Thermographic Image Analysis for Detection of IVDD and Syringomyelia in Canines

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ABSTRACT

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by

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Chairperson: Professor Scott E Umbaugh

Introduction: Intervertebral disc disease (IVDD) and Syringomyelia both are a condition that affects both humans and canines. These diseases are painful and degrade the quality of life for those that suffer from these. The current diagnostic methods for these diseases are Magnetic Resonance Imaging (MRI) and/or Computed Axial Tomography (CAT scan). Both of these diagnostic methods are expensive and time consuming and involve patients being exposed to radiation and strong magnetic fields. In canines in particular, the amount of time it takes to perform one of these scans makes it necessary to sedate the animal as the patient needs to be still during the diagnostic procedure. Use of thermographic imaging for diagnosis, or at least prescreening, patients for IVDD or Syringomyelia will save money, time and possibly prevent needless radiation exposure. This research attempts to show that thermal imaging of patients that are candidates for IVDD or Syringomyelia may be used diagnostically or as a prescreening method. **Objectives:** The main objective of this research is the detection of IVDD and Syringomyelia. At the same time it is also determined which view of the images produces highest number of correct classification. For the detection of Syringomyelia both the sedated and unsedated images are used so it is also determined which group of images produces highest number of classification. In this research image masks are not created by an expert so there is no standard to define the region of interest. Later on, an algorithm is implemented to create mask automatically. **Results:** The overall classification rate for the detection of IVDD is approximately 90% with automated mask using K-nearest neighbor algorithm, K=3. And the left/right lateral view of images provide maximum success rate. For the further treatment of IVDD it is necessary to identify the herniated disc space in the vertebrae. With Multilayer Perceptron (MLP) neural network, the highest classification rate is 97% which indicates that it is possible to classify the herniated intervertebral disc space from the normal disc spaces. That means, thermographic images can be used as a diagnostic tool for the detection of IVDD. The overall classification success rate for the detection of Syringomyelia is approximately 68%. The left/right lateral of head images provides the highest classification rates. But it is difficult to say which type of images provides better classification rate, sedated or unsedated. To get a final conclusion about using thermographic images as a diagnostic tool for Syringomyelia a higher success rate should be achieved. **Methods:** For the detection of IVDD, the thermographic images are classified as *IVDD* and *Normal*, two classification methods are used: Nearest Neighbor and K-Nearest Neighbor. To identify the specific herniated disc space three classification methods are used: K-Nearest Neighbor, Multilayer Perceptron (MLP) neural network and Discriminant Analysis. CVIP-FEPC is used for the K-nearest neighbor algorithm and Partek Discovery Suite is used for the MLP and discriminant analysis. For the detection of Syringomyelia, the thermographic images are classified as *Present* and *Absent* classes, two classification methods are used: K-Nearest Neighbor and Discriminant Analysis. CVIP-FEPC is used for the K-nearest neighbor algorithm and Partek Discovery Suite is used for the discriminant analysis. **Conclusion:** The most effective classification method for the detection of IVDD and Syringomyelia is K-nearest neighbor. To identify the specific herniated disc space the best classification method is Multilayer Perceptron (MLP) neural network. From this research it is found that thermographic images can be used as a diagnostic tool for the pathological condition Intervertebral Disc Disease (IVDD) and further experiments are required to improve the classification success rate for Syringomyelia.

ACKNOWLEDGEMENTS

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CHAPTER 1

INTRODUCTION

Diagnostic imaging is one of the most important tools for detection of any pathological condition. Both veterinary and human medicines require diagnostic imaging. Currently, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) diagnostic methods are available to detect diseases but among them MRI is the best method. But it is an expensive and time consuming diagnostic method and also the radiation of MRI is harmful for the patient's health. So, it is helpful to find an alternative method to diagnose the pathological condition. In this research two specific pathological conditions of canines are considered: Inter Vertebral Disc Disease (IVDD) and Syringomyelia. The aim of this project is to determine whether or not thermographic images can be used for diagnosis of certain canine pathologies. A primary motivation for this research is cost reduction by replacing MRI as the current diagnostic tool with thermographic imaging.

Small breed dogs with short, thick legs are at high risk of Inter Vertebral Disc Disease [Seipel; 2010]. Cost of surgery for IVDD varies throughout the USA. An approximate cost of this surgery is $3000-$7500 [Richards; 2010]. The MRI alone costs $3000- $3500 [LIVS News; 2010]. The target of this research is to reduce this cost of the diagnostic tool.

Syringomyelia is a condition that is associated with Chiari malformation. Chiari malformation is a condition in which the skull is not properly developed and puts pressure on the spinal cord. This pressure interferes with the flow of spinal fluid and can cause a range of symptoms including, weakness, ataxia, and vision problems [Feldstein; 1999]. Syringomyelia is the development of a fluid-filled cyst (syrinx) within the spinal cord and brain. Over time, the cyst may enlarge and damage the spinal cord. To get rid of this condition, the solution is a surgery [National Institutes of Health; 2011]. And the diagnostic method is MRI. If a less expensive diagnostic method, such as thermographic imaging rather than MRI, can be used then it is possible to reduce the overall cost.

To detect the pathological condition IVDD, the thermographic images are classified as *IVDD* and *Normal* classes. Also the specific herniated disc space is determined. The success rate of this experiment indicates that thermographic images strongly correlate with MRI findings. To detect Syringomyelia or the presence of syrinx, the thermographic images are classified as *Present* and *Absent* classes. Both sedated and unsedated thermographic images are used to diagnose this disease. The experimental results with this condition are inconclusive but indicate that there may be a difference between the *Present* and *Absent* classes in the thermographic images.

To analyze the thermographic images for the detection of any pathological condition only the information from the infected or specific area (region of interest) are required. To extract information regarding specific areas in thermographic images an image mask is needed. Most of the image masks are created manually which is a time consuming and unpleasant task. So, in this research an algorithm is developed to create mask automatically.

1.1. Objectives of the Thesis

The aim of this thesis is to investigate the use of thermographic imaging as a diagnostic tool. The objective of this research is listed below:

1. Find an algorithm to automatically generate an image mask that correctly defines the region of interest.
2. Classify the images as *IVDD* or *Normal* to diagnose IVDD.

3. Determine which view of the images, three views are provided, produces the highest number of correct classifications for the pathological condition IVDD.
4. Identify the specific herniated disc space in the vertebrae.
5. Classify the images as *Present* and *Absent* to diagnose Syringomyelia or presence of syrinx.
6. Determine which view of the images, nine views are provided, produces the highest number of correct classifications for the pathological condition Syringomyelia.
7. Determine whether sedated or unsedated images produce the highest number of correct classifications.

1.2. Outline of the Thesis

The thesis is organized as follows:

Chapter 2 presents a literature review of previous research, general description of the diagnostic imaging, pathological conditions and image processing techniques, used in this research.

Chapter 3 provides a brief description of the experimental materials, thermographic image with their corresponding masks and programs. These are used throughout this research.

Chapter 4 explains the implementation of the algorithm to create masks automatically.

Chapter 5 presents the general descriptions of the classification methods and feature analysis, which are used to classify the thermographic images in different classes.

Chapter 6 explains all the experiment results and discussion.

CHAPTER 2

LITERATURE REVIEW

In veterinary medicine, as in human medicine, diagnostic imaging is a very valuable tool in determining the condition and treatment methods of diseases. The purpose of this review is to provide the current and background knowledge of some critical and important topics related to this research. The literature of this research consists of four primary categories: 1) Background 2) Thermographic Imaging 3) Pathological Conditions and 4) The Image Processing Techniques. The information related to pathology as well as engineering, discussed here, are for the readers to understand the purpose of this research and also as background material for the development of the mask creating algorithm presented later in this paper.

2.1. Background

In this section, the currently employed diagnostic imaging methods and some previous research on thermographic images as a diagnostic tool are discussed to understand the importance of this aspect of the research.

2.1.1. Diagnostic imaging methods

Diagnostic imaging is a technology used by doctors to scan through one's body in order to find clues regarding the medical condition of the subject being examined. The technique is used to create a depiction of the activities carried on or the structures formed inside the object body. The technology used for the purpose of diagnosis depends on the symptoms and part of the body being examined. Diagnostic imaging is created in various forms like X-rays, CT scans, nuclear medicine scans, MRI scans and ultrasound.

Few of these testing techniques are painless and easy. Some techniques require the subject to stay motionless for a long time inside the machine which can be quite uncomfortable. While some techniques involve radiation, but the dosage is very low, so they are generally considered to be safe. In certain cases a tiny camera is attached to a long, thin tube called scope, which is inserted in the body through a passageway or opening to see inside a particular organ, such as your heart, lungs or colon. However these procedures requires anesthesia.

Depending on the pathology and the parameters associated with it, different imaging methods are used. Currently, when diagnosing a condition, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) diagnostic methods are available but among them MRI is the gold standard [Richard; 2010][Gonzalez et al.; 2009]. MRI is an expensive and time consuming diagnostic method. It also requires that the patient, canines in this research, remain motionless for the imaging process. While an MRI is a great diagnostic tool for the conditions being studied here, the difficulties and expense associated with it make it desirable to find alternative diagnostic methods. That is the focus of this current research.

2.1.2. Research

The specialists at Long Island Veterinary Specialists [LIVS; 2011] hypothesize that there may be adequate information in thermographic images of the canine patients to detect different pathological conditions. They have enlisted Dr. Scott E Umbaugh and his students to participate in this research and determine whether or not the hypothesis is valid. This research group worked on several projects with thermographic images since 2006. Three investigations of their research are described below:

2.1.2.1. First investigation

At the very beginning this research was started with thermographic images of only 34 canines to differentiate normal and abnormal thermographic patterns in canines as a diagnostic tool [Umbaugh, Solt; Jan 2008]. And the canines of the breed Cavalier King Charles Spaniel were examined to investigate the Chiari malformation, or COMS, pathology. They classified the images as *severe, moderate* and *mild* classes as well as explored the comparison between clinical and nonclinical images. They also investigated the impact of sedation on the canines. In this research, the front of head (A1), top of head (A1D), left side of head (A1LL) and right side of head (A1LR) images were used. The maximum success rate was with top and front of head images, 100%. Secondly, they experimented with the nonclinical images and classified them as *severe, moderate* and *mild* classes of the pathology. The maximum success rate was with top of the head images, 83%. Thirdly, they explored the pattern difference between sedated (CSS) and unsedated (CS) images. They classified the images as *sedated* and *unsedated*. The highest classification rate was 94% with the top of head images. And lastly, they investigated them as *clinical* and *nonclinical* canine images. They used color normalization to improve the success rate and found the *luminance color normalization* is the best color normalization method. Some of these results strongly indicate that there is a difference between the classes of the images but some of the results are inconclusive but still indicate that there may be a difference between the classes of the images.

2.1.2.2. Second investigation

This was continuous investigation of first one. Here the classification was performed using *pairs* of images, instead of single images as in previous investigation [Umbaugh, Solt;

June 2008]. The head images were used, and for this report the pair was top and front of head images. In progress are experiments for the: 1) top and right side, 2) front and left side, 3) front and right side, 4) top and left side. Firstly, they used clinical images and classified them as *severe and moderate* classes of the pathology and they found highest success rate with top and front of head image pair, 100%. Secondly, they used nonclinical images and classified them as *severe*, *moderate and mild* classes of the pathology and they found highest success rate with top and front of head image pair, 78%. Again, they found some of the results strongly support the previous findings but some of them are inconclusive.

2.1.2.3. Third investigation

This research was done with thermographic images of 120 canines. Same as the first investigation, the canines of the breed Cavalier King Charles Spaniel were examined again to investigate the Chiari malformation, or COMS, pathology [Umbaugh, Solt; Jan 2010]. They classified the images as *severe, moderate* and *mild* classes of the pathology to differentiate normal and abnormal thermographic patterns in canines. At first, they experimented with the clinical images that were classified as *severe* and *moderate* classes of the pathology. Here, the front of head (A1), and top of head (A1D) images were used. The highest success rate with the top and front images was 83%. Then they experimented with the clinical images that were classified as *severe, moderate* and *mild classes* of the pathology. Here again the front of head (A1), top of head (A1D) images were used. The maximum success rate with the top and front images was 65%. So after comparing these results they found that the two separate classes in the clinical (*moderate* and *severe*) images are better separable than with the three classes (*mild, moderate* and *severe*) in the clinical images. In other words, including the *mild* class confuses the classifier due to overlap in the *mild* and *moderate* classes.

So after observing these three investigations, it is noticeable that the number of canines increases the success rate decreases. In the first investigation the number of canines was 34 and the success rate was 100%. When the number of canines was increased to 120 then the success rate was decreased to 83% with the same breed canines.

2.2. Thermographic Imaging

Thermographic Imaging is one of the imaging methods that utilizes infrared radiation. Infrared radiation is electromagnetic radiation from electromagnetic spectrum [Maldague et al.; 2001], with a wavelength longer than visible light. Infrared (IR) light starts from the nominal edge of visible red light at 0.7 micrometers, and extend conventionally to 300 micrometers. The range of this radiation is 9-14 micrometer. The frequency range is approximately 400 to 1 THz, [Liew; 2006] for these wavelengths, and includes most of the thermal radiation emitted by objects near room temperature. Microscopically, IR light is typically emitted or absorbed by molecules when they change their rotational-vibrational movements [Gorbunov et al.; 2002].

According to the black body radiation law, all objects emit infrared radiation above absolute zero and the amount of radiation emitted by an object increases with temperature. Thermography makes to possible to measure the variation of temperature and represent the data as an image. To do so, a thermal imaging camera is needed. When viewed through this camera, warm objects stand out clearly against the cooler backgrounds. So, human and other warm blooded animals are easily visible against the background environment. In this research, the warm blooded animal – canines (dogs) were used. The main focus of this work is to diagnose the pathological condition of dogs using thermographic imaging.

2.2.1. Thermographic images

Thermal images or thermographic images are also known as thermograms. As stated earlier, thermograms are actually visual displays for humans. They represent the amount of infrared energy emitted, transmitted, and reflected by an object. Since there are multiple sources of infrared radiation, it is not easy to obtain an accurate temperature of an object. But the thermal imaging camera is capable of performing mathematical algorithms to interpret the data and create an image. This phenomenon can be explained by an easy formula [Maldague et al.; 2001]:

Incident energy = Emitted energy + Transmitted energy + Reflected energy.

Where, Incident energy is the energy that is visible using thermal imaging camera. Actually the viewer can see an approximate temperature variation of the object and its surroundings in the thermograms and the camera performs its operation using multiple sources of data based on the environment surrounding the object, rather than detecting the actual temperature [Maldague et al.; 2001]. An example of thermographic images that was used in this research is shown in Fig. 2.1. These thermal images are supplied by Long Island Veterinary Specialists [LIVS; 2011]**.** The images are in TIF file format as RGB images with 319 columns by 238 rows, 8-bits per pixel per color band. A total of 18 colors are used in these images.

