CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Cancer is a dangerous disease nowadays. Figure 1.1 represents a graphical representation of the tumour response rates for polymer-drug conjugates (PDCs). In order to discover and cure this malignant disease as early as possible, many kinds of examination, such as Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), are required. Each imaging modality has its special imaging mechanism to supply different useful information. Computed tomography (CT) is the most effective and sensitive one. In real medical diagnosis, oncologists, radiologists and other medical experts take a long time to segment medical images for preparing effective treatments. Labeling brain tumours in CT images is highly time-consuming and the existing significant variation among different experts without taking into account, the global 3D bio-structure by Popuri et al (2009). Computer-aided tumour segmentation system is an important application in medical image analysis. Developing a medical image analysis system not only lightens the workload and decreases the error of the doctors but also can provide a quantitative measure about variation of the lung tumour throughout its whole therapeutic treatment. However, it is still a difficult problem to automatically segment tumour regions from CT multi-sequences because of many existing types of tumours with morphological variability, a variety of shapes, appearance properties among individuals and the deformation near the structures, which result in an
abnormal geometry for healthy tissues and lack of prior knowledge about them. Therefore, it is practically meaningful to focus on semi-automatic or fully-automatic segmentation methods on multiple CT scans for medical research, disease monitoring, therapeutic control and so on. Different CT sequences from different excitations can respectively provide different and partly independent information about different tissues, and reflect pathological information about the tumours. As the tumour consists of different biological tissues, the CT alone cannot give complete information about abnormal tissues. Combining different complementary information can enhance the segmentation of the tumours. Therefore, radiology experts always combine the multi-spectral CT information of one patient to make a decision on the location, extension, prognosis and diagnosis of the tumours.

Figure 1.1 Graphical representation of the tumour response rates for polymer-drug conjugates (PDCs)

1.2 COMPUTED TOMOGRAPHY (CT) IMAGES

Computed tomography (CT) is a radiological modality which furnishes clinical data in the recognition, differentiation and delineation of the ailment. It is the preliminary diagnostic modality for a number of challenges and is extensively acknowledged as an addition to supplementary imaging methods.
In this hypothesis, medical CT images play a very important part as a sphere of application. Hence it is essential that an introduction to CT is aptly offered.

In the traditional X-ray imaging, the overall thickness of the body is projected on a film: structures superimpose and is very difficult to differentiate. One of the problems is the loss of information about its depth. Assume that a small lung carcinoma is observed in a front-to-back chest photograph (Figure 1.2(a)). The radiologist is incompetent to assess the precise spot of this carcinoma in the forward and backward direction. But it is possible to make a lateral photograph (a side view), though the carcinoma may vanish behind the rib. In such cases, a cross-sectional image is a must Figure 1.2(b). This actually materialized when Geoffrey N. Hounsfield offered the first CT scanner in 1972. The innovative method of computed tomography (CT) reconfigures a cross-sectional image of the body from a ‘virtual pile of X-ray photographs’. A tomographic image represents an image of a slice through the body. The term ‘tomography’ is of Greek origin. In Greek language, the term ‘tomos’ means slice and the meaning of ‘graphein’ is ‘to write’. Therefore, the word tomography exactly refers to ‘writing slices’. Structures and lesions which could not be visualized earlier can presently be seen with considerable lucidity. The schematic diagram of the CT scanner is offered in Figure 1.3. A lean collimated beam of X-rays moves through the body as a detector which evaluates the communicated intensity. The collimator is a group of thin lead tubes or an array of small holes in a lead plate, resulting in a thin straight beam of X-rays. Evaluations are conducted in a huge number of points as the source and detector are moved past the body jointly. The equipment is subsequently rotated somewhat about the body axis and again scrutinized. This is replicated at, 1° intervals for 180°. The intensity of the communicated beam for several points of each scan, and for each angle, is forwarded to a computer which reconfigures the image of the slice. The image is reflected on a computer monitor.
1.2.1 Historical Background

