scan data	n issues are
Malik,			pairwis	accordin	addressed
2004			e	g to the	
			clusteri	nature of	
			ng,	the	
			Nystro	corpus	
			m	callosum	
			method	,	
				introduce	
				d	
				А	
				variation	
				of the	
				spectral	
				segmenta	
				tion with	
				multi-	
				scale	
				graph	
				decompo	
				sition	
				Mech	
				anism.	
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 Table 2.1 (b) : Image Segmentation related work

Ref no, Autho rs and year	Perfor mance parame ter used	Data base used	Issues Addres sed	Authors Remark	Our Findings
[7] C. Gomil a and F. Meyer, 2003	Success ive position s of the same object.	Synt hetic imag e	Object tracking is formula ted as a joint proble m of segmen tation & matchin g	JSM for 2D and 3D images, efficient solution to reduce the complexi ty of the matching algorith ms	Region splitting, Matching partition. Matching of occluded region is carried out
[15] J. Malik, S. Belong ie, T. K.	Textons , eigen vectors, canny	Synt hetic imag e	partitio ning graysca le images into	Contour and texture Analysis	Pixels which are not oriented/o reinted are

Leung, and J. Shi., 2001	edge detector ,cue, contour ,texture		disjoint regions	Canny edge detector	considere d
[19] Lina Yi, Guifen g Zhang, and Zhaoc ong Wu,20 12	Classifi cation accurac y	Synt hetic imag e	Extract semanti c meanin gful objects	scale- synthesis method, EEMW algorith m HSRI segmenta tion	Land cover category type of image for multi scale segmentat ion, region segmentat ion is used
[24] Micha el E. Farmer , and Anil K. Jain,20 05	Classifi cation accurac y	Synt hetic imag e	Wrappi ng segmen tation, Classifi cation, FSS and EM algorith m	Classific ation accuracy , Feature extractio n, Context- based segmenta tion	image segmentat ion, feature extraction, classificati on

Morales-Gonzalez et al. (2013) [2] described about graphbased 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. (2010) [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. (2007) [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 (2006) [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. (2012) [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. (2006) [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. (2005) [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. The summary of image classification related work is given in Table 2.2 (a) and Table 2.2 (b).

Table 2.2 (a). Image classification related work	Table 2.2	(a):	Image	classification	related	work
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Ref no, Autho rs and year	Perform ance paramet er used	Data base used	Issues Address ed	Authors Remark	Our Findin gs
[2]A. M.Gon zalez, N,A.M endoza , A.G.A lonso, E.B.G- Reyes,	Support Thres- hold, Isomor- phism Threshold	COIL 100 ETH 80	Positive definite kernels betwee n labeled graph VEAM, APGM Algorit	FAS Mining Algorith m classifyi ng images to improve graph	FAS in terms of edge and vertex Authors explore classific ation framew

Jose E.M- Pagola 2013			hm	efficienc y	ork
[4]A.E lsayed, F.Coe nen,C. Jiang, F.G.Fi nana,V .Slumi ng,201 0	gSpan algorith m TCV, Quad tree, use of feature vectors construct ed from Frequent sub- graphs	Synthe tic image	Isomor phism Thresho ld, Support Thresho ld	MR Image Classifi cation, Image Mining	Techniq ue for approxi mate solution of spectral partitio ning for image & video segme- ntation based on Nystrom extensior
[8] E. Aldea, J. Atif, and I. Bloch, 2007	Driac, RBF,Ma rginalize d kernel, SVM Classifie r	Synthe tic image	comput ation specific properti es of image- based graphs	Average gray value of region, Region surface in pixels	Image based graph concept describ ed by authors

Ref no, Autho rs, year	Performa nce paramete r used	Data base used	Issues Addres sed	Authors Remark	Our Findings
[11] F.J.Hu ang and Y.LeC un ,20 06	SVM, Convolu tional net, Reconigiti on accuracy	COIL NORB	SVM with Gaussia n Kernel	investigat ed two types of popular discrimina tive learning methods: Support Vector Machine	Convolutional networks, on the other hand, yield good Recognition accuracy with low computational complexity.
[12] F	Accuracy	ImageN	Multi	Stochastic	Binary one vs