2.2.3. Thermal imaging camera

Informally a thermal imaging camera is known as a TIC. This type of camera depicts infrared radiation as visible light and allows human to see areas of heat through smoke, darkness, or heat-permeable barriers. A thermal imaging camera consists of five components: an optic system, detector, amplifier, signal processing, and display. [Gibson, 2010]

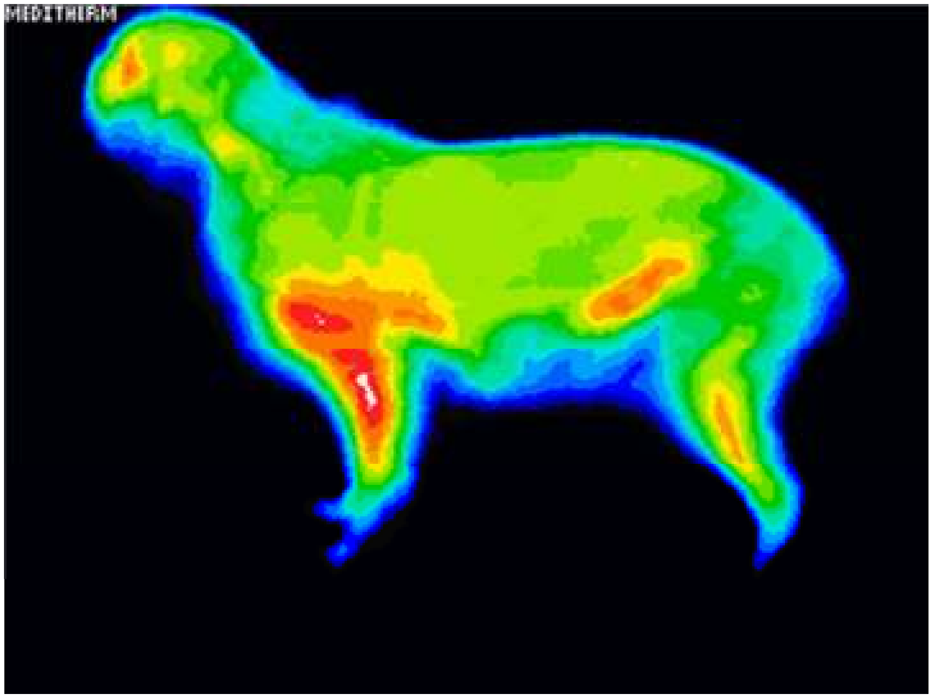


Figure 2.1. Thermographic image of a dog

In 1929, the Hungarian physicist Kálmán Tihanyi invented this camera; it was an infrared sensitive electronic television camera for anti-aircraft defense in Britain. It was known as a night vision camera. Thermal imaging cameras are typically handheld, but may be helmet-mounted. They are constructed using heat- and water-resistant housings, and ruggedized to withstand the hazards of fireground operations. Thermal imaging cameras pick up body heat, and they are normally used in cases where people are trapped were rescuers cannot find them [Anthony; 2002].

In this research, the thermal images are from Long Island Veterinary Specialists [LIVS], taken with a Meditherm Med2000 IRIS. [Umbaugh, Solt; 2008]. Conventional thermal imaging systems are commonly used in industrial applications. They use complex camera technology because they are designed to operate in a wide variety and often hostile, conditions where speed is a prerequisite and because of these requirements the cameras are costly. But the med2000™ offers accurate measurements at less than half of the cost of conventional infrared cameras. This camera is simple, easier-to-use and more durable.

The med2000™ has two parts: the IR camera and a standard PC or laptop computer. This camera is designed based on clinical requirements and it is the only digital infrared thermal imaging system designed for medical applications [Meditherm; 2011]. The weight of this camera is 2.1Kg, temperature range is 18℃ to 40℃ and the price range is $18,500-$34,850 [Meditherm Specifications; 2011].

2.3. Pathological Conditions

A pathological condition is defined as "an abnormal anatomical or physiological condition and objective or subjective manifestations of disease, not classified as disease or syndrome" [Stanley; 2010]. Simply stated it is an abnormal condition observed in the mechanism or structure of object's body involved in the dysfunction of tissues or organs. Such conditions are usually macroscopic and are a common symptom for various diseases. In this research two conditions of canines are considered: IVDD and Syringomyelia.

2.3.1. IVDD

IVDD stands for Inter Vertebral Disc Disease. Aberrations of the pads between the vertebral discs in the spine are known as inter vertebral disc disease. These pads do the work of absorbing shock in order to dissipate the forces applied to spine. It has two layers inside portion is known as nucleus pulposis which has a gelatinous texture and the outside cover is fibrous known as annulus, thus it resembles a jelly donut. Sometimes due to routine wear and tear the intervertebral disc gets damaged, which is referred to as 'IVDD-intervertebral disc disease' or 'Disc disease' or 'Slipped disc'.

IVDD is highly suspected to be a hereditary disease of dogs and dogs with dwarf legs. If any puppy has been suffering from this disease, the degeneration of the discs begins to occur within the first few months of life, but the actual disc herniation typically occurs around 3 to 6 years of age [Richards; 2010]. Dogs have 31 vertebrae:

- Cervical (neck)- 7
- Thorasic (chest) - 13
- Lumbar (lower back) – 7
- Sacral (pelvis) - 3 (fused)

Vertebrae are separated by soft tissue, called a vertebral disc, which acts like a shock absorber and forms an elastic cushion between vertebrae which allows movement, minimizes trauma and shock and helps connect to spinal column. As the disc ages, the inner part of the vertebral disc degenerates, decreases its water content and becomes hard, so loses its elastic property. So it loses its ability to resist compression or withstand forces placed upon them. If too much force is placed on them, they can get squeezed or expand or rupture. A rupture normally occurs in an upward direction, so the disc extrudes into the spinal canal, where the spinal cord is located.

The dogs may become paralyzed because they cannot move their legs properly. When a dog has this disease it can cause a range of symptoms including slower movement, reduced activity, stiffness, difficulty walking and jumping, head held high or nose to the ground, very tense abdomen, hunchback due to muscle tension, shaking, crying, and /or the inability to move rear legs and loss of bladder and bowel control.

IVDD can occur anywhere throughout the spinal cord; thorasic, lumber and sacral regions as shown in Fig. 2.2. IVDD is signaled either because of the force of the disc material hitting the cord, or due to the disc material compressing the spinal cord [Neurology Endowment; 2009].

This is specifically one of the conditions that will be trying to detect and classify using thermographic images. At the same time another focus with this condition is to find out the specific herniated disc space. To detect and classify IVDD and to identify the specific disc space, only the regions of interest (ROI) of the entire images are required. For the first case study, the regions of interest with different image views is shown in Fig. 2.3 and for the second case study, the ROI is shown in Fig. 2.4. Unlike shown in Fig. 2.4, for thermographic analysis the ROIs actually have no space between them.

2.3.2. Syringomyelia

Syringomyelia, also known as hydromyelia, is a pathological disorder in which a fluid-filled neuroglial cavity or cyst formed in spiral cord and brain. This cyst is known as syrinx, a rare pathological condition. In medical terms, when a watery, protective substance that normally flows around the spinal cord and brain, transporting nutrients and waste products, collects in a small area of the spinal cord, forms a cyst. Cyst in spinal cord known as syringomyeli and the one formed in brain stem is known as syringobulbia. [National Institutes of Health, 2011]

When a syrinx expands and prolonged over time, it destroys the center of the spiral cord and interrupts the neurological pathways within the spiral cord. As the spiral cord connects brains and nerves, the damage results in pain, weakness, stiffness in the back, shoulder, arms or legs and these symptoms come on quite gradually. Usually the signs and symptoms of this condition vary depending on the size, location and type of the syrinx.

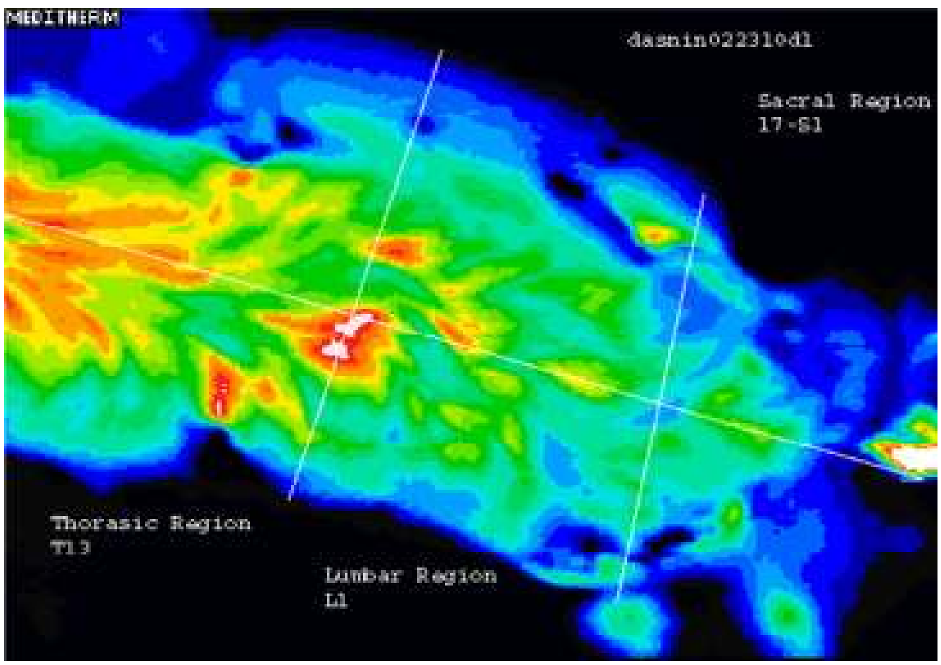
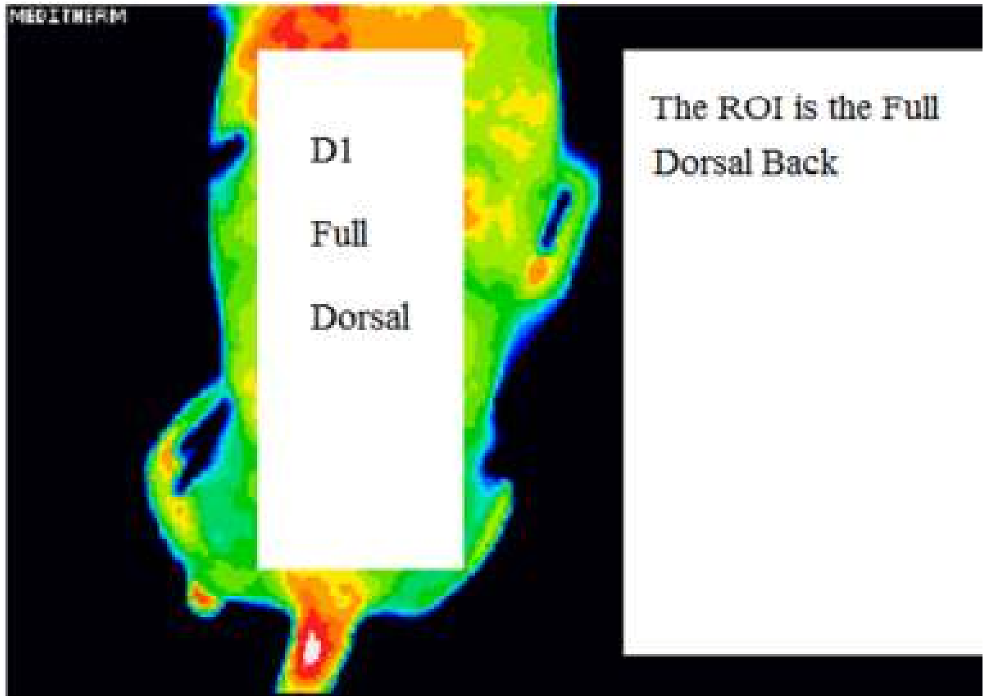
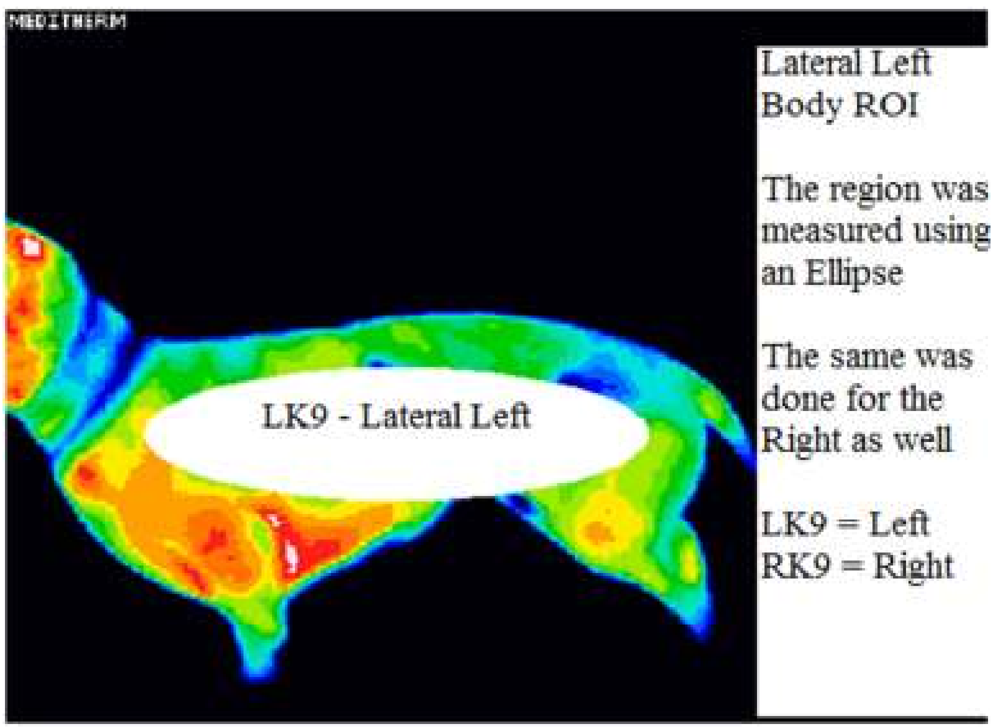


Figure 2.2. Possible herniated regions of IVDD

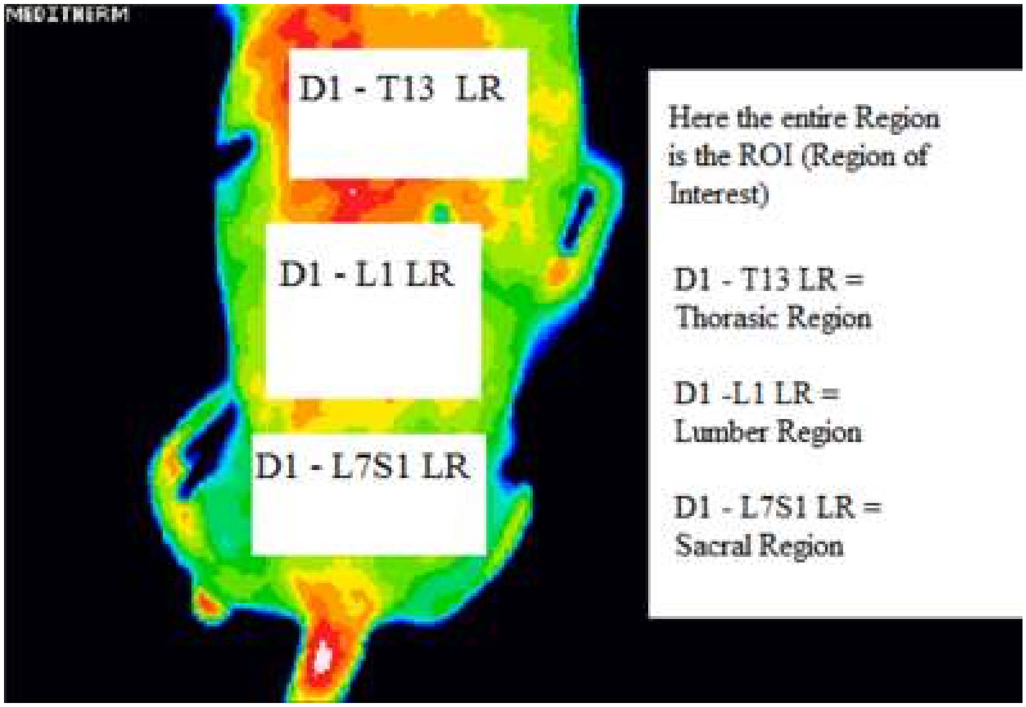


(a) Dorsal

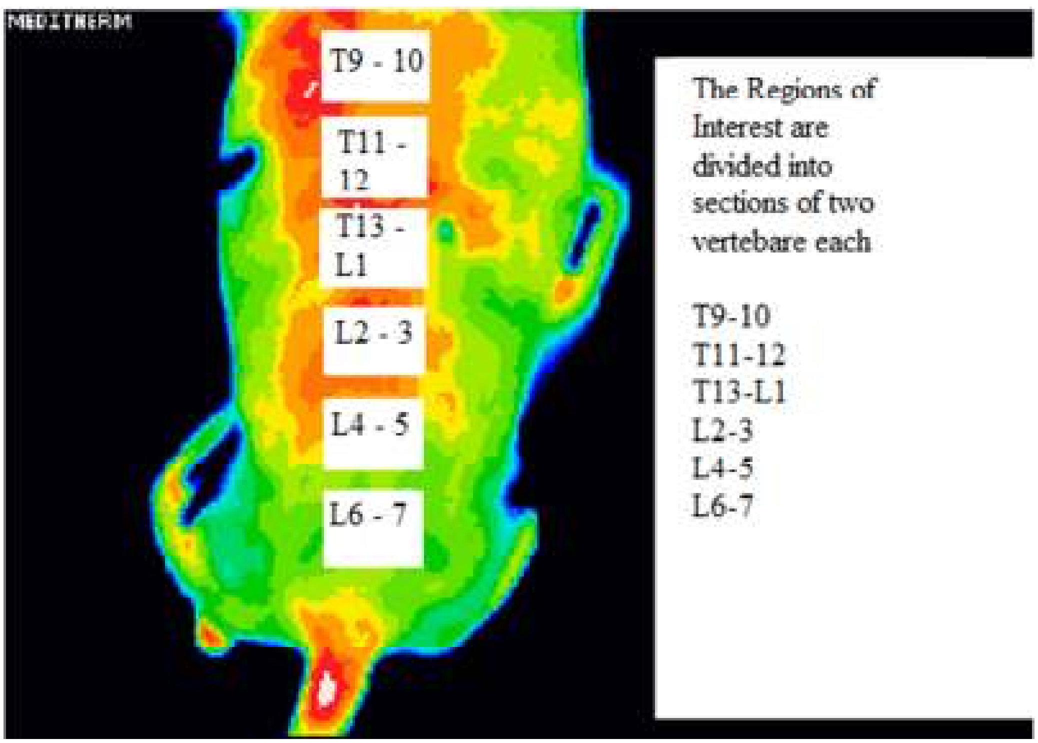


(b) Left lateral

Figure 2.3. Region of Interest (ROI) to detect IVDD



(a) Entire region



(b) Each region contains two vertebrae

Figure 2.4. Region of Interests (ROI) to detect specific disc space

A syrinx can be diagnosed usually by an impenetrable central cord syndrome or other characteristic neurologic deficit, predominantly due to pain and temperature sensory deficits in a capelike distribution. An MRI of the entire spinal cord and brain is required to diagnose a syrinx. Previously, myelograms and CAT scans were employed in diagnosis. But in this research, thermographic image of the head and of body of canines are used to diagnose this disease [Feldstein; 1999].