In 1917, Johann Radon effectively proved that 2-D section images could be reconfigured by means of mathematical conversion of projected data such as employing a Radon transform. Projected data are line integrals such as summations of image values registered across an object at certain angle as exhibited in Figures 1.4(a) and 1.4b. The association between projected data and x-ray images like maps of the impact of decrease was not clear. Nevertheless, motivation was superior since section x-ray images would have the capability to make superb contrast section images of the body by segregating interference from overlapping tissues. Even with the skills of transforming x-ray images into projections, imaging instrumentation and computing power was not able to furnish this capacity well in advance, therefore it took many years for the technology to catch up with the hypothesis. By the 1960s, various research labs were competent to rebuild x-ray section images from x-ray projections attained from physical objects. In the 1970s x-ray computed tomography (CT) was officially launched for clinical use, which was followed by quick technological sophistication. As rebuilt images appeared just like thin sliced tissue sections which are employed for microscopic scrutiny, the term "Tomography", exactly conveying the meaning of cross section of a picture, was followed, and early x-ray tomographic imaging systems were known as Computed Axial Tomographic or “CAT” scanners.
Nevertheless, widespread exploitation has discarded this designation in favor of computed tomography or just CT. In 1979 two early investigators, A. M. Cormack and Godfrey Hounsfield, were awarded the Nobel Prize for Computed Tomography.

Figure 1.4  A CT image (a) and its projections $p_{0}(r)$ (b) presented as an image called a Sonogram
1.2.2 Principles of Operation

There are two stages which are essential to obtain a CT image. In the first phase, physical dimensions of the reduction of X rays traverse the patient in diverse directions, and in the second mathematical evaluations of the linear attenuation coefficients, \( m \), all over the slice are conducted. The relative process is shown as follows. The patient continues to remain inactive on the test table while the X-ray tube rotates in a circular orbit around the patient in a plane perpendicular to the length-axis of the patient as shown in Figure 1.5. A fan-shaped beam of changeable thickness (1-10 mm) sufficiently extensive to pass on both sides of the patient is employed. The X-ray tube is identical to but further dominant than those employed in planar radiography. The image receptor is an assortment of many small separate receptors. Readings from the receptors are furnished into a computer which after several computations generate a tomogram of the patient representing a map of linear attenuation coefficients \( \mu \).
In third-generation CT scanner, the X-ray tube and the receptor array are located on opposite sides of the patient and both rotate around the patient during data acquisition. In this particular situation, the receptor array consists of about 700 pressurized Xenon detectors. In fourth-generation CT scanner, only the X-ray tube rotates around the patient and the receptor array which is situated in the outside of the scanning frame remains stationary.

The arrangement of the X-ray tube and the receptors has undergone a huge change over the years, the special technical solutions being labeled as ‘generations’. CT scanners employed today are of third-or fourth-generation as shown in Figure 1.5 (a) and (b). An arrangement whereby the X-ray tube and the receptor array rotate jointly is characteristic of the third generation of CT scanners, whereas the fourth generation has an overall ring of receptors that continues to be still and only the X-ray tube rotates. CT scanners are presently offered in which the X-ray tube circles the patient while the examination table moves about endlessly, in order that the X-ray tube moves in a spiral orbit around the patient. They are generally known as spiral CT scanners.
CT appeared as one of the earliest editions of digital radiology. The receptors evaluate the X-rays passing through a slice of the patient in various positions constituting one protrusion of the patient. The evaluation in any one receptor is a dimension of the alleviation in the patient along the path of a specific ray. At the back of a harmonized object, the receptor estimation is equal to \( I = I_0.e^{-\mu x} \), where \( I_0 \) represents the receptor’s estimation in the absence of the object and \( \mu \) the linear attenuation coefficient for the object, \( x \) characterizes the object thickness along the path of the related ray, and \( e \) stands for the base of the natural logarithm (e=2.718).