Perron nin, Z Akataa , Zaid Harcha ouib and C Schmi d, 2012		et10K	scale SVM	gradient algorithm	rest SVM, also presented an algorithm to compute entire regularization Weighted paths for the problem of multiple kernel learning. Suard et al. Aprro SVM(2005) [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 the new product of the prod
[13] F. Suard, A. Rakoto mamo njy and A. Bensrh air,200 6	Gradient computati on, 11 norm and 12 norm	ETH-80	3D structur e of objects Graph Kernel HOG kernel	a method for object categoriza tion. The aim is to depict images by labeled graphs and histogram s of oriented gradients.	histograms of mong several pedestrian and non-pedestrian graphs with oriented SVM method. gradients, improvemenSh and Malik (2001) [16] explained image segmentation as a in graph partitioning problem, the normalized cut, for classification segmenting the graph. The normalized cut criterion measures results. 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
[21]M. Cuturi, K. Fukum izu, and J P. Vert, 2005	Gaussian kernel SVM	MNIST	Semi group kernel Entropy kernel	Integral representa tion of positive definite kernel	Positive measure for total association within the subgroups. A definite computational method based on this idea has been developed kernels for and applied to segmentation of brightness, color, and texture image images. Shawe-Taylor and Cristianini (2004) [17] described classification the concepts about the pattern analysis, clustering, kernel methods, kernel matrix, and different types of kernels. Wu and Rehg (2009) [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

Bach et al. (2004) [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. (2004) [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 We and Reng (2009) [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. (2013) [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 (2012) [22] described content based image retrieval approach where the texture and color features are extracted through wavelet transformation and color histogram. Nilsback and Zisserman (2009) [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 (2005) [24] presented a framework for segmentation and classification that follows the wrapper methods of feature selection. This approach wraps the segmentation 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. 2006 [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 (2004) [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 (2006) [27] discussed an approach in structural pattern classification to define a dissimilarity measure on patterns and then apply a distance-based nearestneighbor 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 (2006) [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. (2012) [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. (2012) [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. (2007) [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 (2004) [32] discussed three semi-supervised algorithms where first one is deriving graphbased 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. (2013) [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 Method. Texture feature is extracted by Gray Level co-occurrence matrix and texture descriptor.

Peng and Gu (2005) [34] implemented watershed transform using a multi-degree immersion simulation in which simulation procedure changed to multi-degree, such that flood step is different on each degree of intensity, the presented implementation resists the over segmentation problem. Lazebnik et al. (2006) [35] presented an approach for recognizing scene categories based on approximate global geometric correspondence. This technique works by partitioning the image into increasingly fine sub-regions and computing histograms of local features found inside each subregion. Vishwanathan et al. (2007) [36] defined unifying framework for random walk kernels on graphs using extensions of linear algebra concepts for Reproducing Kernel Hilbert Spaces (RKHS). RKHS can be applied to directed and undirected graphs. Gartner (2003) [37] explained kernels on labeled directed graphs with general structure, computing a strictly positive definite graph kernel is just like solving the graph isomorphism problem and inner product in a feature space indexed by all possible graphs, where each feature counts the number of sub graphs isomorphic to that graph.

Jebara (2003) [38] explained the approach for modeling images and related visual objects as bags of pixels or sets of vectors. Bag of pixels subspace benefits from automatic correspondence estimation, giving rise to meaningful linear variations such as morphings, translations, and jointly spatiotextural image transformations. Wang et al. (2011) [39] explained Conventional linear subspace learning methods like principal component analysis (PCA), linear discriminant analysis (LDA) derive subspaces. Also proposed Subspace Indexing Model on Grassmann Manifold (SIM-GM) partitions the global space into local patches with a hierarchical structure; the global model is approximated by piece-wise linear local subspace models. Grassmann manifold distance is applied in such way that, SIM-GM is able to organize localized models into a hierarchy of indexed structure. Fu and Huang (2008) [40] explained the approach for image classification based on correlation tensor analysis (CTA), which is designed to incorporate both graph-embedded correlational mapping and discriminant analysis in a Fisher type of learning manner. CTA learns multiple interrelated subspaces to obtain a low-dimensional data representation reflecting both class label information and intrinsic geometric structure of the data distribution. LeCun et al. (2004) [41] explained the learning methods for generic object recognition with invariance to pose, lighting and surrounding clutter. They have also explained about jittered-textured and jittered cluttered dataset, where the classifier must simultaneously detect and recognize objects. Harchaoui and Bach (2007) [42] explained different type of kernel families like walk kernel, tree walk kernel, histogram kernel, weighted tree kernels. In this paper, three features are explained, first is histogram with gradients, integrated it with multiple kernel learning such as SIFT features, second one is extensions of kernels on structured data used in bioinformatics, such as the nontottering trick, third is kernel-based framework carries directly over clustering, semi-supervised classification, and dimensionality reduction. The summary of Graph kernels related work is given in Table 2.3 (a) through Table 2.3 (g).