2.4. The Image Processing Techniques

In this research, a bunch of images were used and to process them only specific area information are required. To extract information regarding specific areas in thermographic images, image masks are needed. So, a bunch of image masks were created manually using *CVIPtoos->Utilities-> Create-> Boarder Mask*. This is a time consuming task. To get rid of this process, manually creating image masks, an algorithm is implemented in Chapter 4. The image processing techniques which are used to obtain the algorithm are explained below:

2.4.1. Extract band

The thermographic images are color images consist of three bands Red (R), Green (G) and Blue (B). *Extract band* creates monochrome images (single band images) from the color images by extracting a single color plane [Umbaugh; 2005 and 2010]. In CVIPtools these three bands R, G and B are represented as band1, band2 and band3 respectively.

2.4.2. Binary threshold

This technique sets pixels of value greater than the threshold value (set by user) to 255 and those less than and equal to threshold value are set to zero [Umbaugh; 2005 and 2010]. This is a similar operation of *histogram thresholding segmentation*.

2.4.3. Morphological filtering

Morphological filtering is used to simplify the segmented images. This filtering facilitates the search for object of interest. It is used to smooth the image outline, to fill small holes, to delete unwanted multiple objects and so on [Umbaugh; 2005 and 2010]. Depending on its operations, there are four type of different filtering are available and all these are used in the proposed algorithm in Chapter 4. They are explained below:

2.4.3.1. Morphological dilation

Morphological dilation filtering is used to expand an image object. It helps to fill small holes in the object and connect disjoint objects in the image [Umbaugh; 2005 and 2010].

2.4.3.2. Morphological erosion

Morphological erosion filtering is used to erode the unwanted objects or boundaries of the object of interest. It actually shrinks the object of interest [Umbaugh; 2005 and 2010].

2.4.3.3. Morphological closing filtering

Morphologic closing filtering consists of morphological dilation followed by morphological erosion of an image [Umbaugh; 2005 and 2010]. It is used to fill in small holes in objects.

2.4.3.4. Morphological opening filtering

Morphologic opening filtering consists of morphological erosion followed by morphological dilation of an image [Umbaugh; 2005 and 2010]. It is used to eliminate small objects from an image.

CHAPTER 3

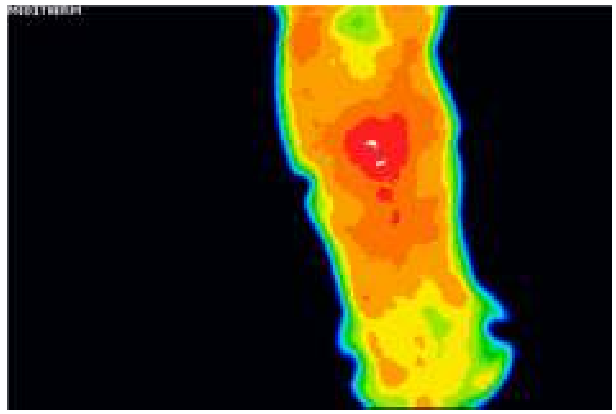
EXPERIMENTAL MATERIALS

The goals of this research are to prove thermographic images can successfully be used as a diagnostic tool by correctly classifying thermographic images of canines with or without the pathology, and to obtain an algorithm that will create the image masks automatically. In this research, six main programs were used: CVIPtools, CVIP-ATAT, CVIP-FEPC, Color Normalization Software, Partek Discovery Suite and Microsoft Excel with 3961 thermographic images and their respective manually created masks, created using CVIPtools software.

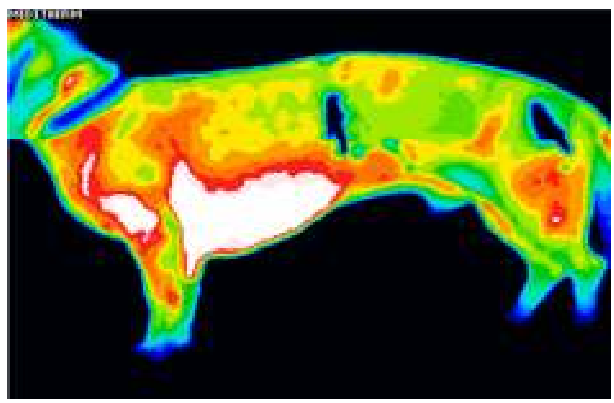
3.1. Thermographic Images

The research was started with a total of 272 thermographic images with three different views: dorsal, left lateral and right lateral of two categories; *clinical (IVDD)* and *control (normal)*, for a total of 438 thermograghic images of the dorsal view of 73 canines to identify the specific herniated disc space. Additionally, a total of 3251 thermographic images in two groups: *sedated* and *unsedated*, with nine different views; front, top, left lateral, right lateral of head and dorsal, left lateral, right lateral, front, back side of the body of two categories; presence of *syrinx* and absence of *syrinx*.

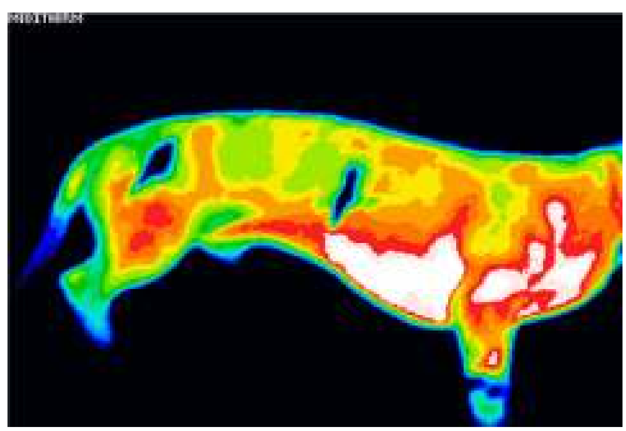
For the detection of IVDD, the experiment was with 96 dorsal images of canines, 88 images of left lateral views and 88 images of right lateral views. In the 96 dorsal view images, 83 were of canines with the pathology and 13 images were of normal canines. In the 88 left lateral view images, 76 images were of canines with pathology and 12 were images of normal canines. In the 88 right lateral images, 76 images were of canines with the pathology and 12 were images of normal canines. Examples of thermographic images of the three views of a clinical canine and of a normal canine are shown in Fig. 3.1 and in Fig. 3.2 respectively.



(a) Dorsal

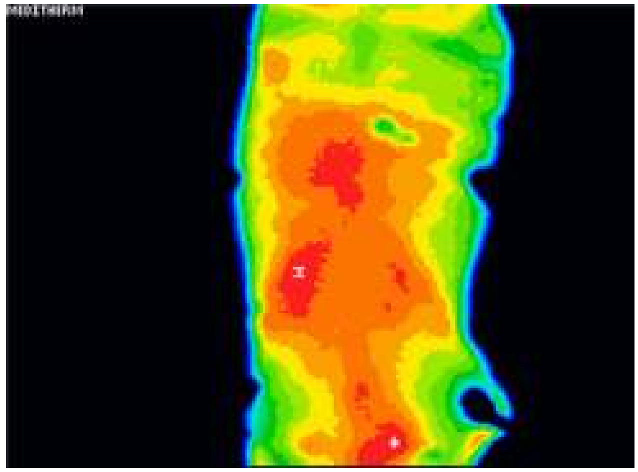


(b) Left lateral



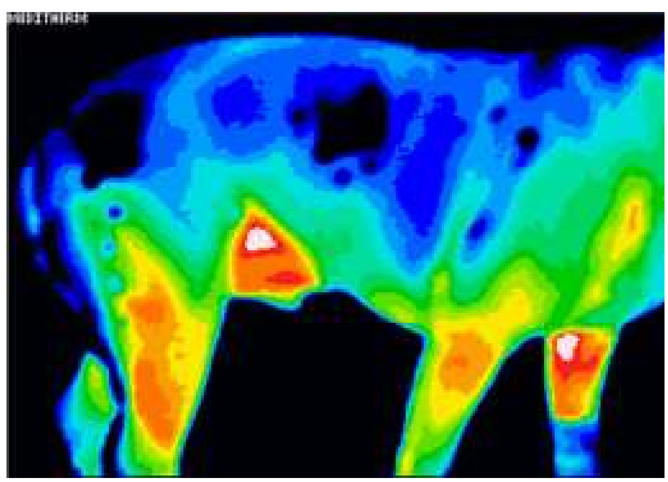
(c) Right lateral

Figure 3.1. (a) Dorsal, (b) Left lateral and (c) Right lateral view thermographic images of a clinical canine to detect IVDD.



(a) Dorsal

(b) Left lateral



(c) Right lateral

Figure 3.2. (a) Dorsal, (b) Left lateral and (c) Right lateral view thermographic images of a normal canine to detect IVDD.

To identify the specific herniated disc space, 73 dorsal images of canines, of which 58 are of clinical (IVDD) class, and 15 are of the control (normal) class, were divided into six areas, two in the thoracic region and three in the lumbar region. Specifically, T9-T10, T11-12, T12-L1, L2-L3, L4-L5, L6-L7 where, T is for Thoracic region and L in for the Lumbar region. So, for this experiment the total number of thermographic images was 438. In 438 images, 116 images of canines were with the pathology (IVDD) and 322 were image of normal canines. An example is shown in Fig. 3.3 where the six regions are drawn.

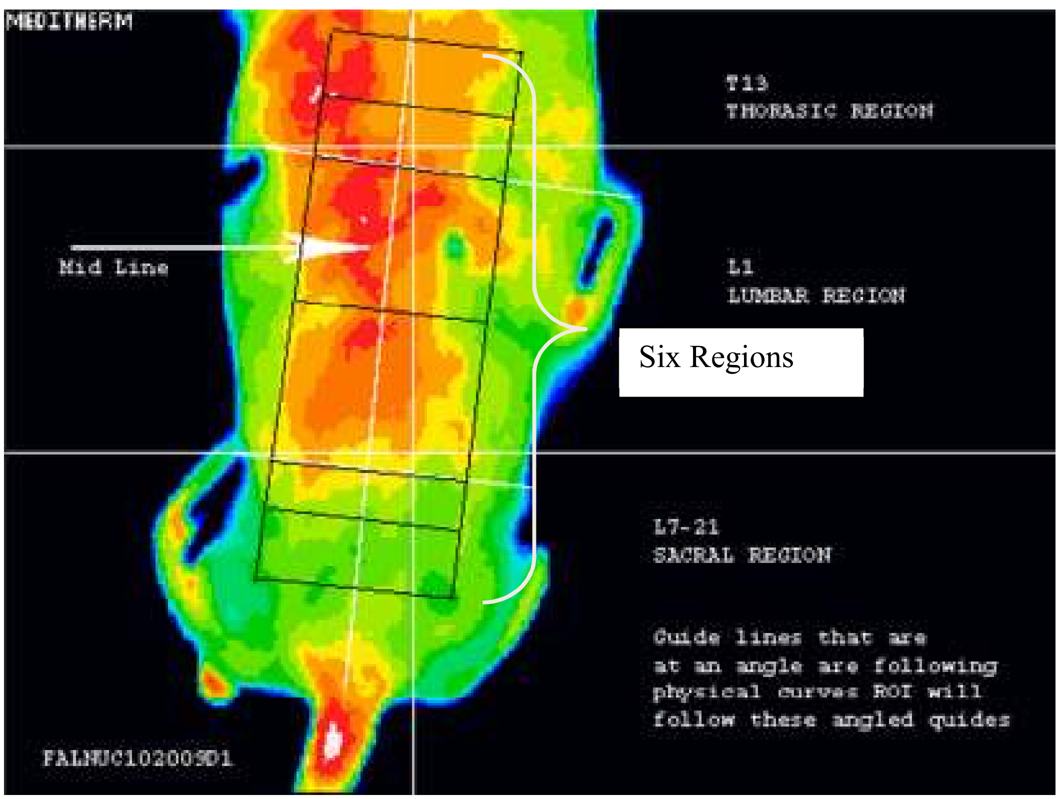


Figure 3.3. Six Regions drawn by black lines.

To determine the presence of syrinx, the first experiment used two types of images: head image and body image. These images can be divided into two groups: sedated and unsedated. The sedated group consists of six different views images: front, top, left lateral, right lateral of head and left lateral and right lateral of body. The unsedated group consists of nine different views of images: front, top, left lateral, right lateral of head and dorsal, front, back, left lateral and right lateral of body. And every view of images has two classes: presence of syrinx and absence of syrinx. This experiment was done with a huge number (3251 images) of images of 274 canines. The details are shown in Fig. 3.4. From Fig. 3.4 it can be seen that the images are mainly divided into two categories: Head images and Body images.

From Fig. 3.4, for the images of head in sedated group there were 144 front view images, 152 top view images, 156 left lateral images and 152 right lateral images. In case of the unsedated group, there were 195 front view images, 274 top view images, 275 left lateral images and 155 right lateral images. The detail information is shown in Table 3.1. Examples of thermographic images of head for both sedated and unsedated group with these four views are shown in Fig. 3.5 and in Fig. 3.6 respectively.

Again from Fig. 3.4, for the body images in sedated group, there were 146 left lateral images and 143 right lateral images. In case of the unsedated group, there were 276 dorsal view images, 277 front view images, 251 back view images, 285 left lateral images and 274 right lateral images. The detail information is shown in Table 3.2. Examples of thermographic images of body for both sedated and unsedated group with two and five different views are shown in Fig. 3.7 and in Fig. 3.8 respectively.