When the evaluations from the receptors have been amassed in the computer, the tube is rotated to a different angle and a new projection profile is estimated. When a full rotation is over, the table with the patient is shifted to a nearby location and the succeeding slice can be evaluated. By means of specified data from sets of projection profiles through all volume element (voxels) in a slice of the patient for enough number of rotation angles (projections), the average linear attenuation coefficient \( \mu \) for each voxel can be computed. This process is known as reconstruction. Each value is assigned by a gray scale value on the display-monitor and offered in a square picture segment (pixel) of the image.

1.3 ANATOMY OF THE LUNGS

The lungs characterize sponge-like organ in the chest which work effectively as a segment of the respiratory mechanism. The right lung consists of three lobes and the left lung is smaller in size with two lobes so as to furnish space for the heart. Air goes through the nose or the mouth, and thereafter proceeds through the trachea and each bronchus before passing
through the lungs. The lungs are a pair of sponge-like, cone-shaped organs. Oxygen is taken into the lungs when air is inhaled. Lung tissue forwards oxygen to the bloodstream on its way to the remaining organs of the body. Cells discharge carbon dioxide as they accept oxygen. The bloodstream transports carbon dioxide back to the lungs, and the carbon dioxide makes an exit from the body when air is exhaled. The anatomy of the lung is depicted in Figure 1.6.

The lung, the site of gas exchange, is filled with air that has low density (about 1000 HU) on CT images. In addition to air, pulmonary vessels and bronchi are the principal constituents of the lung regions. Lung regions include the left and the right lungs. The left lung is further separated into two lung lobes (upper lobe and lower lobe) by an oblique fissure. The right lung is separated into three lung lobes (upper lobe, middle lobe, and lower lobe) by oblique and horizontal fissures. The geometry of the bronchial airways in the human chest can be approximately described as a binary tree structure. The trachea (the root of the airway tree) divides into two main branches (left primary bronchi and right primary bronchi), which enter the right and the left lungs. The primary bronchi further divide into five (two left, three right) lobar bronchi that enter each lung lobe respectively. The lobar bronchi divide repetitively and generate 8–10 segmental bronchi trees in each lung region.

The pulmonary artery and veins are also distributed in a tree structure like that of the bronchial airway in the lung regions. The branch of the pulmonary artery always runs parallel to the bronchi.
1.4 LUNG TUMOUR TYPES

Nowadays, lung tumour has become one of the main causes for increasing mortality among children and adults. Figure 1.7 shows the incidence of tumour in various age groups. In addition, lung cancer is an ailment of abnormal cells increasing in large number and developing into a tumour. Cancer cells can be taken away from the lungs in blood, or lymph fluid which enfold the lung tissue. Metastasis happens when a cancer cell departs from the site where it has commenced and travels into a lymph node or to a different segment of the body through the bloodstream. Figure 1.8 shows the 5-year survival rates over the past decades.
Cancer which begins in the lung is called primary lung cancer. Though there are several diverse categories of the ailment, they are mainly segregated into two important categories as shown below:

- **Benign**
- **Malignant**

### 1.4.1 Benign

A benign tumour is a mass of cells that lacks the ability to invade neighbouring tissue or to metastasize. These characteristics are required for a tumour to be defined as cancerous, and therefore benign tumours are non-cancerous. Also, benign tumours generally have a slower growth rate than malignant tumours and the tumour cells are usually more differentiated (cells have normal features). Benign tumours are typically surrounded by an outer surface (fibrous sheath of connective tissue) or remain with the epithelium. Although benign tumours will not metastasize or locally invade tissues, some types may still produce negative health effects. The growth of benign tumours produces a "mass effect” that can compress tissues and may cause nerve damage, reduction of blood to an area of the body, tissue death and organ damage. The mass effect of tumours is more prominent if the tumour is within
an enclosed space such as the cranium, respiratory tract, sinus or inside bones. Although most benign tumours are not life-threatening, many types of benign tumours have the potential to become cancerous (malignant) through a process known as tumour progression. Figure 1.9 shows the nodule growth from the benign stage to the last malignant stage.