	.3 (a). GI	арп кегие	eis i ciate		
Ref	Perfor mance	Databa	Issues Addre	Authors Remark	Our Findings
Autho	parame	se useu	ssed	Keinai K	Findings
rs and	ter				
year	used				
[9] F.R.Ba ch,G.R .G.Lan ckriet, M.I.Jo rdan,2 004	Conic duality and optimal ity Conditi ons	ionosph ere and breast cancer subset of Adult dataset	l1nor ms l2 norms MY regula rized SKM	the algorith m selects kernels that define non- linear mapping s on subsets	SMO- based algorith m is significa ntly more efficient
				of input features.	
[10] F. R. Bach, R. Thibau x, and M. I. Jordan , 2004	Runnin g time comple xity, regulari sation weight, eigen values	Boston dataset and liver dataset	Block l1nor m regula rizatio ns, Conic combi nation of kernel s	Presente d an algorith m to compute entire regulariz ation paths for the problem of multiple kernel learning.	empirical results shows suggeste d algorith m scales quadratic ally in the number of kernels, but cubically in the number of data points.
[14] F. Suard, V. Guigu e, A. Rakoto mamo njy, and A. Benshr air, 2005	Classifi cation rate	Bench mark images with good lighting	Kernel metho ds- SVM Classif ier &grap h kernel s	Describe d a pedestria n with a graph	presente d a kernel method based on graph for pedestria n recogniti on.

Table 2.3	(b):	Graph	kernels	related	work

Ref no, Author s and year	Perform ance paramet er used	Data base used	Issues Addres sed	Authors Remark	Our Findi ngs
[16]	Computa	Diffe	Graph	Normalised	compu
Jianbo	tion	rent	theorati	cut citeria	tationa
Shi and	time,Gau	Synt	с	for	1
Jitendra	ssian	hetic	approac	segmentati	metho

Malik ,2 000	noise,eig en vectors	imag es	hes to image segmen tation	ng graph also presented an efficient algorithm for computing the minimum normalized cut	d has been develo ped and applie d to segme ntation of bright ness, color, and texture image s
[17]J.Sh awe- Taylor, N. Cristian ini, 2004	-	-	kernel method s and Pattern analysis	Ranking, Clustering, diffusion kernels	Kernel algorit hm
[18] J. Wu, J.M. Rehg 2009	Accurac y	Calte ch 101 objec t recog nitio n datas et, 15 class scene recog nitio n datas et, and the 8 class sport s event s datas et	K median clusteri ng Histogr am interacti on kernel- HIK codebo ok	Histogram Intersection Kernel (HIK) is used as the similarity measure in clustering feature descriptors that are histograms	Autho rs Propos ed a HIK based codeb ook genera tion metho d which runs almost as fast as k- means and has consist ently higher accura cy than k- means codeb
L20JL.Z hang,M. Song,X. Liu,J.ju Bu, C.Chen	classific ation accuracy , Color intensity	Paris , Oxfo rd ETH- 80	anter and intra view segmen t graph, Multi-	segment graph– grassman manifold,,fi xed-point iterations-	rMSG K, used to build repres entatio