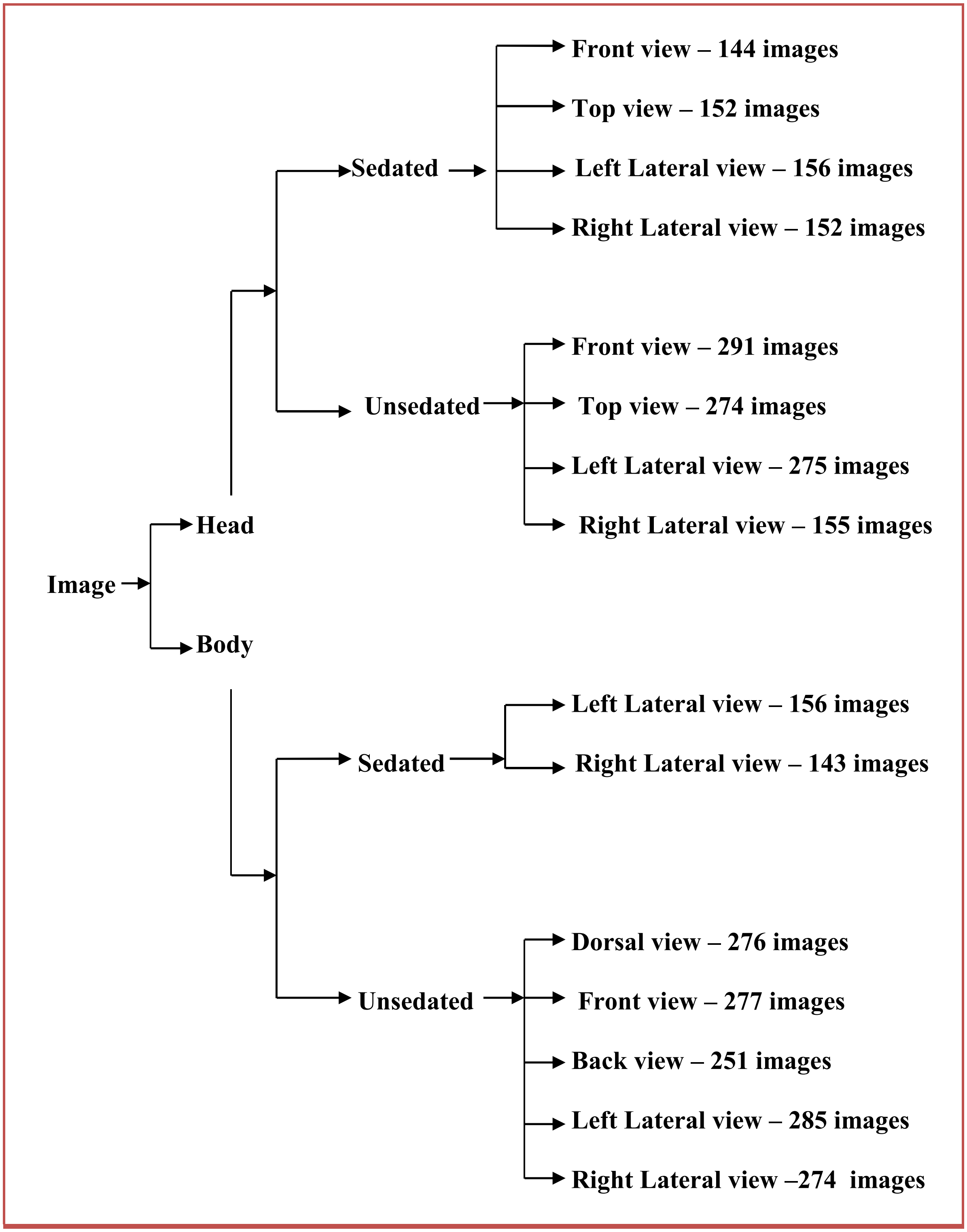


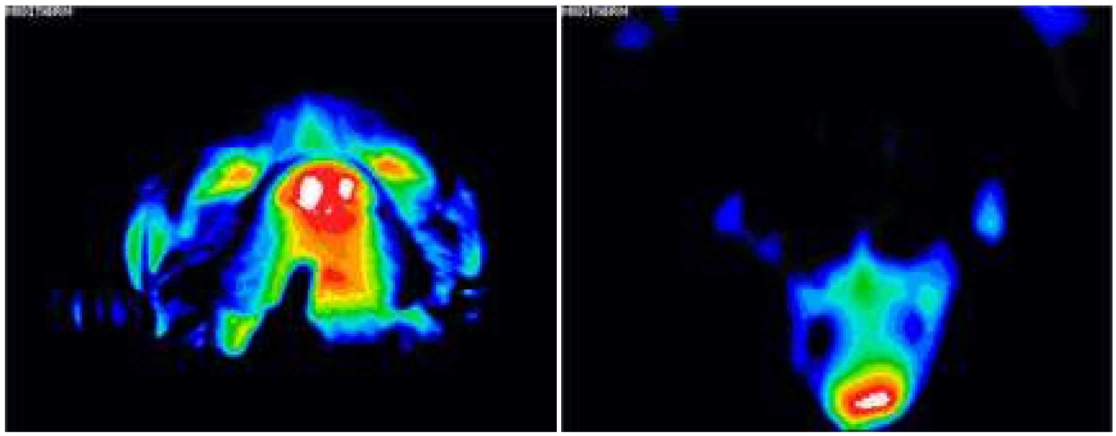
Figure 3.4. Detail information of thermographic images used for the experiment to know the presence and absence of syrinx.

Table 3.1: Detail information of thermographic images- head of the canines

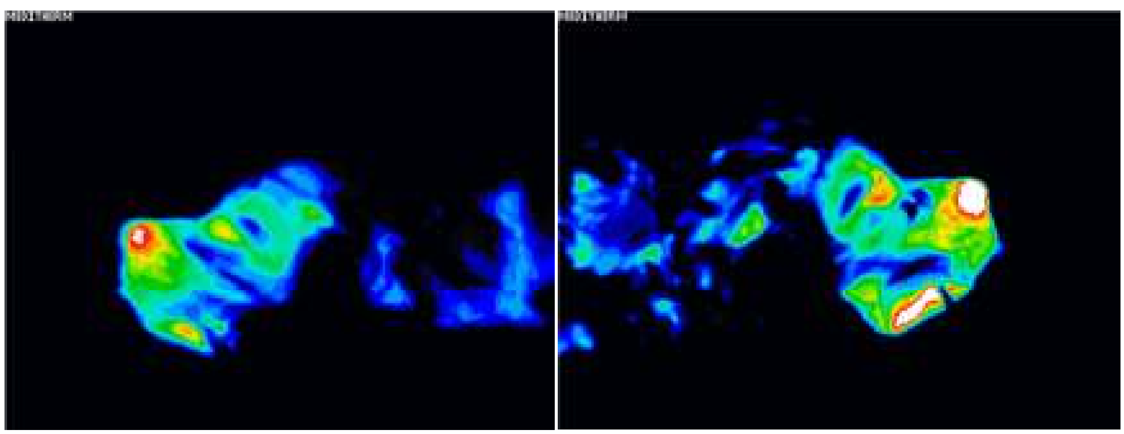
Image Views	**The number of Images**					
	Sedated Group			Unsedated Group		
	Presence of syrinx	Absence of syrinx	Total	Presence of syrinx	Absence of syrinx	Total
Front View	86	58	144	195	96	291
Top View	93	59	152	175	99	274
Left Lateral view	95	61	156	175	100	275
Right Lateral View	93	59	152	105	50	155

Table 3.2: Detail information of thermographic images- body of the canines

Image Views	**The number of Images**					
	Sedated Group			Unsedated Group		
	Presence of syrinx	Absence of syrinx	Total	Presence of syrinx	Absence of syrinx	Total
Dorsal view	-	-	-	177	99	276
Front View	-	-	-	180	97	277
Back View	-	-	-	164	87	251
Left Lateral view	89	57	156	182	103	285
Right Lateral View	85	58	143	176	98	274

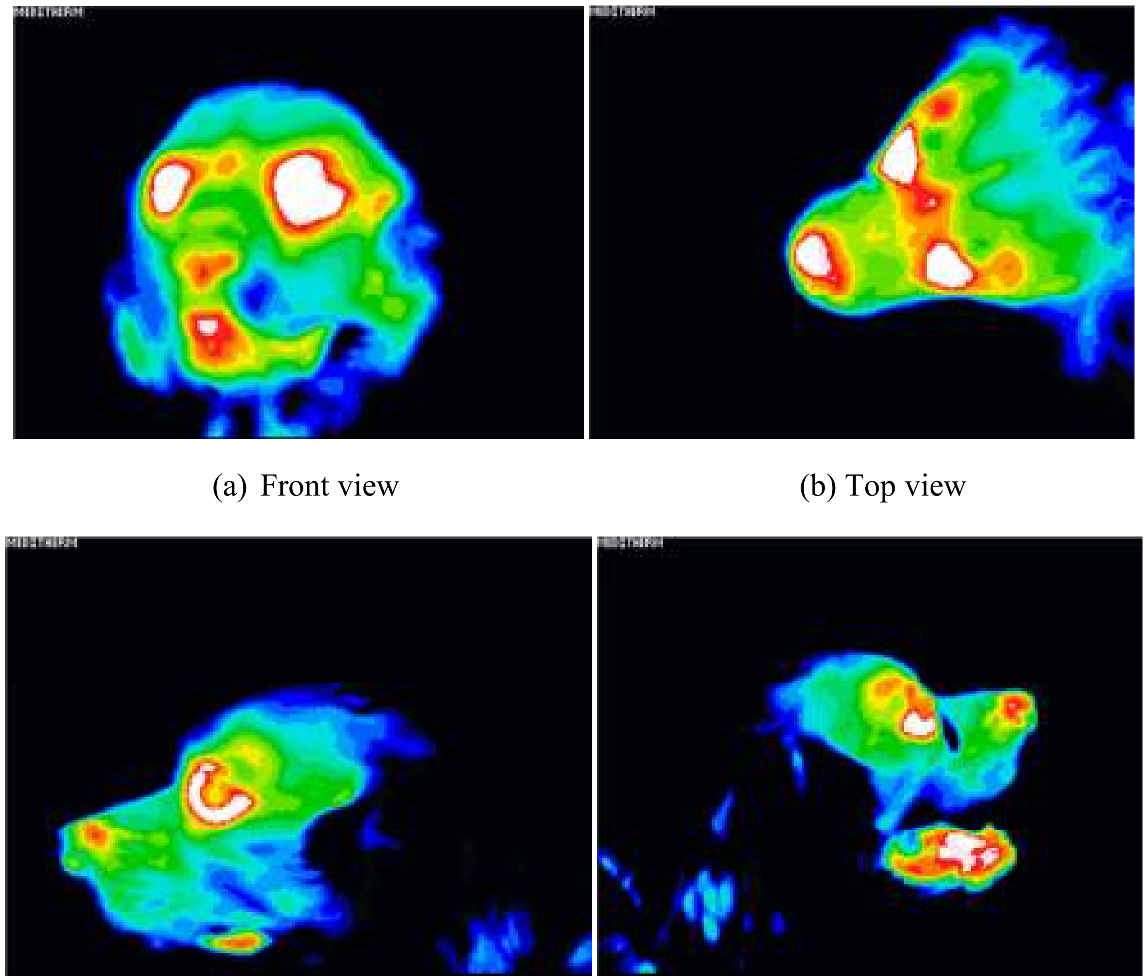


(a) Front view (b) Top view



(c) Left lateral view (d) Right lateral view

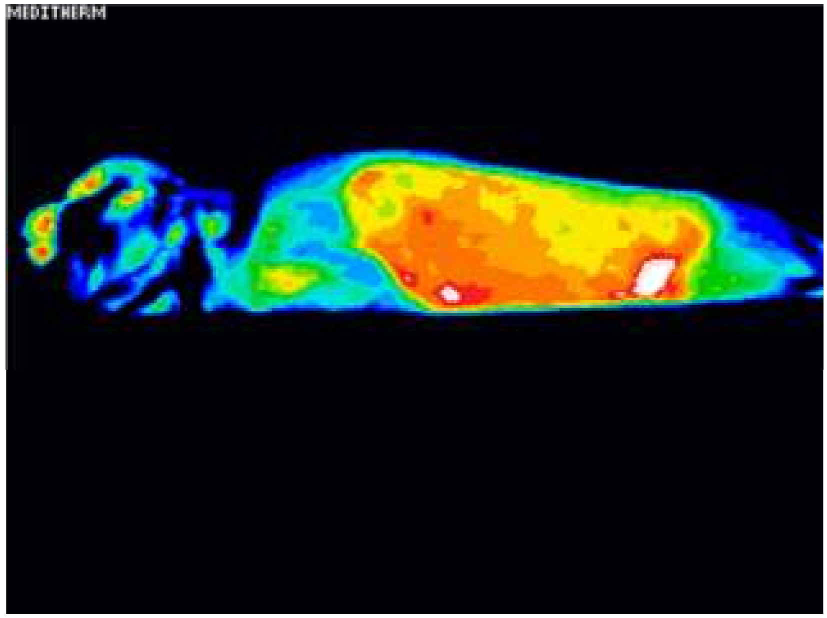
Figure 3.5. Thermographic images of head from four different views for sedated group.



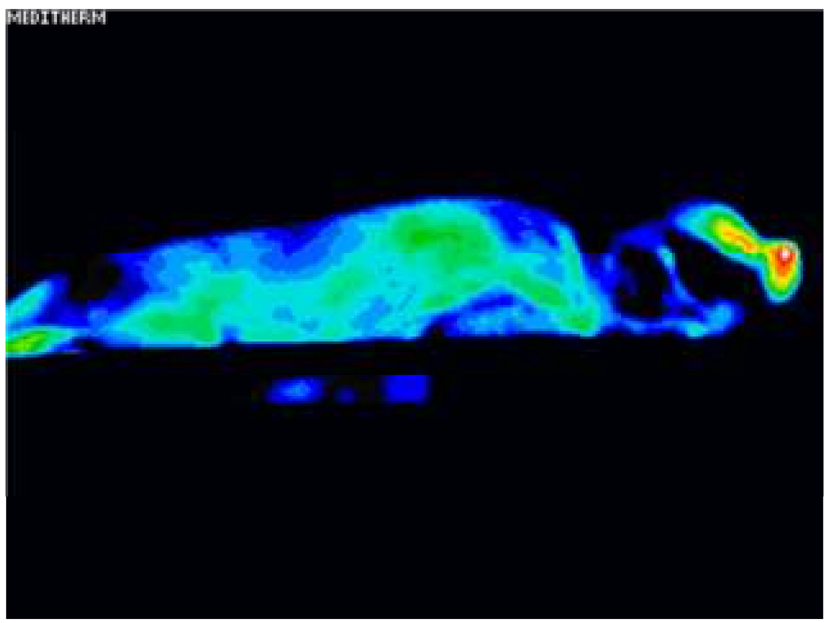
(a) Front view (b) Top view

(c) Left lateral view (d) Right lateral view

Figure 3.6. Thermographic images of head from four different views for unsedated group.

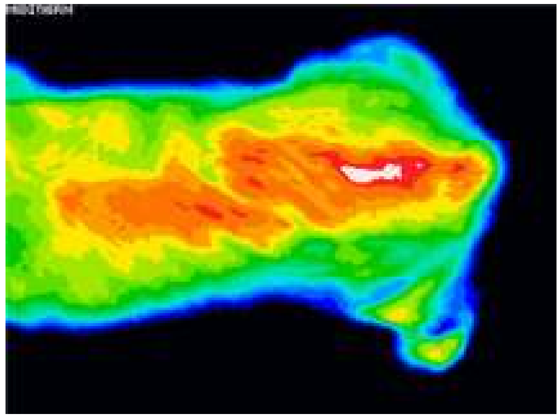


(a) Left lateral view

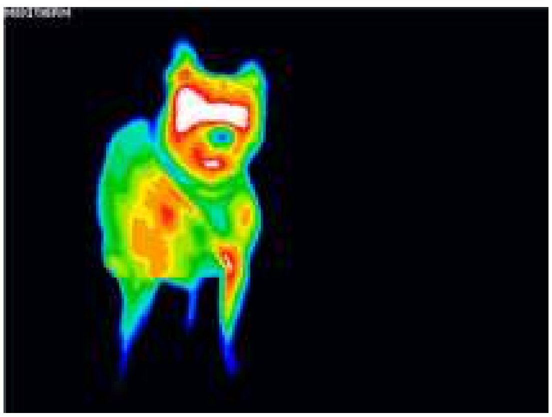


(b) Right lateral view

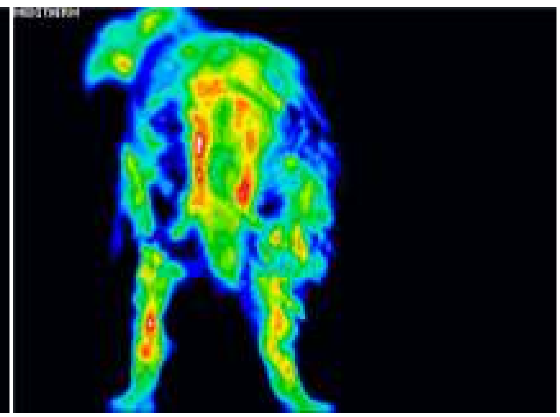
Figure 3.7. Thermographic images of body from two different views for sedated group.