![Figure 1.9 Nodule growth](image)

### 1.4.2 Malignant

Malignancy is most familiar as a characterization of cancer. A malignant tumour is not self-limited in its growth, is capable of invading adjacent tissues, and may be capable of spreading to distant tissues. Malignancy in cancer is characterized by invasiveness and metastasis. Malignant tumours are also characterized by genome instability. Figure 1.10 shows the tumour-affected CT lung image.

![Figure 1.10 CT scan images (a) normal patient (b) tumour patient, Lung fields (right and left) and tumour area marked by red lines](image)
One of the most important factors in classifying a tumour as benign or malignant is its invasive potential. If a tumour lacks the ability to invade adjacent tissues or spread to distant sites by metastasizing, then it is benign, whereas invasive or metastatic tumours are malignant. For this reason, benign tumours are not classed as cancer. Benign tumours will grow in a contained area usually encapsulated in a fibrous connective tissue capsule. The growth rates of benign and malignant tumours also differ, benign tumours generally grow more slowly than malignant tumours. Although benign tumours pose a lower health risk than malignant tumours, they can both be life-threatening in certain situations. There are many general characteristics which apply to either benign or malignant tumours, but sometimes one type may show characteristics of the other. For example, benign tumours are mostly well differentiated and malignant tumours are often undifferentiated. However, undifferentiated benign tumours and differentiated malignant tumours can occur. Although benign tumours generally grow slowly, cases of fast growing benign tumours have also been documented. Some malignant tumours are mostly non-metastatic such as in the case of basal cell carcinoma.

1.5  NEED FOR PRE PROCESSING ON CT IMAGES

Images usually contain one or more types of noise and artifact. In medical images, because of diagnostic and therapeutic applications, this issue is critical. Specially in CT images, inhomogeneous fields, patient motions during the imaging times, thermal noise and existance of any metal things in imaging environment are some reasons that can create noises and artifact, though in most of the times, are not very important because of human studies on images. But these are one of the main causes for computational errors in automatic or semi-automatic image analyzing methods, and so it is needed to be removed by preprocessing procedures before any analysis.
Enhancement is one of the most fundamental tasks in image analysis. It aims to improve the quality of an observed image so that subsequent processing, such as image segmentation, classification and interpretation, can be performed with higher accuracy. During the past several decades, image enhancement has been extensively studied, and a large number of enhancement algorithms have been proposed in the literature. However, due to the intrinsic dilemma of suppressing noise and preserving image details, it still remains a major challenge to enhance images, especially textured images. Traditional image enhancement algorithms can be broadly grouped into two categories: (i) spatial domain methods, including the median filter, Gaussian filter, bilateral filter by Weiss (2006), Fleishman et al (2003), anisotropic diffusion filter by Gerig et al (1992), Perona & Malik (1990), partial differential equation-based and total variation minimization-based enhancement by Rudin et al (1992) and (ii) transform domain methods, including the wavelet-based by Chang (2000), Portilla et al (2003), curvelet-based by Starck et al (2002), translation-invariant by Coifman & Donoho (1995) and sparse representation-based enhancement. Many of those algorithms attempt to decompose the observed image into a smooth (noise-free) one and an oscillatory (noisy) one by separating the low frequency signal from the high frequency signal since they assume that the noise-free image is smooth or piecewise smooth and is corrupted by additive white noise. However, due to their dynamic and stochastic nature, most textured images do not meet the smoothness assumption, and hence cannot be effectively denoised by those traditional approaches.