2013	distributi on		view object classific ation, Direct walk kernel Fast segmen t graph kernel	based acceleratio n and conjugate gradients- based acceleratio n.	n of multi- view image s
[21]M. Cuturi, K.Fuku mizu,J P.Vert, 2005	Regulari zation Width of Gaussian kernel	Semi - grou p kerne l, Entro py kerne l, k- IGV kerne l	Inverse generali zed varianc e on RKHS associat ed with kernel	positive definite kernels through an integral representati on theorem proved	Autho rs presen ted semigr oup Kernel s, these kernel s can be natural ly applie d on compl ex object s seen as molec ular measu res.
Table 2.3	(c). Granh	kornols	related wa	rlz	

Table 2.5	(c): Grapi	i kernels re	elated work	Ś.	
Ref no, Author s and year	Perfor mance parame ter used	Data base used	Issues Addres sed	Author s Remar k	Our Findin gs
[22]Ma nimala Singha K.Hema chandra n, 2012	Color feature, Color histogra m, Haar discrete wavelet transfor m	WANG	Wavele t based color histogra m, Quantiz ation, Similari ty Matchi ng, Haar Wavele t, Precisio n &	Similari ty betwee n the images is ascertai ned by means of a distance functio n.	WBCH based image retrieva l reduces comput ational steps and increase in retrieva l speed.

			Recall.]	[27]M.	Chicke	string	String	kernel	nearest-
[23]Mar	Colour	Oxford	Flower	flower	Image	1	Neuhau	n pieces	and	and	method	neighbo
ia-Elena	distribu	17	segmen	segmen	specific		s and H.	dataset	graph	edit	is able	r
Nilsbac	rion,	Flower	tation	tations	backgro		Bunke,2	Tool	datasets	distance	to	classifie
k,	netal	Dataset	using	can be	und and		006	dataset		, Graph	improv	rs can
Andrew	detectio		color	signific	foregro			Pendigi		matchin	e	be
Zisserm	n		and	antly	und			ts		g, Edit	classifie	ormed
an,			shape	boosted	color			dataset		distance	rs based	by
2009			model	by	models			Chromo		based	on tree	support
				using	and			some		functio	edit	vector
				image-	ground			dataset		ns	uistance	machin
				specific	labelled					Kernel		es using
				colour distribu	into					method		the
				tion	foregro					s in		propose
				tion	und and					pattern		d kernel
					backgro					recognit		functio
					und					ion		ns
					regions		Table 2.3	(d): Graph	n kernels r	elated worl	Υ. Υ	
					using a		Ref no,	Performa	n Data	Issues	Author	Our
					trimap		Author	ce	base	Address	s s	Findi
[25]M.F	L1norm	Sample	Dissimi		The		s and	paramete	er used	ed	Remar	ngs
•	,EMD	silhouet	larity	approxi	propose		year	used			K	
Demirci	algorith	tes	betwee	mate	d		[28]	gradient	Synt	Gradient	To	Autho
,A. Shelsouf	m	dataset,	n object	graph	framew		Nassir	operator	, hetic	calculati	perform	rs
Snokoui andah V		MPEG-	pairs, Distorti	represe	OFK		Saiman,	Edge pixe	el imag	on,	image	presen
anuen, i		7	on tree	ntation	the		2000	pointer.	e	K means	tation	nrohle
Keselm		dataset,	DCA	1n acomote	input			Edge		clusterin	and	m of
an,L.		Kimia	PCA, Granh	ic space	trees			length (N).	g	edge	undesi
Bretzne		dataset	edit	through	isometri			Edge		Region	detectio	rable
r,			distance	an	cally			strengths	s.	growing	n	over
Sven J.			,	isometri	into a			edge		detection	tasks	segme
Dickins			euclide	с	geometr			pointer		ucicciioi	region	ntation
on,			an	Embed	ic space						growin	results
2011			distance	ding	under						g &	produc
				techniq	the l1						edge	ed by
				ue	norm.T						detectio	the
				proble	o match many to						n	waters
				m	many						techniq	algorit
				overco	EMD						ues.	hm.
				me	algorith							when
					m							used
					under							directl
					ll norm							y with
					used							raw
	Homog	WebKB	Structur	propose								image
[26] M.	eneous	and	al	d a	Structur							s is
Hein	hibertia	Reuters	kernels,	structur	al							solved
and O.	n	data set	gaussia	al	Kernels		[20]N A	Substituti	o Synt	Graph	9	Rando
Bousqu	metrics,	USPS	n	kernel	on		costa-	n matrix	hetic	based	a granh-	m
et,2004	ance	dataset	kernels,	which	probabi		Mendoz	Cub	lands	image	based	image
	metrics		Hibertia	18	measur		a, A.	isomorph	is cape	reperese	image	genera
	metrics		n	indepen	es		Gago-	m thresho	ld imag	ntation	represe	tor is
			metrics	uent or	••		Alonso,	Isomorph	es,se	VEAM.	ntation	used
			VS	dominat			Jose E.	m thresho	ld a	APGM	and a	to
			positive	ing			Medina-	accuracy	scape	algorith	framew	obtain
			kernels	measur			Pagola,	Lecaracy	ımag	m,	ork	the
			KUIIUIS	e			2012		es	Frequen	t for	collect
L	1		1			J				approxi	graph-	1011 01