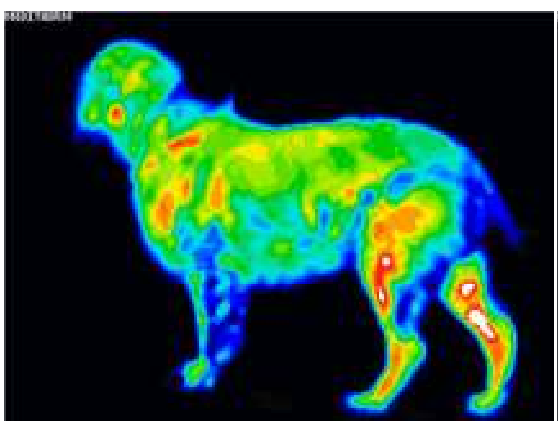
(a) Dorsal view



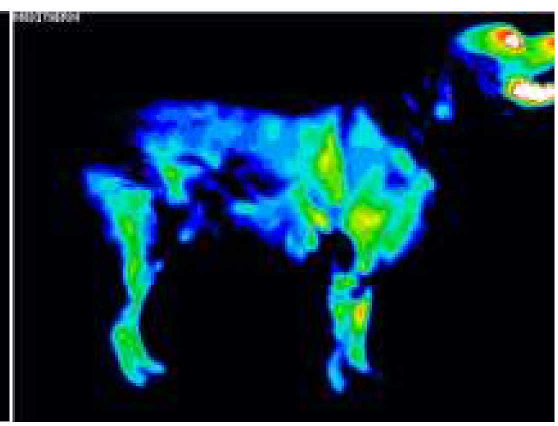
(b) Front view



(c) Back view



(d) Left lateral view



(e) Right lateral view

Figure 3.8. Thermographic images of body from five different views for unsedated group.

3.2. Masks

To detect IVDD there were 272 manually created image masks for the three different views thermographic images; dorsal, left lateral and right lateral. These masks created using CVIPtools, with *Utilities-> Create-> Border mask.* The final goal is to classify images correctly, so it is required to have ideal masks for the images to start the experiment. Expert created masks were not readily available since manual creation of the masks is time consuming and fraught with potential error. However, hand drawn masks were created and example masks from Fig. 3.1 and Fig. 3.2 images are shown in Fig. 3.9 and Fig. 3.10 respectively.

To find the specific herniated disc space, there were 438 image masks, created using CVIPtools again, *Utilities-> Create- > Border mask*. An example is shown in Fig. 3.11 where six masks of the image for the six specific regions.

For the diagnosis of syrinx, there were total 3261 image masks for nine different views of thermographic images in both sedated and unsedated group. They were created manually using CVIPtools, *Utilities-> Create- > Border mask*. Example masks from Fig. 3.5, Fig. 3.6, Fig. 3.7 and Fig. 3.8 are shown in Fig. 3.12, Fig. 3.13, Fig. 3.14 and Fig. 3.15 respectively.

(a) Dorsal

(b) Left lateral

(c) Right lateral

Figure 3.9. Masks of the (a) Dorsal, (b) Left lateral and (c) Right lateral view thermographic images shown in Fig. 3.1

(a) Dorsal

(b) Left lateral

(c) Right lateral

Figure 3.10. Masks of the (a) Dorsal, (b) Left lateral and (c) Right lateral view thermographic images shown in Fig. 3.2

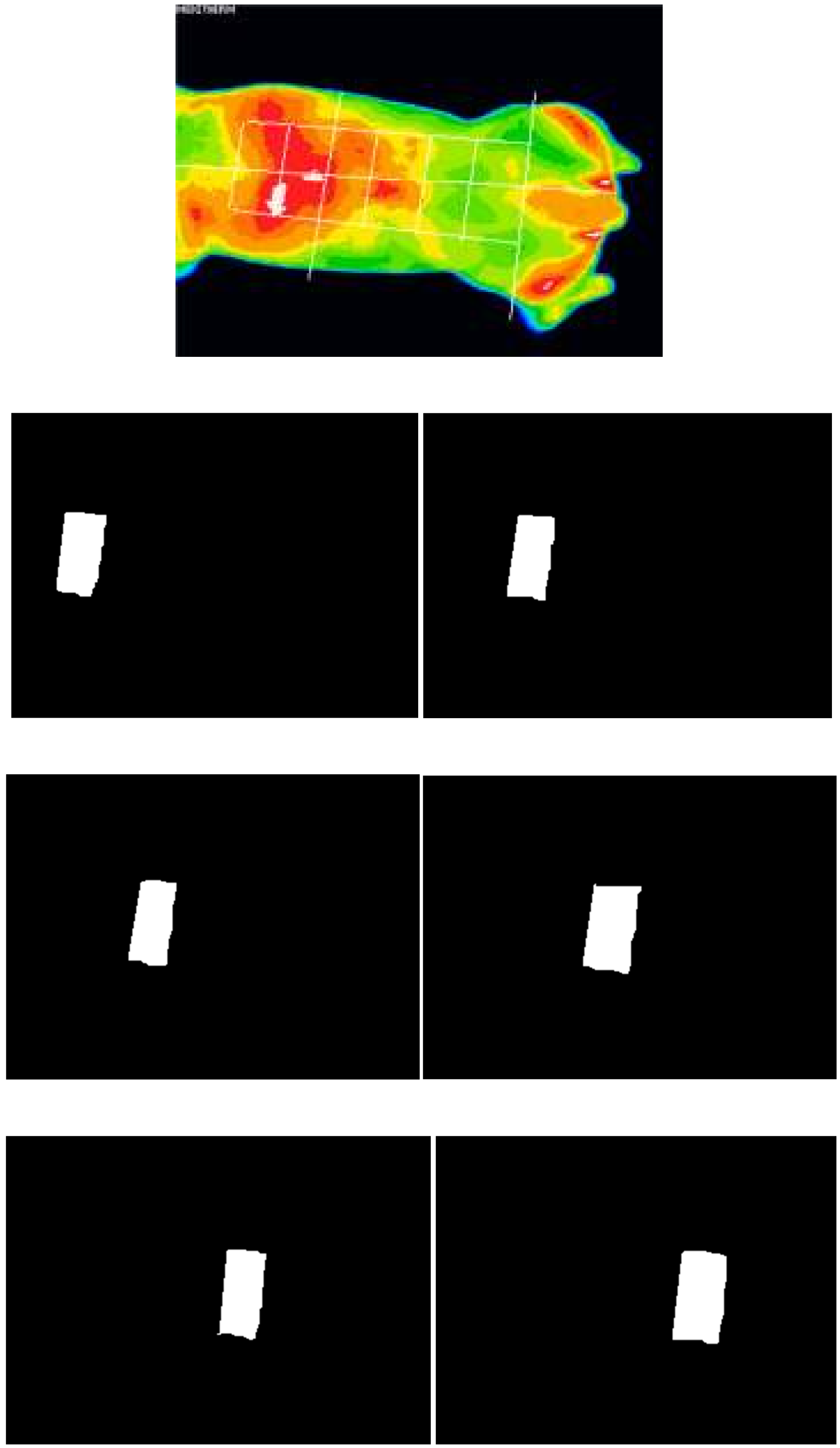
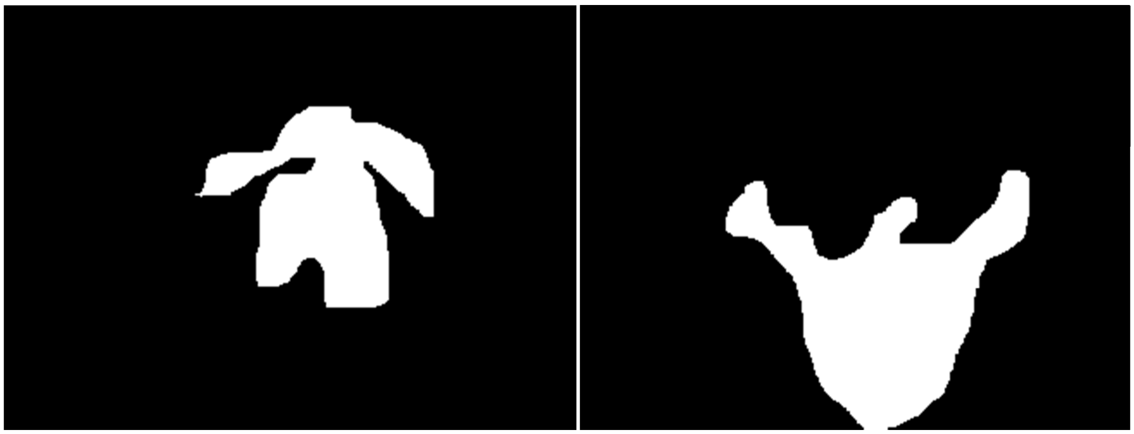
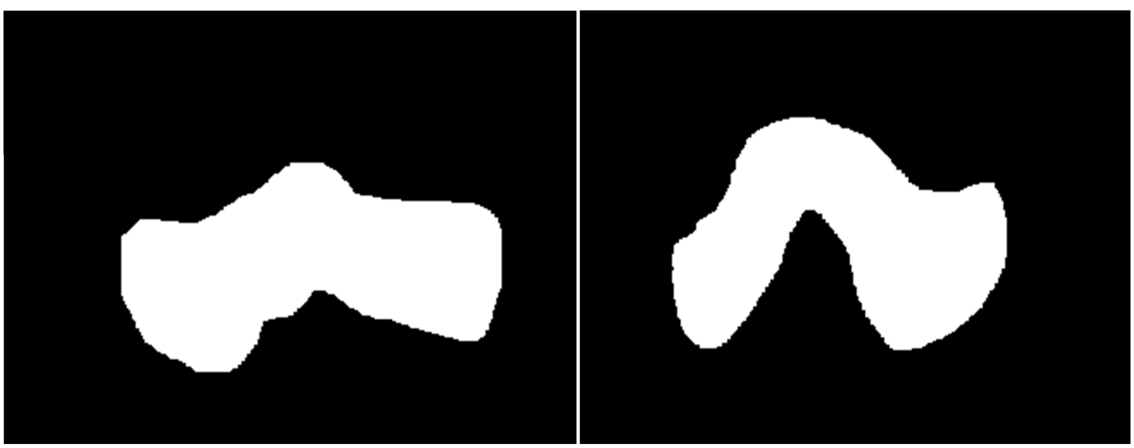


Figure 3.11. Six masks of the image, shown at the top, for the six specific regions



(a) Front view (b) Top view



(c) Left lateral view (d) Right lateral view

Figure 3.12. Masks of the four different view thermographic images shown in Fig. 3.5

(a) Front view (b) Top view

(c) Left lateral view (d) Right lateral view

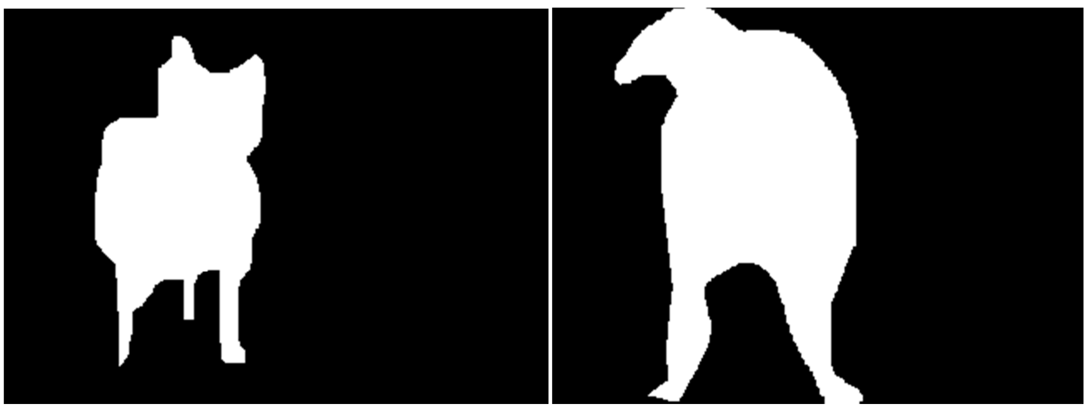
Figure 3.13. Masks of the four different view thermographic images shown in Fig. 3.6

(a) Left lateral view

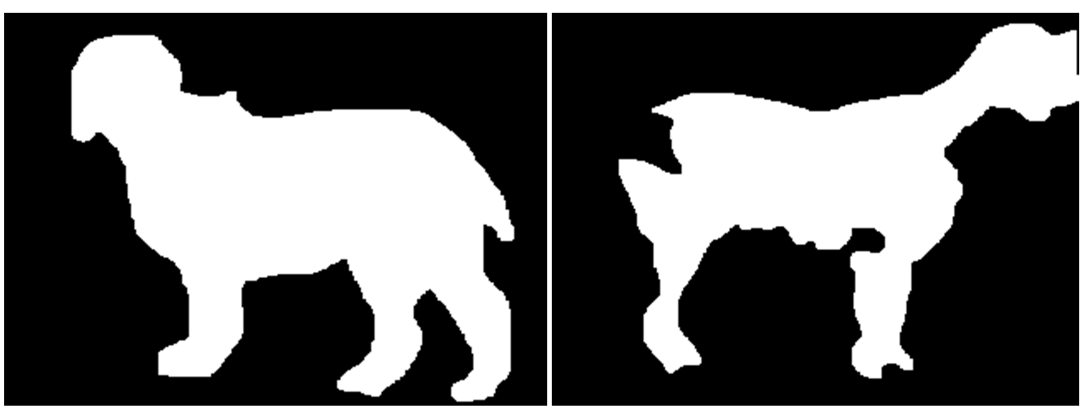
(b) Right lateral view

Figure 3.14. Masks of the two different view thermographic images shown in Fig. 3.7

(a) Dorsal view



(b) Front view (c) Back view



(d) Left lateral view (e) Right lateral view

Figure 3.15. Masks of the five different view thermographic images shown in Fig. 3.8

3.3. Programs

The functions and the purpose of the CVIPtools, CVIP-ATAT, CVIP-FEPC, Partek Discovery Suite and Microsoft Excel software that was used in this research, are explained below:

3.3.1. CVIPtools (Computer Vision and Image Processing Tools)

CVIPtools [CVIPtools; 2010] is a Windows based application that allows for the processing and analysis of digital images for the purpose of better understanding and visualization of the underlying concepts for computer vision and image processing [Umbaugh; 2005 and 2010]. This software processes one image at a time and produces an immediate result. This software was developed by the Computer Vision and Image Processing (CVIP) Laboratory in the Department of Electrical and Computer Engineering of Southern Illinois University Edwardsville (SIUE). In this research, CVIPtools was used to create the image masks manually and to find an algorithm to create masks of the thermographic images automatically.

3.3.2. CVIP-ATAT (CVIP Algorithm Test and Analysis Tool)

CVIP-ATAT [CVIP-ATAT; 2010] is also a Windows based application that automates the testing and analyzing of potential algorithms. This tool allows the user to process a large number of images at one time with many algorithmic possibilities. This tool allows for parameter variations in a single experimental run in order to get the best result. This tool can be called a front-end tool because the primary purpose of this tool is to find out the best potential algorithm to process a batch of images for any particular application. Mainly this tool was used in this research to obtain a specific algorithm to create image masks automatically. In this part of the research 272 thermographic images were used, and since testing and analyzing of 272 images is very time consuming CVIP-ATAT was ideal for this purpose.

3.3.3. CVIP-FEPC (CVIP Feature Extraction and Pattern Classification)

CVIP-FEPC [CVIP-FEPC; 2010] is a tool that automates the process of testing the various combinations of features and pattern classification methods. First, the user selects a set a features and pattern classification techniques. Then, the application will automatically cycle through all the combinations of those features and run each pattern classification combination on them. Finally, the application produces output for the tests indicating the success for each particular set of options. This process helped us converge upon the optimal features and classification technique.

3.3.4. Color Normalization Software

The color normalization software allows the conversion of the original thermographic images into four color normalized mathematical spaces: a) luminance, b) normalized grey, c) normalized RGB, d) normalized RGB luminance [Umbaugh, Solt; Jan 2008]. This conversion is based on temperature data provided by Long Island Veterinary Specialists [LIVS; 2011].