1.6 TUMOUR SEGMENTATION

Segmentation is an image processing function for differentiating an anatomical configuration from the neighbouring tissue. Tumour or metastasis segmentation is a significant issue for cancer follow-up, where the oncologist takes keen enthusiasm in estimating the modification in the dimension of the tumours. Early response forecast paves the way for the oncologist to revise
the therapy, which results in a superior survival rate Tuma (2006). At present, radiologists evaluate the tumour in one dimension with a view to assess the cancer cure as in Therasse et al (2000). Estimating the reaction of a cure can also be performed by a bi-or tridimensional standard. Clinical investigation Tuma (2006), Prasad et al (2002), Tran et al (2004) demonstrates that volume dimensions (3D) furnish a superb depiction of the tumour reaction. Volume dimensions necessitate the segmentation of the tumours, which takes an unduly long time-duration when it is done physically. In addition, the volume of manual delineations is subjected to intra- and inter-observer inconsistency, which is evaluated at around 8% for liver tumours by Bellon et al (1997). Hence, mechanized or semi-automatic tumour delineation techniques are needed. This article concentrates its attention on the segmentation of liver tumours in contrast-enhanced CT images. As tumours habitually possess divergent shapes and intensities, the segmentation tends to be very complicated. The gray values of tumour depend on the type of tumour, the delay between the contrast injection and the image acquirement, the contrast dose and the patient physiology. Generally, liver tumours are endowed with an approximate round shape. Nevertheless, the shape can be impacted by the neighborhood of blood vessels, the edges of anatomical configurations, the kind of cancer, etc. Certain semi-mechanized techniques are readily offered for the segmentation of CT liver tumours. They comprise techniques dependent on watershed such as the paintbrush technique by Maes et al (1995), deformable versions such as the active contour algorithm by Yim & Foran (2003), Lu et al (2005) and a region growing method by means of various limitations by Zhao et al (2010). Parallel techniques are on the lookout for locating optimal thresholds in accordance with a numerical assessment. However, these techniques have a general quality which calls for a certain amount of client interface. Recently, a variety of segmentation techniques have been developed for medical images. Among them, some of the few methods like cellular automata and level set evaluation are discussed below.
1.6.1 Cellular Automata

In the late 1940s, Von Neumann & Olman presented cellular automata as a model for investigating the behavior of complex systems. A cellular automaton is a mathematical model for systems with multiple simple components which collaborate to make complex patterns. The behaviour of each component is defined based on the behaviour of its neighbours. The cellular automaton is a discrete, decentralized, self-organized system which can make an ordered structure starting from a stochastic state. This system can reduce entropy during time. It should be mentioned that in the cellular automata, computations are done in a parallel manner. In this model, space is defined as a grid of cells in which each cell is a state memory. In each step, the cell considers the adjacent neighbours, and using transmission state rules takes its next discrete state. Besides, every cell can process independently from the other cells. There are different neighbourhood structures for cellular automata. In general, let us consider each ordered set of cells as neighbours. The first neighbourhood type is Von Neumann which includes 4 non-angular cells related to the central cell. The other neighbourhood type is Moore which includes all 8 neighbours around the cell. These two types of neighbourhoods are the most famous ones called nearest neighbours as shown in Figure 1.11.

![Neighborhood model (a) Von Neumann and (b) Moore](image)

**Figure 1.11** Neighborhood model (a) Von Neumann and (b) Moore
1.6.2 Level Set Evaluation

The level set method by Osher & Sethian (1988), Malladi et al (1995) is a popular segmentation technique based on embedding the shapes of objects as the zero level set of a higher dimensional surface. The higher dimensional surface evolves according to the image and surface features, and these results in localized image features in the zero level set. The level set methods can be extended to any higher dimension. Moreover, the contours in the zero level set can change the topology such as merging or breaking into parts. The level set methods are very robust in taking image properties into account, and the zero level interfaces can deform to extract contours in pixel-wise detail. However, in some cases global or prior information must also be considered with local properties during evolution. The prior information is essential especially in medical imaging applications where the images are very noisy, they have low contrast and some parts of organ contours are missing. In medical imaging applications, human organs and even pathological cases have similar contours, however the level set method cannot take advantage of common shapes without using prior information.