			mate sub graph, RBF Kernel Function	based image classific ation are propose d	image s. quad- tree to repres ent each image in a tree form. a graph to repres ent each	Ref no, Authors and year	adjusted for each image suc that a fixe number of features i extracted Table 2. Perfor mance para meter used	th ch of s d 3 (e): Gra Data base used	marking, Substruct ure mining, image search ph kernels re Issues Addresse d	sed object classific ation based on the LP Boost formula tion. elated work Authors Remark	s and code book
[30] N.	Efficiency,	Synt			image in the collect ion is constr ucted from each respec tive tree Autho	[32] O. Chapelle and A. Zien, 2004	Fixed param eters of Svm, Tsvm, Manif old algorit hm	g50c g10 Coil 120 Text Uspst	Labelled and unlabelled points , Semi supervised classificati on graph	LDS (Low Density Separatio n), combinin g TSVM and SVM algorith ms.	pairwise distances compute d by the graph algorith m attempt to reflect the cluster assumpti
Guan, D. Tao, Z. Luo, B. Yuan, 2012	accuracy	hetic 1 Synt hetic 2 Reut ers- 2157 TDT- 2	NeNMF, Optimu m gradient, NENMF for regulariz ed NMF	Discuss ed NENM F for 11 norm regulari sed, NENM F for 12 norm regulari sed and NENM F Manifol d regulari zed	rs presen ted nonne gative matrix factori zation solver which sequen tially optimi zes one matrix factor with anothe r	[33] Poorani M, Prathiba T, Ravindra n G, 2013 [34] Shengcai Peng,	Precisi on Recall Time Memo	Wang databa se Brain MRI data,	Shape features are extracted using Hu Moments, CBIR, Color Descriptor , Color Histogram , Threshold set of images	computat ional steps are effectivel y reduced with the use of Wavelet transfor mation	on similarit y measure using integrate d features can be carried out using Euclidea n distance provide high accuracy resisted over- segmenta
[31] Nowozi n, K. Tsuda, 2007	Harris- Laplace interest point operator and the SIFT feature descriptor The interest point operator threshold is	VOC 2005 Datas et	Methods for supervise d object classifica tion, Supervis ed classifica tion, Unsuper vised image	derived and validate d two practica l method s for unsuper vised ranking and supervi	Image catego rizatio n with high accura cy Svm used with histogr am feature	Lixu Gu,2005	Water shed region s	cardia c CT data	The applicatio n that was manifestat ions of disease from CT/MRI data	good result with lower cost in comparis on with topograp hical distance based approach	tion problem effectivel y. It decrease s the amount of segmente d areas to 0.3%- 1.2%