3.3.5. The Partek Discovery Suite

The Partek Discovery Suite [Partek; 2005] provides modern methods of data analysis and visualization with classical statistics to find solutions to a wide variety of pattern analysis and recognition problems. It is used to find correlations, contributions, cause and effect relationships, trends and predictability patterns, to solve complex pattern analysis and recognition problems. The combined spread sheet are imported to the Partek by going to *file -> import xls* sheet. While importing make the type field categorical (fixed) which make that particular column fixed for classification and also make the attribute of that column as class for priority classification

3.3.6. Microsoft Excel

Microsoft Excel was used for inputting data into table form. Excel has many calculus and trigonometry functions that can be useful for this type of research.

3.4. MRI Results

The Magnetic Resonance Imaging (MRI) results were supplied by Long Island Veterinary Specialists [LIVS; 2011]. They gave individual result of every thermographic image of all canines. The MRI diagnosis results of the pathological conditions, IVDD and Syringomyelia were enlisted in this result spreadsheet. Based on this information, the pattern classification was done in this research.

CHAPTER 4

THE ALGORITHM FOR AUTOMATIC MASK CREATION

To detect and classify any pathological condition, only the region of interest (ROI), that is the affected areas, are required. To establish thermographic images as a valid diagnostic tool the image and the specific area are required to create an image mask. Since the masks created are not created by an expert, there is no standard to define the region of interest. Consequently, two methods of creating the masks are explored; one is manually created masks and the other is automatically created masks. Experiments will be performed with both types of makes to determine which one will create the best masks. To compare the masks, feature analysis and classification are will be used.

In this section the algorithm to create masks automatically is described. Three different views of the thermographic images: dorsal, left lateral and right lateral are considered. The regions of interest (ROI) for different views, need to be extracted from the entire image using the algorithm, are shown in Fig. 4.1. The algorithm obtained is shown in Fig. 4.2-(a). For this purpose two programs were used: CVIPtools and CVIP-ATAT.

4.1. CVIPtools and CVIP-ATAT

The CVIPtools environment was used to determine potentially useful processes and the range of parameters to test during the algorithm's development. In CVIPtools, several images with different views were experimented with and the procedure and processes were selected to test in CVIP-ATAT. CVIP-ATAT was used to select the optimal algorithm for the images. A range of the parameters was set for each stage in the algorithm. To obtain the specific parameters CVIP-ATAT was used. For algorithm comparison, subtraction energy was used as a metric, using the manual images as ideal images. The highest value of subtraction energy denotes the “best” algorithm for the image. Explanations of each stage of the algorithm are given in the next section.

4.2. Algorithm Implementation

The program that was used initially to find out the steps of the algorithm is CVIPtools and then, CVIP-ATAT was used to implement the algorithm to obtain the image mask The steps of the algorithm along with CVIP-ATAT are explained below:

4.2.1. Input images

After opening a project in CVIP-ATAT the first step is to provide the input images and ideal images. Input images are the thermographic images. The CVIP-ATAT software had been used to perform the algorithm development and test three times for three different views of images. First, 96 dorsal view images were set as input images, then 88 left lateral images and lastly 88 right lateral images. At the same time their respective manually created masks were put as ideal images. After inputting the images, the next step is the process selection.

4.2.2. Extract band

In the CVIP-ATAT software, in the process section, the steps of the algorithm were set. So the ‘Extract Band’ was set as the first step and the parameter was 1-1-3. It provides one band gray level image since the input images are three band images and the increment was set one. The red, green and blue (R,G,B) components are defined as band1, band2 and band3 respectively in CVIP-ATAT. So for each image, this software provides three gray level images. An example is shown in Fig. 4.3 where it is noticeable that only the R band/ Red band image is important.

Any particular band was not fixed because the perfect band for an image varies image to image. So to keep the algorithm versatile every band of an image was taken. Another example is shown in Fig. 4.4 where G band/ Green band is important.

4.2.3. Binary threshold

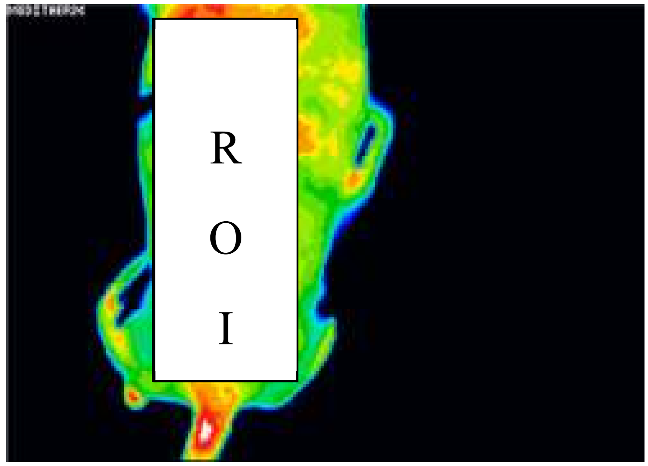
Binary threshold is the second stage of the algorithm. From the first stage, gray level images were obtained. The binary threshold process provides binary images where only ‘0’ and ‘1’ are used to represent the images. Since the image masks which were trying to be created are nothing but a binary image, the binary threshold had been used to convert the gray level images to binary images. A threshold value of 128 was used. It value was chosen as a default value in CVIP-ATAT.

4.2.4. Morphological filtering

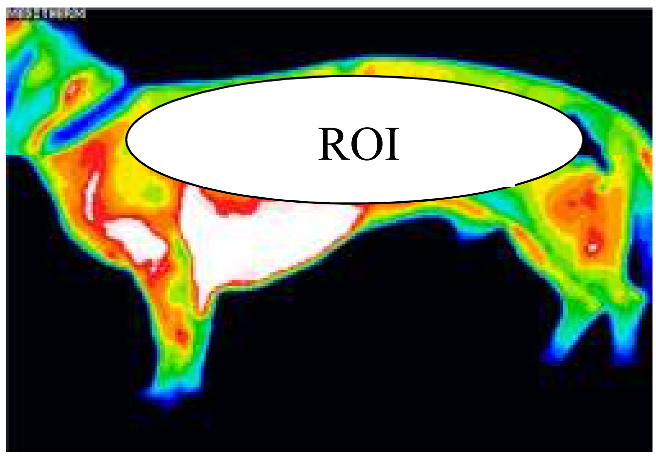
Morphological filtering can be used to simplify segmented images [Umbaugh, S.; 2005 and 2010]. Four operations are possible: *closing, opening, erosion* and *dilation*. In this algorithm *closing, erosion* and *dilation* operations were used. The sequence of these operations is shown in Fig. 4.2(b) and these were entered in CVIP-ATAT as stages four to seven.

The morphological closing operation was used for fill the holes, erosion was used to remove the unwanted projections and dilation was used to expand the region of interest. The parameter values were tested for each stage were: 1-1-60. A large range was tried to find the best possible value.

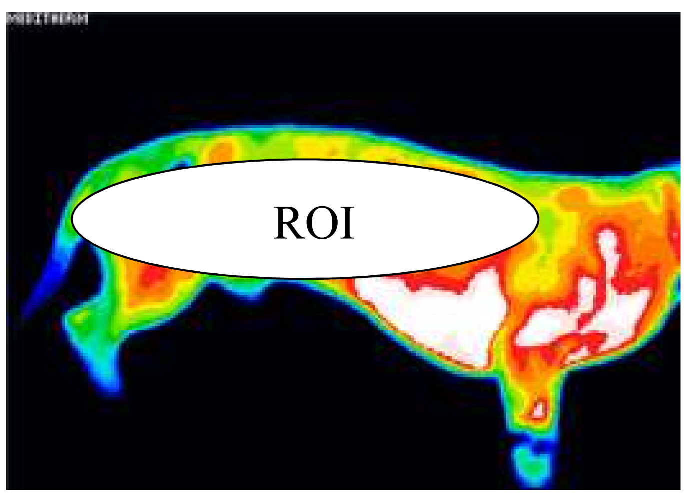
After placing all the stages, the next step was to run the algorithm in CVIP-ATAT. When the execution of the algorithm was complete, the images were compared using subtraction energy and only the images with the highest subtraction energy were selected. These images are the desired automated masks.



(a) Dorsal



(b) Left lateral



(c) Right lateral

Figure 4.1. Region of Interest (ROI) for (a) Dorsal, (b) Left lateral and (c) Right lateral view to detect IVDD.

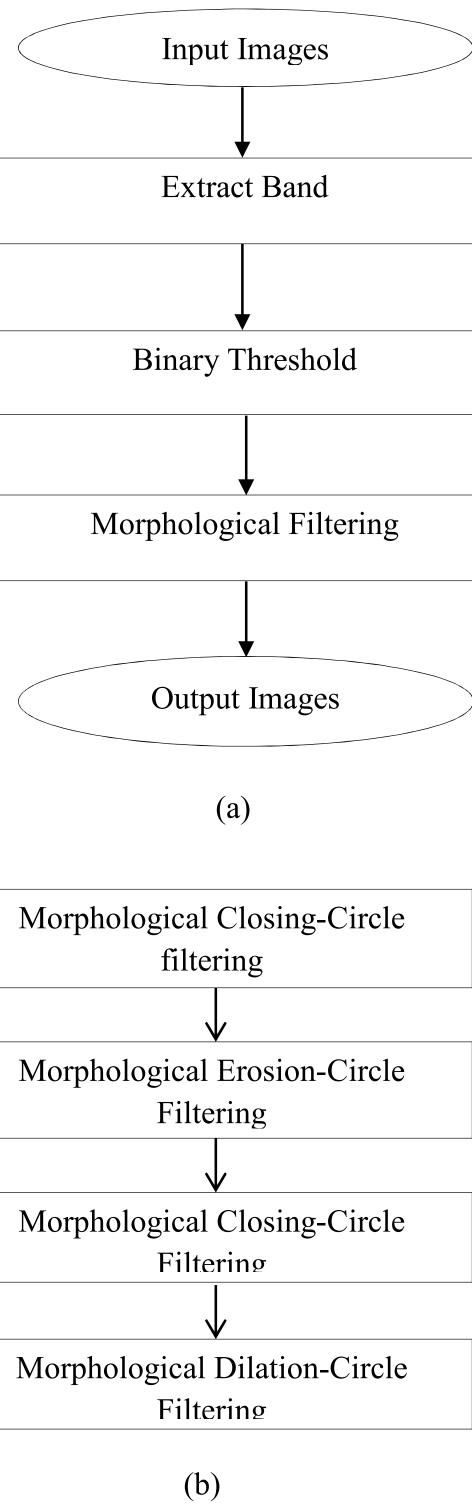
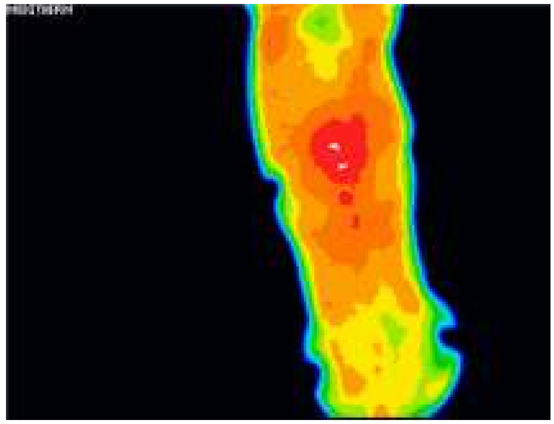
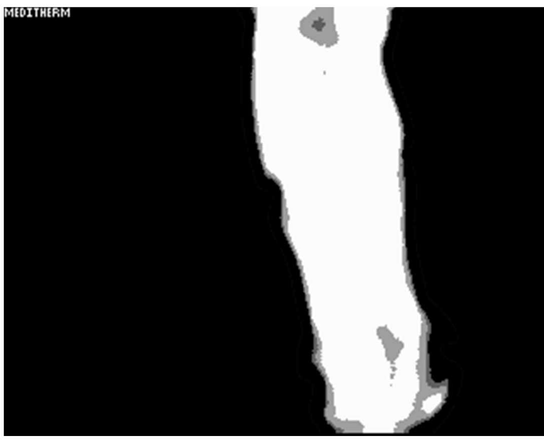


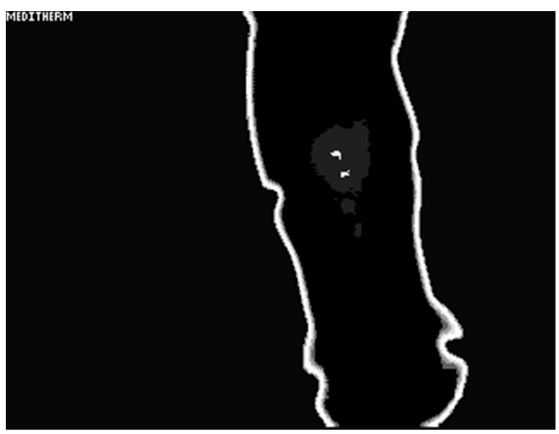
Figure 4.2. (a) Flowchart of the algorithm for automated mask. (b) Sequences of Morphological filtering



(a) Original image



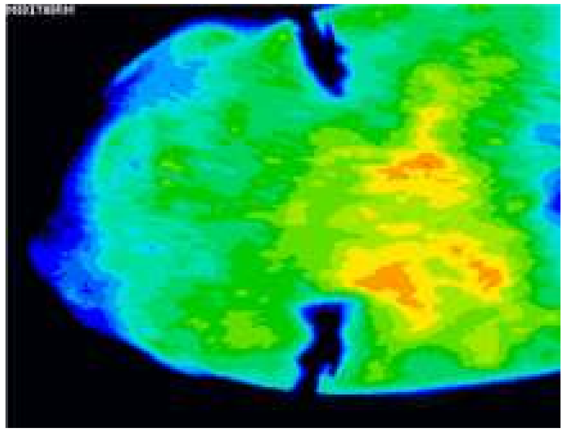
(i) R band image (ii) G band image



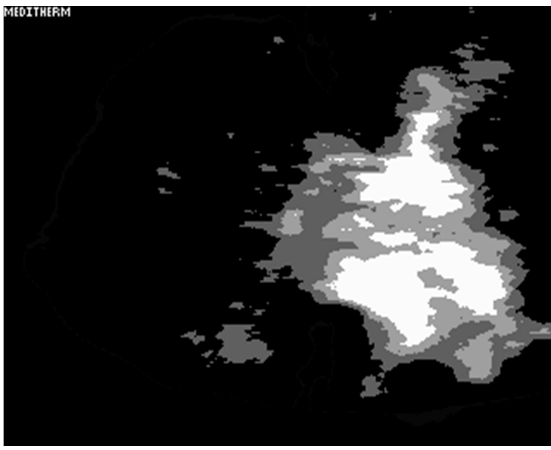
(iii) B band image

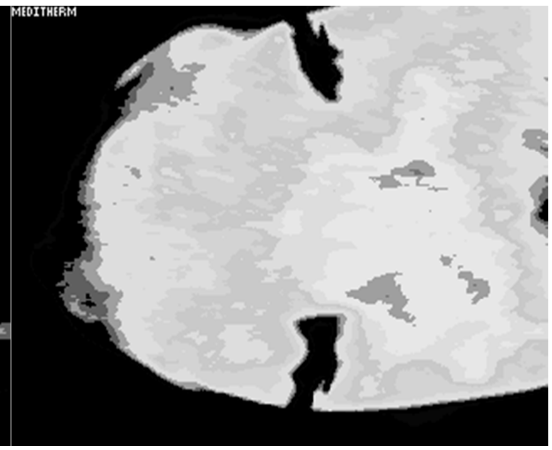
(b) Different band images

Figure 4.3. (a) Original image (b) Different band images of the original image.

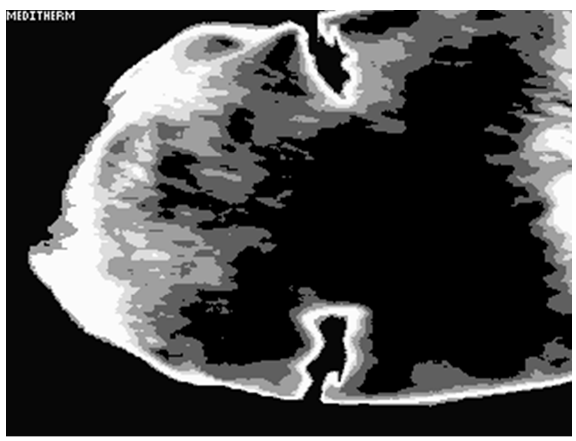


(a) Original image





(i) R band image (ii) G band image



(iii) B band image

(b) Different band images

Figure 4.4. (a) Original image (b) Different band images of the original image.