There are a number of proposals for using shape priors in the literature. The authors Leventon et al (2000) incorporated prior knowledge about the intensity and curvature of the structure based on training data modeled through a Gaussian distribution and principal component analysis to recover the covariance matrix of probability density function of shapes and alternate between segmentation and imposing prior knowledge. The studies Chen et al (2001 & 2002) used an average model as a prior in its implicit function for a given curve, and they found the transformation that projects it closer to the zero-level set of the implicit representation of the prior. The prior knowledge is modeled through a Gaussian distribution on the space of distance functions by performing singular value decomposition on the set of
registered training set, and objects are recovered according to various data-driven terms in Tsai et al (2001). The author Rousson & Paragios (2002) constrained the level set to follow a shape global consistency by creating a shape model with Gaussian density function and shape prior is imposed by the comparison between the model and the evolving contour.

1.7 FEATURE EXTRACTION

The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features that distinguish one input pattern from another. The extracted features provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image.

1.7.1 Wavelet Transform

Wavelet analysis is a particular time-or space-scale representation of signal which has found a wide range of applications in physics, signal processing and applied mathematics in the last few years. Wavelets are mathematical functions that divide data into different frequency components and then study each component with a resolution matched to its scale. For example, they can be advantageous compared to traditional Fourier methods in analyzing physical situations in which the signal contains sharp spikes. They were developed independently in the fields of mathematics, quantum physics, electrical engineering and seismic geology. Because of their interdisciplinary origin, wavelets appeal to scientists and engineers of many different backgrounds.

Several aspects of wavelets will be discussed which include an overview on the families of wavelets, scale-varying basic functions, the continuous wavelet transform, the discrete wavelet transform, the fast wavelet
transform, adapted waveforms, time-frequency location, construction of ortho-normal wavelet bases and multi-resolution analysis, Haar and Shannon wavelets, Wigner distribution for signal analysis and regularity of wavelets. Recent advances have shown wavelets to be an effective and often necessary mathematical tool for signal processing in physics and engineering sciences. Interchanges between these fields and further mathematical developments during the last ten years have led to many new wavelet applications, for example, image compression or new descriptions in fluid mechanics including turbulence. In addition, they have become essential in the world of information storage and retrieval and are used in computational imaging.

1.7.2 Statistic Features

The analyzing methods have been done until now using the values of pixel intensities, pixel coordinates by Selvaraj et al (2007), Carlos Parra et al (2003), Alan Wee-Chung Liew & Hong Yan (2006), and some other statistic features such as mean, variance or median which have much error in the determination process and low accuracy and robustness in classification.

**Mean:** The mean is defined as the sum of the pixel values divided by the total number of pixels values.

\[
\text{Mean, } M = \frac{1}{pq} \sum_{i=1}^{p} \sum_{j=1}^{q} x(i, j) \quad (1.1)
\]

**Standard Deviation:** The Standard Deviation \( \sigma \) is the estimate of the mean square deviation of gray pixel value \( x(i, j) \) from its mean value \( M \). Standard deviation describes the dispersion within a local region. It is determined using the formula
Standard deviation, \( \sigma = \sqrt{\frac{1}{pq} \sum_{i=1}^{p} \sum_{j=1}^{q} (x(i, j) - M)^2} \) \hspace{1cm} (1.2)

**Range:** The Range R has two elements. One is minimum pixel intensity value placed inside the block, and the other one is maximum pixel intensity value inside the block.

\[
\text{Range, } R = \text{Min. value of pixel intensity and Max. value of pixel intensity in a block}
\] \hspace{1cm} (1.3)

**Pixel Orientation:** The pixel orientation has 2 elements, the first element is the minimum angle inside the block, and the second one is the maximum angle inside the block.

\[
\text{Pixel Orientation, } PO = \tan \left( \frac{y - m}{x - m} \right)
\] \hspace{1cm} (1.4)

where,

- m is the point which is required to measure the value
- y is a point in the Y-axis of the first quadrant
- x is a point in the X-axis of the first quadrant

### 1.8 CLASSIFICATION

#### 1.8.1 K-Nearest Neighbour Classifier

A nearest neighbour classifier is perhaps the simplest of all statistical classifiers. For each case to be classified, the feature vector representing that case is compared with the vector representing every other case in the training set, usually using the Euclidean distance, \( d \), between the vectors.
\[ d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \] (1.5)

where \( n \) is the number of elements in the vector, and \( x \) and \( y \) are the vectors being compared.