						without losing its	2003	on time of graph	different goals	general structur	based on label	ion recog
[35] S. Lazebnik , C. Schmid, and J. Ponce	Classif ication accura cy	Caltec h 101 dataset Graz dataset	multi- degree concept scene category reconigit on,featur extraction pyramid matching	In cat a bas i mc e tiv n, py n g ke sub an cor his n ir fea ov res	nage egoriz tion a difica on of ramid batch mage and mputin g stogra as of nage atures er the ulting sub gions	authors introduce d kernel- based recogniti on method that works by computin g rough geometri c correspo ndence on a global scale using approxi mation techniqu e adapted from the pyramid		isomorphi c graphs with matrix power		Comput ing a strictly positive definite graph kernel is same as solving the graph isomorp hism proble m	es of all possible walks in the kernel. Efficien t comput ation of these kernels is made possible by the use of product graphs	g the struct ure of graph s and famil y of kerne ls based on walk s whic h inclu des the kerne l being polyn omial ly comp utabl e.
[36] S.Vishwa nathan,K. M.Borgw ardt N.N.Schr audolph 2007	Sylves ter equati on, conjug ate gradie nt (CG), and fixed- point iterati on (FP)	MUT AG and PTC, Protei n, enzym e Datase t	Linear system, Random walk,pro uct graph,fix d iteration	Co ra d v g e ke s ess eq r sol l li sy	mpute d ndom valk raph ernels is entiall y uivale nt to ving a arge near stem.	matching Authors discusse d iterative methods, including those based on Sylvester equation s, conjugat e gradients , and fixed- point iterations	[38] T. Jebara , 2003	Gaussian mean, covarianc e, appearanc e subspaces	images of digits, intensity images of single faces, intensity images of multiple individuals	manifol d of multipl e configu ration, PCA Manifol d Learnin g, Bag of pixels vs vectors	Propose d a bag of pixels or vector set represe ntation for images. a gray scale image can be conside red as a collecti	Auth ors explo red perm utatio n invar iance for deali ng with imag es that are organ
Table 2.3 Ref no, Author	(f): Graph Perform	a Data	related wo	rk ssues ddree	Auth	or Our Findi					on of N pixels	ized into colle
s and year	paramet r used	e	A	sed	Rema k	ar ngs					with spatial	ction s of
[37] T. Gartner, P. A. Flach, and S.	Labeled graph, polymino mial	Exper s car out blo	riment k rried t on la ocks di d with o	ernels on ibeled rected raphs	Prese ed appro h conce	nt comp utatio ac n of kerne pt 1					coordin ates (X;Y) and an intensit	s, vecto r sets or
Wrobel,	computat	th	ree	with	ually	y funct					У	bags

					coordin	of		ors	ter	used	ssed		
					ate (I).	pixe	el	and	used				
[20]			Minnerf	T in com	Tre de contre	5				CMU	Carral	T	A
[39] Xinchao	D	.,.	Research	system		(1)	n	[40] Yun	ion	PIE	ation	or and a second	nroposed
Wang,	on	101	Asia	tree	Model	are	P	Fu	accurac	Yale-	based	both	to use
Zhu Li,	performa	an 1	Multimedia	structur	on	the		and	y,	B	on	correlation	correlatio
Dachen	ce,		(MSRA-	e,	Grassn	reco	g	Thom	face	Exte	similar	measure and	n tensor
g Tao 201	Running	g	MM) Image	hierarc	ann	nitio	С	as S. Huan	recongit	nded	ity	tensor	analysis
1 1	time		dataset and	model,	Manifo	l n rat	e	g,200	ion	Yale-	measu	representatio	appearanc
			Essex	Rando	GM)	SIM	[_	8	error	В	incorp	II, CIA	e-
			University	m walk	for	GM	I		rate		orated		based
		1	human face	kernel	large	agai	n				with		discrimina
			dataset		subject	st					superv		nt
					nattern	of	e				multili		learning
					recogni	f glob	a				near		Authors
					ion.	1					subspa		evaluated
					SIM-	mod	e				ce		the
					GM	15, e o					learnin		performan
					partitic ns the	glob	, a				g can		ce of proposed
					manifo	l I					nally		CTA
					d space	PCA	ι;				impro		algorithm
					into	2)	n				ve		for face
					local	are	Р				classif		recognitio
					patches with a	the					perfor		n
					hierarcl	reco	g				mance		
					ical	n rat	e l				,		
					structu	of					CTA		
					e, and train	SIM	[-				benefit		
					local	GM	[s from		
					subspa	agai	n				embed		
					e	thos	e				ding		
					for	of					tensor		
					classifi		l				analys		
					ation.	ls· 3	e	F411	Test	NOD	15 mable	nonon non orto	lincor
						com	p	[41] Y.Le	error	B	m of	results of	classifier.
						are	Ĩ.	Cun,	rate for	datas	recogn	generic	K Nearest
						the		F	unseen	et	izing	shape	Neighbor
						exec	c n	J.Hua	objects	4	generi	recognition	Pairwise
						time	e	and	backgro	sets:	visual	using	Support
						of		L.Bot	und	norm	catego	image	Vector
						SIM	[- r	tou,2		d-	ries	classification	Machines
						agai	n	004		unifo	with	methods	with
						st	-			rm	invaria	operating on	Gaussian
						thos	e			set	pose.	various input	and
						of				jitter	lightin	ns	Convoluti
							a			ea- unifo	g, and		onal
						mod	e			rm	surrou		Networks
						1				set	oluttor		are used
Table 2.3	8 (g): Grap	h ker	nels related	work		-				jitter	ciutter		classifier
Ref	Perfor	Data	Issues	Authors)ur dina-				ed-			for
Auth	parame	base	Auare	Kemark		ungs				red			datasets