CHAPTER 5

FEATURE ANALYSIS AND PATTERN CLASSIFICATION

To develop a classification algorithm, the images are divided into two sets: a training set and a test set. Typically, these training and test sets are equal in size, but to get a maximum success rate the training set can be increased. The larger the training set the higher the success rate may be. But, with a larger test set, a maximum success rate is a better indicator of a good algorithm. But manually creating training sets and test sets is a time consuming process. There is an alternative process to test the algorithm called the leave-one-out method [Umbaugh, S.; 2005 and 2010]. In this method only one image is in the test set at a time and all the rest are in training set, and the testing cycles through all the images. For each individual test the samples in the training set are used to test the one image in the test set. This method can be modified to the leave-K-out method. In this method, K number of images will be in each test set. For example, if K=10 that means 10 images are in each test set with the other samples in training set. All of these three methods were used in this research.

In this chapter, the classification methods, those were used to diagnose the images, are described. For the classification methods two software packages were used: CVIP-FEPC and the Partek Discovery Suite.

5.1. CVIP-FEPC

CVIP-FEPC has been described in Chapter 3. Generally, the CVIP-FEPC, Feature Extraction and Pattern Classification, allows for batch processing and tests all combinations of features and pattern classification techniques selected.

5.1.1. Classification methods

There are a number of classification methods available in CVIP-FEPC with the testing method of leave-one-out. Among them two classification methods were considered here to classify the images: Nearest neighbor and K-nearest neighbor. Initially, two methods were used but with the very first experiment, detection of IVDD, it was found that K-nearest neighbor provided better classification results than the nearest neighbor. So, after that nearest neighbor was not used. These two classification method are depicted below:

5.1.1.1. <u>Nearest neighbor</u>

Nearest neighbor is the simplest algorithm to implement. This algorithm actually identifies a sample from the test set and relies on distance measures, similarity measures or a combination of measures. If it uses distance measures then it will look for the smallest number (the “distance” or “error”), measured between the object of interest feature vector and other feature vectors of the samples in the training set [Umbaugh, S.; 2005 and 2010]. If it uses similarity measures then it will look for the largest number, measured between the object of interest and other samples in the training set. This algorithm ranks all the objects in terms of their distance from or similarity with a query object. Then this object is compared with all samples in the training set and identified as the same class as the closet sample in the training set using the measures, mentioned above.

5.1.1.2. <u>K-nearest neighbor</u>

The nearest neighbor is not a robust algorithm. To make it more reliable it is modified to an algorithm called the K-nearest neighbor method. This method also classifies objects based on the closest training samples in the feature space. It makes decisions not by selecting the closest sample but by considering a group of close samples in the training set [Umbaugh, S.; 2005 and 2010]. The object of interest is compared to all of the samples in the training set. When K=1, it is the nearest neighbor method. When K=4, the unknown object will be assigned to the class, most common among its four nearest neighbors.

5.1.2. Distance or similarity metric

Distance measures and similarity measures are used to compare objects or feature vectors before performing the classification. With a distance measure, the difference between two feature vectors is measured and with a similarity measure, the closeness between the two feature vectors is measured. Two feature vectors are in the same class when they have a small difference or a large similarity [Umbaugh, S.; 2005 and 2010]. There are a number of distance and similarity measures methods are available in CVIP-FEPC. Among them the Euclidean distance is the most commonly used and was used in this research**.**

Euclidean distance: It is the square-root of the sum of the least squares of differences between vector components. [Umbaugh, S.; 2005 and 2010] This can be explained as follows,

Consider the following two vectors A and B.

$$A = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \text{ and } B = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

So the Euclidean distance is,

$$\sqrt{\sum_{i=1}^{n}(a_i - b_i)^2} = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_n - b_n)^2}$$

5.1.3. Data normalization method

Data Normalization is done to put data into same/similar range and/or give similar stats. There is a number of data normalization in CVIP-FEPC. Among them, *standard normal density* and *softmax scaling* data normalization were used in this research.

5.1.3.1. Standard normal density normalization

Standard normal density normalization is a statistical based method to normalize data (vector components) which is performed by subtracting the mean from each vector components and dividing by its standard deviation. This can be explained as follows, given a set of k feature vectors, [Umbaugh, S.; 2005 and 2010]

$\mathrm{F_j} = [\mathrm{F_1}, \mathrm{F_2}, \ldots., \mathrm{F_k}]$, with n features in each vector.

$$\mathrm{F_j} = \begin{bmatrix} f_{1j} \\ f_{2j} \\ \vdots \\ f_{nj} \end{bmatrix} \text{ for } j = 1, 2, \ldots., k.$$

Mean: $m_i = \frac{1}{k}\sum_{j=1}^{k} f_{ij}$ for $i = 1, 2, \ldots., n$.

Standard Deviation: $\sigma_i = \sqrt{\frac{1}{k}\sum_{j=1}^{k}(f_{ij} - m_i)^2} = \sqrt{\frac{1}{k}\sum_{j=1}^{k}(f_{ij})^2 - {m_i}^2}$ for $i = 1, 2, \ldots, n$

Then, each feature component, the mean is subtracted from and divided by the standard deviation.

$f_{ijSND} = \frac{f_{ij} - m_i}{\sigma_i}$ for all i, j

5.1.3.2. Softmax scaling normalization

Softmax scaling is a non-linear normalization method, which compresses data into the range 0 to1. [Umbaugh, S.; 2005 and 2010] This normalization takes two steps,

Step1: $y = \frac{f_{ij} - m_i}{r\sigma_i}$ where m_i = mean, f_{ij} = feature vector, σ_i = standard deviation and r = user defined factor.

This step is similar to mapping the data to standard normal density. The only difference is that it uses a user defined factor 'r'. For small values of 'y' the process is linear. Here, factor 'r' determines the range values of the feature f_{ij} [Umbaugh, S.; 2005 and 2010].

Step2: $f_{ijSMC} = \frac{1}{1+e^{-y}}$ for all i, j

Where f_{ijSMC} is the normalized data and this normalization changes the shape of the distribution.

5.1.4. Features

There are five primary types of features for an image object: *shape features, histogram features, texture features, color features* and *spectral features*. Among them *histogram feature, texture features* and *spectral features*, available in CVIP-FEPC, were used to analyze the images in this research.

5.1.4.1. Histogram features

Histogram features are statistical based features which provide information about the characteristics of the gray-level distribution for an image [Umbaugh, S.; 2005 and 2010]. The histogram features are *mean, standard deviation, skew, energy* and *entropy*. The *mean* is the average value which represents the brightness of an image, the *standard deviation* represents the contrast of the image, the *skew* measures the asymmetry of the mean, *energy* is a constant value for an image with a maximum value of 1 and decreases as the gray levels are more widely distributed and *entropy* measures the number of bits needed to code the data [Umbaugh, S.; 2005 and 2010]. In this research all the features except the *mean* were used to analysis the images.

5.1.4.2. Texture features

Texture is a function of image size and is related to the object itself as well as to the magnification. Texture can be measured by using the second-order histogram of gray levels. This method is also referred as the *gray-level co-occurrence matrix* method. These texture features are based on two parameters: distance and angle where the distance is the pixel distance between the pairs of pixels and angle is the angle between the pixel pairs. However, the most useful features found using these methods are: *energy, inertia, correlation, inverse difference* and *entropy* [Umbaugh, S.; 2005 and 2010].

In this research, all the texture features were considered using a pixel distance of six. In CVIP-FEPC, there is an option to choose the old texture function or the new texture function. The difference between these two functions is in the processing of zeros in the *co-occurrence matrix*, corresponding to black areas in the image. The black areas in our images correspond to areas we have masked out and we do not want to be considered. In the old texture function, zeros were processed in a special way, but in the new texture function the zeros are not processed at all. So, the size of the matrix is reduced since the top row and first column are removed (all zeros). In this research, both of these two functions were considered. The purpose of using these two functions was to verify that they provide similar results, explained in Chapter 6.

5.1.4.3. Spectral features

Spectral features are frequency/sequency-domain based features with the primary metric being *power*. These features actually measure the power in specific regions in the spectrum. These regions can be box, ring or sector shaped. Spectral features can also be used as texture features. In this research, spectral features were used with ring and sector values of three.

5.2. Partek Discovery Suite

The Partek Discovery Suite has been described in Chapter 3. There are three predictive/diagnostic modeling tools we used to classify the images: *Discriminant analysis, Variable selection,* and *Multilayer perceptron*.

5.2.1. Multilayer Perceptron Neural Network

Multilayer perceptron (MLP) neural network is extensively used in numerous applications including pattern classification, function approximation, system identification, prediction and control, speech and natural language processing [Minsky and Papret, 1969]. This network consists of three types of layers: the input layer, the output layer and the hidden layers. The feature data is fed into the input layer and the output generates the classification. The other intermediate layers are called hidden layers. There can be any number of hidden layers, but it is advisable to use only one hidden layer in practice [Bishop; 1996].

However, the basic unit of this network, called a neuron, performs two functions: the combining functions and the activation functions. Different types of activation functions can be used but in Partek Discovery Suite, *linear, sigmoid, softmax* and *Gaussian* are available for activation. In this research, *sigmoid* and *softmax* are used as activation functions. The activation function performs a non-linear transformation. The functionality of the network is determined by specifying the strength of the connection paths, called weights, and the threshold parameter of each neuron. The input layer usually acts as an input data holder and distributes inputs to the first hidden layer. The inputs then propagate forward through the network and each neuron computes its output according to the learning rule chosen. In this research, the most popular learning algorithm extensively used to train MLP neural network, the backpropagation algorithm is used.

5.2.2. Discriminant Analysis

Discriminant analysis is a process which is used for classification of a set of objects into predefined classes. In this process, the class of the object of interest is determined based on a set of variables known as input variables or features. The model is created based on a set of samples for which the classes are known. This set of samples is also known as the training set.

Discriminant analysis in Partek uses two types of discriminant functions: Linear and Quadratic. In Partek discovery suite, it has an option to specify the prior probability either equal or proportional. In this research, both of the functions are used in different cases with equal prior probability.

Linear discriminant analysis uses linear function where a set of linear discriminant function is calculated from a common covariance matrix and within-group means [Partek Help; 2005]. Quadratic discriminant analysis uses quadratic function where a set of quadratic discriminant functions is calculated from within group covariance matrices and within group means [Partek Help; 2005]. In both cases the discriminant functions are used to partition the feature space into the various class regions.

5.2.3. Variable Selection

Variable selection is a modeling process which is used to identify the set of appropriate variables (features) to obtain a better or optimum classification success rate. Sometimes too many variables or bad variables can be a cause of lower success rate for a predictive model. This process helps to increase the classification rate.

This analysis of selecting specific variables helps to classify the objects perfectly and removes the unwanted variables that may lead to the false predictions. In the Partek Discovery Suite *variable selection* is performed by using 2 different methods: by evaluating the "good set of variables" to use for better classification or by depending on the lowest error rate to find the "best set" for classification. Both of these methods belong to the evaluation criteria where *variable evaluation model for class labeled data* is chosen.

With the classification model, there are two functions available for variable selection: Linear Discriminant analysis and Quadratic Discriminant analysis function. Both *discriminant* analysis functions help to choose the variables that are more appropriate to perform classification. And in this research the quadratic function was determined to provide the best results.

All of these techniques, used to minimize the error rate, are performed by choosing the evaluation error either by *percentage incorrect* or by *posterior error.* The *percent incorrect* is calculated as follows:

Percent Incorrect = (No. of Samples misclassified/Total no. of Samples)*100.

Posterior error finds the average posterior error measured overall samples. Posterior error for a given sample is calculated by computing the posterior error by the model subtracted from the true posterior probability [Partek Help, 2005]. In this research, *posterior error* is used as evaluation error in *modeling error criteria*.

CHAPTER 6

RESULTS AND DISCUSSIONS

The results of this research are discussed in this chapter in two sections. In the first section, results are presented in table form and in the second section, results are shown in the picture form. Firstly, classification results for thermographic image analysis as a diagnostic tool are presented and discussed. Secondly, the automated masks, created using the algorithm from Chapter 4, are shown in picture form. Then the comparison between the manually created masks and automated masks, as which one is better using pattern classification technique, is shown in graphical form.

6.1. Thermographic Image Analysis

As stated earlier, to analyze the thermographic images, two pathological conditions were considered, IVDD and Syringomyelia. So at first, the results for the detection of IVDD and then for Syringomyelia are presented below:

6.1.1. IVDD

The experiments for the detection of IVDD using thermographic images were divided into two main parts and they are:

Part 1: The detection of IVDD using thermographic images or in other words, classify the images as *IVDD* (clinical condition) or *Normal* (control)

Part 2: Identify the specific herniated disc space in the vertebrae, as mentioned in the MRI result spreadsheet.

6.1.1.1. Result and discussion for part 1

To detect IVDD using thermographic images CVIP-FEPC was used. After running the CVIP-FEPC on these thermographic images the classification result was obtained that, as is shown in Table 6.1, the manually created masks for the dorsal, left and right lateral views produced the classification result as 87.50%, 88.64% and 88.64% respectively. However, in all cases it was able to find a combination of features that yielded results greater than or equal to 87.50% classification and left lateral or right lateral view provides the highest classification result. These experiments used nearest neighbor and K-nearest neighbor where K=3 as classification methods; Euclidean distance and vector inner product as distance and similarity measure technique and standard normal density normalization as data normalization technique with histogram standard deviation, skew, energy, entropy and texture features with a texture distance = 5.

Table 6.1: Classification results for three different views of images

Image View	Number of Images per Class	Number of Image Correct	Number of Image Error	Number/ Percent correct
Dorsal	IVDD: 83 Normal: 13	84	12	87.5%
Left Lateral	IVDD: 76 Normal: 12	78	10	88.64%
Right lateral	IVDD: 76 Normal: 12	78	10	88.64%

CVIP-FEPC was run three times for three different views of images on all of the texture and histogram features. The results for each view were different. It does not appear that single set of features works "best" for all views. These experiments were performed using old texture features of CVIP-FEPC.

For the dorsal manually created masks, nearest neighbor, vector inner product, and standard normal density normalization with texture inertia, histogram standard deviation and histogram entropy provided the best result, 84 out of 96 were correct.

For the left lateral manually created, K-nearest neighbor where K = 3, Euclidean distance, and standard normal density normalization with texture inertia, texture energy and histogram standard deviation provide the best classification result, 78 out of 88 were correct.

For the right lateral manually created mask, K-nearest neighbor where K = 3, Euclidean distance, and standard normal density normalization with texture inverse difference, texture energy and texture inertia provide the best classification result, 78 out of 88 were correct.

6.1.1.2. Results and discussion for part 2

In this part, to identify the corresponding herniated disc space in the vertebrae total seven sets of experiments were performed on the dorsal images of the clinical and normal dogs among them six sets of experiments were done by CVIP-FEPC with old texture features and one of them was done using Partek Discovery Suite and CVIP-FEPC with new texture2 features. Only the specific vertebrae of the 58 clinical dogs identified by the MRI as exhibiting IVDD, supplied by Long Island Veterinary Specialists [LIVS; 2011], were classified as *IVDD*. The other areas on those dogs were classed as *NON-IVDD* including all areas of 15 normal dogs since they do not have any specific disc as IVDD. These experiments used *K-nearest neighbor* from CVIP-FEPC to classify with K = 2, 3 or 8;

Euclidean distance metric as distance measure technique; standard normal density normalization and softmax scaling data normalization with r =1 as data normalization technique; spectral 3x3 features, histogram standard deviation, skew, energy, entropy and texture features with a texture distance = 2 and 5. And all the images were dorsal view images. To improve the success rate *Multilayer Perceptron (MLP)* neural network and *Discriminant analysis* were used from Partek Discovery Suite.