The class assigned to the new case is that of the nearest case in the training set. Instead of the single nearest neighbour (1-nn), the majority class of the nearest three (3-nn) or five (5-nn) cases is often used. Nearest neighbour classifiers have been widely used, are easy to understand and are nonparametric.

### 1.8.2 Support Vector Machine Classifier

The Support Vector Machine (SVM) is a successfully parametric method which has been widely used to get accurate results in many multiple-class pattern recognition applications. As introduced in Selvathi (2007), Vapnik (1995), SVM, which fits to classify data of high dimensions and from multiple sources particularly, extends the use of kernels which are crucial to incorporate prior knowledge into practical applications. Other recent developments have shown the benefits of multi-kernel SVM by Wang et al (2008) & Rakotomamonjy et al (2007). Multi-kernel SVM has more potential for fusion of the data from heterogeneous sources at the expense of computation complexity. A simplification is one-class SVM, which is derived from two-class situation SVM. In one-class SVM, the training points just involve the class to be separated from the others by Zhou et al (2005). It has been proven in Bach (2008) that when the kernel function can be decomposed into a large sum of individual and basic kernels which can be embedded in a directed acyclic graph, the penalty functions can be explored by inducing norms such as the \( l_1 \)-norm. Then the kernel selection process is possible to perform through a hierarchical kernel learning framework.
SVM is a learning tool based on the structural risk minimization principle from the statistical learning theory. SVM are based on a linear machine in a high dimensional feature space, nonlinearly related to the input space, which has allowed the development of somewhat fast training techniques, even with a large number of input variables and big training sets. On the exaggeration power of learning functioned machines, SVM gives certain advantage for limitations. The general process of SVM is illustrated in figure 1.12. A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space.

Figure 1.12 General diagram of classification using SVM

SVM have been used successfully for the solution of many problems including handwritten digit recognition, object recognition, speaker identification, face detection in images, text categorization, etc. The overall algorithm is presented in below section.
Algorithm

1. Define an optimal hyper plane: maximize margin 

2. Extend the above definition for non-linearly separable problems: have a penalty term for misclassifications.

3. Map data to high dimensional space where it is easier to classify with linear decision surfaces: reformulate problem so that data is mapped implicitly to this space.

The decision boundary (shown by the line) is able to provide good separation of the two classes, although there are still a few patterns which would be incorrectly classified by this boundary.

The establishment of two parallel hyper planes is given by

- Minimize \( \frac{\|w\|^2}{2} \) \hspace{1cm} (1.6)
- With \( y_i(w.x_i + b) \geq 1 \) \hspace{1cm} (1.7)

1.9 OUTLINE OF THE THESIS

An image enhancement scheme and tumour detection system on lung computed tomography (CT) images are studied in this thesis. The purpose of this thesis is to design and develop a tumour classification system providing a performance enhancement over the other state-of-the-art algorithms with an adequate increase in complexity.

Chapter 2 presents literature reviews of related topics. This chapter begins with discussions of image enhancement, tumour detection and
classification of medical images. Following this, a survey on three types of medical images and related researches are given in this chapter.

Chapter 3 introduces the basic concept and definitions of tumour detection approach like cellular automata, support vector machine and discrete wavelet transform and Matlab, where these properties are shortly reviewed.

The fourth chapter presents a medical image enhancement approach which completely improves the visual quality with the help of wavelet shrinkage adaptive histogram equalization.

The fifth chapter provides a tumour segmentation scheme using hybridization of cellular automata (CA) and level set which solve the difficulty of individual performance of CA and level set.

The sixth chapter presents a novel approach for tumour classification using multi-kernel support vector machine that removes the limitations of support vector machine.

Finally, the conclusion is presented in Chapter 7 of the thesis.