		set jitter ed- clutte red set			
[42] Zaid Harc haoui and Franc is Bach, 2007	Several paramet ers tuned for each kernel. Some are Kernels betwee n Segmen ts Coeffici ent in kernel μ betwee n kernel histogra m is optimal value and λ for longer walk	Coil1 00 Corel 114	Semi superv ised and Multip le kernel learnin g	Histogram,T ree walk, Weighted tree explained with results	Tree Walk Kernel for Segmentat ion, Image classificati on

III.PROPOSED APPROACH

3.1 Main idea

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 3.1.



3.1 Block Schematic of proposed approach



3.2 Feature Database Extraction

3.2 Feature database Extraction

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 in Figure 3.2.

An approach for the feature extraction is summarized



Step 3 \longrightarrow Obtain the features for different	Procedure:- Step by step representation
regions based on graph kernel	Step 1 \longrightarrow Read the Segmented Image
Step 4 \longrightarrow Obtain the features for complete image	Step 2 \longrightarrow Mark the Region as the Nodes
r	Step 3 \longrightarrow Connect the Adjacent Regions
Step 5 \longrightarrow Form the feature vector for the given	Step 4 \longrightarrow Find the Attributes of the
image	Nodos
Step 6 \longrightarrow Store the feature vector	
	Step 5
Step 7 If feature database creation	Step 6
Then	STOP Stop 7 North the control do in the commented
Then	Step / — Mark the centroids in the segmented
Repeat the Step 1 through	legion
Step 5	STOP
Else	
Eise	Step- 4 in Approach for the Feature Extraction of
STOP	Image
	(Feature of the complete image)
2 in American I. for the Explore Entropy of Lange	Input:- Color or Gray Image
ep- 2 in Approach for the Feature Extraction of Image	Output:- Complete Image Features
(watersnea Segmentation)	Procedure:- Step by step representation
Input :- Color of Gray Image	Step 1
Output :- Segmented Image	database or query image)
Procedure:- Step by step representation	Step 2 — Golor Features and Wavelet Transform
Step 1 \longrightarrow Read the Color Image and Convert it	of the Image
to Grayscale	Step 3 — Obtain the Features
Step 2 \longrightarrow Use the Gradient Magnitude as the	Step 4 — Record the Features
Segmentation Function	Step 5 — Form the Feature Vector
Step 3 \longrightarrow Mark the Foreground Objects	STOP
Step 4 Compute Background Markers	
Step 5 \longrightarrow Compute the Watershed	3.3 SVM Based Classification
Transform of the Segmentation Function	Class 1
Step 6 \longrightarrow Visualize the Result	Class 2
	Feature Vector Classification as
	Classed Travel

An Approach For The Image Classification Input:- Color or Gray Image (Query)

Image (Graph kernel based features)

Input :- Segmented Image

Output :- Region Features



IV. EXPERIMENTAL RESULTS

Experimental set up:

The approach discussed in Chapter 4 is implemented using (MATLAB 7.10.0.499) (R2010a). The experimentations 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 experimentations 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.

Screen 1











V. CONCLUSION

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.

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