First Set: 438 image objects were used, of which 116 image objects were of *IVDD class*, 322 were of *NON-IVDD*. Original thermographic images were used with pattern classification method K-nearest neighbor where K=8 and leave-one-out as testing method. The best two classification results are shown in Table 6.2. For this experiment, K-nearest neighbor where K = 8, Euclidean distance, and standard normal density normalization with texture energy, texture inverse difference, texture entropy and histogram skew provide the best classification result, 315 out of 438.

Table 6.2: Results from first set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=2)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inv diff Texture entropy Histogram skew	Standard Normal Density	315/438	71.9%	1/2044
Texture inertia Texture inv-diff Histogram Std. Dev	SoftMax1	313/438	71.5%	1/2044

Second Set: In this case only those images were used that have guides created by Long Island Veterinary Specialists (LIVS). That means, the image masks were created followed by the expert instruction to avoid misclassification in the first set of experiments. So, for this set of experiments 246 image objects were used, of which 65 objects were of *IVDD* class, 181 were of *NON-IVDD*. Here also original thermographic images were used with pattern classification method K-nearest neighbor where K=8 and leave-one-out as testing method. The best two classification results are shown in Table 6.3. For this experiment, K-nearest neighbor where K = 8, Euclidean distance, and standard normal density normalization with texture energy, texture inertia, histogram energy and histogram skew provide the best classification result, 189 out of 246.

Table 6.3: Results from second set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=5)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia Histogram Std. Dev Histogram skew Histogram energy	Standard Normal Density	189/246	76.8%	1/2044
Texture correlation	SoftMax1	187/246	76.0%	2/2044

Third Set: In this set 243 color normalized Luminance image objects, obtained using color normalization software, were used of which 65 objects were of IVDD class, 178 were of NON-IVDD and these were guided images by LIVS. For this experiment the images were color normalized using the Luminance color transform. In this experiment, pattern classification method K-nearest neighbor where K=2 and leave-one-out as testing method were used. The best two classification results are shown in Table 6.4. For this experiment, K-nearest neighbor where K = 2, Euclidean distance, and standard normal density normalization with histogram standard deviation, histogram energy and histogram skew provide the best classification result, 182 out of 243.

Table 6.4: Results from third set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=5)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Histogram Std. Dev Histogram skew Histogram energy	Standard Normal Density	182/243	74.9%	1/2044
Histogram Std. Dev	SoftMax1	181/243	74.5%	3/2044

Fourth Set: 243 color normalized *Normalized Grey* image objects, obtained using color normalized software, were used of which 65 objects were of *IVDD* class, 178 were of *NON-IVDD* and these were also guided images by LIVS. For this experiment the images were color normalized using the *Normalized Grey (NormGrey)* color transform. In this experiment, pattern classification method K-nearest neighbor where K=8 and leave-one-out as testing method were used. The best two classification results are shown in Table 6.5. However, for this experiment, K-nearest neighbor where K = 8, Euclidean distance, and standard normal density normalization with texture energy, texture inertia, texture inverse difference and histogram energy provide the best classification result, 180 out of 243.

Table 6.5: Results from fourth set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=5)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia Texture inv-diff Histogram energy	Standard Normal Density	180/243	74.1%	2/2044
Texture correlation Histogram energy Histogram entropy	SoftMax1	179/243	73.7%	15/2044

Fifth Set: In this set images were used only if the guides from LIVS were available. The experiment was performed on 243 color normalized *Normalized RGB* image objects, obtained using color normalized software, of which 65 objects were of *IVDD* class, 178 were of *NON-IVDD*. For this experiment the images were color normalized using the *Normalized RGB (NormRGB*) color transform. In this experiment, pattern classification method K-nearest neighbor where K=3 and leave-one-out as testing method were used. The best two classification results are shown in Table 6.6. However, for this experiment, K-nearest neighbor where K = 3, Euclidean distance, and softmax scaling data normalization with spectral 3x3, texture inertia, texture correlation, texture entropy and histogram standard deviation provide the best classification result, 181 out of 243.

Table 6.6: Results from fifth set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=2)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Spectral 3x3 Texture inertia Texture correlation Texture entropy Histogram Std. Dev	SoftMax1	181/243	74.5%	1/2044
Texture inertia Texture inv-diff Histogram Std. Dev Histogram skew Histogram entropy	SoftMax1	179/243	73.7%	5/2044

Sixth Set: In this set also images were used only if the guides from Long Island Veterinary Specialists were available so 243 color normalized *Normalized RGB-Luminance* image objects, obtained using color normalized software, were used of which 65 objects were of *IVDD* class, 178 were of *NON-IVDD*. For this experiment the images were color normalized using the *Normalized RGB-Luminance (NormRGBLum)* color transform. In this experiment, pattern classification method K-nearest neighbor where K=8 and leave-one-out as testing method were used. The best two classification results are shown in Table 6.7. However, for this experiment, K-nearest neighbor where K = 8, Euclidean distance, and softmax scaling data normalization with spectral 3x3, texture correlation and histogram standard deviation provide the best classification result, 180 out of 243.

Table 6.7: Results from sixth set

Best two classification results of 2044 experiments Minimum Features (texture pixel dist=5)	**Data normalization method**	**Number correct**	**Percent correct**	**Number of experiments with the success rate**
Spectral 3x3 Texture correlation Histogram Std. Dev	SoftMax1	180/243	74.1%	1/2044
Texture inertia Texture correlation Histogram Std. Dev	SoftMax1	179/243	73.7%	7/2044

Seventh Set: This was a repetition of the second set. 246 images were used of which 65 images were of the *IVDD* class, 181 were of *NON-IVDD*. So, this experiment was performed on the original thermographic images. But the difference between these and the second set of experiments were as follows: 1) the new texture2 features of CVIP-FEPC was used, 2) Preliminary experimentation with neural networks (Multi-layer Perceptron or MLP) was performed using Partek Discovery Suite and 3) Preliminary experimentation with Partek Discovery Suite's Discriminant Analysis was performed.

With CVIP-FEPC 4096 experiments were performed using new texture2 features. In this experiment, pattern classification method K-nearest neighbor where K=8 and leave-one-out as testing method were used. However, for this experiment, K-nearest neighbor where K=8, Euclidean distance, and standard normal density normalization with Spectral 3x3, texture energy, texture correlation, texture entropy, histogram standard deviation, histogram skew, histogram energy and histogram entropy provide the best classification result, 187 out of 243. So the success rate is 75.7%.

After doing all the experiments stated above to improve the success rate, which was around 75%, next move was to change the classification method with a different classification software, Partek Discovery Suite. So, discriminant analysis was used as predictive/ diagnostic modeling with linear discriminant function. To do this experiment, among 246 images 124 were selected randomly as test set of which 33 were of *IVDD* class and 91 were of *NON-IVDD* class and 122 were as training set of which 32 were in *IVDD* class and 90 were in *NON-IVDD* class. The overall classification result is shown in Table 6.8.

Table 6.8: Classification Results: Discriminant analysis

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
IVDD	65	48	18	73.8%
NON-IVDD	181	181	0	100%
Total	246	229	18	93.1%

The features, which were used to provide the best classification result in CVIP-FEPC in most of the cases, were used in this case. So, histogram energy, texture energy, texture inertia, texture inverse difference and texture entropy were chosen to do this experiment. Now the success rate is 92.7%.

After getting 93.1% success rate, next step was to do the same experiment again using neural network (MLP) classification method of Partek Discovery Suite. A neural network with different number of layers with different number of neurons was designed. And finally, a three layer network was created with twelve neurons at the input layer, one neuron at the hidden layer and two neurons at the output layer and the neuron types were sigmoid and softmax respectively. To train the network back-propagation algorithm and to test leave K-out method where K=10 was used. For this experiment, 226 images were considered of which 64 were in *IVDD* class and 162 were in *NONO-IVDD* class. To improve the success rate 20 bad quality images were discarded. The classification result is shown in Table 6.9. The features histogram energy, texture energy, texture inertia, texture inverse difference and texture entropy, were used for linear discriminant analysis method, were used in this case too. And now the success rate is 97.3%.

Table 6.9: Classification Results: Multi-Layer Perceptron (MLP)

	Number of images per class	**Number of images correct**	**Number of images error**	**Percent correct**
IVDD	64	59	5	92.19%
NON-IVDD	162	161	1	99.38%
Total	226	220	6	97.3%

At the end in this seventh set of experiments, the maximum success rate was 97% which indicates that the experiment was successful in classifying the herniated intervertebral disc space from the normal disc spaces and correlates with the MRI findings. The most effective classification method is the multilayer perceptron (MLP), a type of neural network. And the best set of features with the MLP result of 97% success is: histogram energy, texture energy, texture inertia, texture inverse difference and texture entropy (texture distance = 5). The best classification results of this set are shown in Table 6.10.

Table 6.10: Results from seventh set

Best classification results Features (texture pixel dist=5)	Data normalization method	Classification method	Test method	Number of image correct	Percent correct
Histogram energy Texture energy Texture inertia Texture inv-diff Texture entropy	SoftMax1	MLP (Partek, CVIP-FEPC selected features)	Leave K out, K = 10	220/226	97.3%
Histogram energy Texture energy Texture inertia Texture inv-diff Texture entropy	SoftMax1	Linear discriminant (Partek, CVIP-FEPC selected features)	Train/Test set	115/124	92.7%
Spectral 3x3 Texture energy Texture correlation Texture entropy Histogram Std. Dev Histogram skew Histogram energy Histogram entropy	Standard Normal Density	K-Nearest neighbor K = 8 (CVIP-FEPC, new texture2 features)	Leave-one-out	187/246	75.7%

But one thing was noticeable from all of the seven set of experiments. From the second set of experiment, the best single feature was texture correlation, with no color normalization, texture distance =5, K-Nearest neighbor classification with K = 8, and softmax scaling data normalization. These parameters and this feature alone achieved 76% classification success.

6.1.2. Syringomyelia

For the detection of Syringomyelia, or the presence of syrinx in canines, CVIP-FEPC was run for each view of sedated and unsedated images of head and body of the canines. First, all the views of head images were considered and then the body images. These experiments used K-nearest neighbor to classify with K = 5; Euclidean distance metric as distance measure technique; standard normal density normalization and softmax scaling data normalization with r =1 as data normalization technique; spectral 3x3 features, histogram standard deviation, skew, energy, entropy and texture features with a texture distance = 6. Leave-one-out was used as the testing method. The images of clinical canines identified by the MRI as exhibiting the presence of syrinx, supplied by LIVS, were classified as *Present* and the images of normal (absence of syrinx) canines were classified as *Absent*. To improve the classification results all the experiments, done with CVIP-FEPC, again were performed with the Partek Discovery Suite. With Partek two diagnostic/predictive modeling methods were used: Discriminant Analysis and Variable Selection. Discriminant analysis was performed with quadratic discriminant functions and equal prior probability. This method was done with the no cross-validation and also with the 1-level cross validation (full "leave-one-out" method). With variable selection method, the classification model was quadratic discriminant analysis and the search method was backward (minimum best score). The classification results are discussed according to the view of images.

6.1.2.1. Thermographic images – head of the canines

There were four different views of the thermographic images of the canines' heads; top, front, left lateral and right lateral and images of each of the views were both sedated and unsedated images. To classify the images perfectly or to detect the presence and absence of syrinx, two software packages were used: CVIP-FEPC with both old texture and new texture2 features and the Partek Discovery Suite for all of the experiments.

6.1.2.1.1. Front view

For this view of images total eight sets of experiments were performed. With CVIP-FEPC four sets of experiments were performed, with each set having 2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. Another two sets of experiments were performed with the Partek Discovery Suite, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.1.1.1. Experiments with sedated images

For the experiments with the sedated group, 144 images were used of which 86 were in *Present* class and 58 were in *Absent* class. A total of four set of experiments were done with this group. For these experiments the original thermographic images were used.

First set: FCVIP-FEPC was run with old texture features to classify the thermographic images. The best two classification results with old texture features are shown in Table 6.11. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with only texture energy provided the best classification result, 88 out of 144. The success rate was 61.1%.

Second Set: This set of experiment was a repetition of the first set. But the difference was CVIP-FEPC was run with the new texture2 features to classify the images. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy and texture entropy provided the best classification result, 92 out of 144. So the success rate was 63.88%. The best two classification results with the new texture2 features are shown in Table 6.12.

Table 6.11: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy	SoftMax1	Present:86 Absent:58	88/144 61.1%	7/2046
Texture inv-diff Texture inertia	SoftMax1	Present:86 Absent:58	87/144 60.4%	4/2046

Table 6.12: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture entropy	SoftMax1	Present:86 Absent:58	92/144 63.88%	1/2046
Texture entropy	SoftMax1	Present:86 Absent:58	87/144 60.42%	1/2046

Third Set: Since the success rates of the experiments with CVIP-FEPC were not satisfactory, the next step was to perform the experiment with the Partek Discovery Suite with the same images. In this experiment, discriminant analysis was done with no cross-validation. In this case, all the features (43 features) were used. The feature set from the first experiment, CVIP-FEPC with old texture features, was used for Partek Discovery Suite. In CVIP-FEPC, experiment no. 2046 uses all the features to classify the images. And only the original data had been used because it was found that original data provided better result than normalized data. The classification result with no cross-validation is shown in Table 6.13.

Table 6.13: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	53	5	91.38%
Present	86	86	0	100%
Total	144	139	5	96.53%

The success rate was 96.53%. To obtain a better result, the next step was to use variable selection modeling with a quadratic discriminant analysis model to determine the best features. Using the backward search method it was found that four features among 43 features were not useful for quadratic discriminant analysis model to get the minimum best score. So, those features were discarded and only 39 features were considered. After removing these features the discriminant analysis with quadratic discriminant function and equal prior probability was performed again. And the success rate became 97.92%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.14.

Table 6.14: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	58	55	3	94.83%
Present	86	86	0	100%
Total	144	141	3	97.92%

After obtaining 97.92% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 55.56%. The overall classification result with 1-level cross-validation (Full "leave-one-out") is shown in Table 6.15.

When no cross-validation was performed, all the images were in training set and the success rate exhibits that the model was trained perfectly but when 1-level cross validation was performed it misclassified the *Absent* class images. And it also happened for other views images, explained later in this Chapter.

Table 6.15: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	58	8	50	13.79%
Present	86	72	14	83.72%
Total	144	80	64	55.56%

Fourth Set: This experiment is same as the third set of experiments. The only difference was that here the features of the second set of experiments, CVIP-FEPC with new texture2 features, had been used. And the rest of the experimental procedure was exactly the same as the third set of the experiments. The discriminant analysis with no cross-validation was performed with 43 features and the success rate was 94.44%. The overall classification result with no cross-validation is shown in Table 6.16.

Table 6.16: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	50	8	86.21%
Present	86	86	0	100%
Total	144	136	8	94.44%

After using the variable selection with backward search, it was found that five features were not useful for quadratic discriminant analysis model. So, after removing these features the discriminant analysis was performed again with 38 features and the success rate became 95.14%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.17.

After obtaining 95.14% success rate with no-cross validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 60.42%. The overall classification result with 1-level cross-validation (Full “leave-one-out”) is shown in Table 6.18.

Table 6.17: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	51	8	87.93%
Present	86	86	0	100%
Total	144	137	8	95.14%

Table 6.18: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	7	51	12.07%
Present	86	80	6	93.02%
Total	144	87	57	60.42%

6.1.2.1.1.2. Experiments with unsedated images

For the experiments with the unsedated group, 291 images were used of which 195 were in *Present* class and 96 were in *Absent* class. Another four sets of experiments were done with this group. And for these experiments original thermographic images were used.

Fifth Set: CVIP-FEPC was run with old texture features to classify the unsedated thermographic images. The best two classification results with old texture features are shown in Table 6.19. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with spectral 3x3, histogram standard deviation, histogram entropy and histogram energy provided the best classification result, 195 out of 291. The success rate was 67.01%.

Table 6.19: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Spectral 3x3 Histogram Std. Dev Histogram entropy Histogram energy	SoftMax1	Present:195 Absent:96	195/291 67.01%	1/2046
Histogram entropy	SoftMax1/ Standard Normal Density	Present:195 Absent:96	194/291 66.67%	3/2046

Sixth Set: This set of experiments was a repetition of the fifth set of experiments. But the difference was CVIP-FEPC was run with the new texture2 features to classify the images. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with histogram standard deviation, histogram entropy and histogram energy provided the best classification result, 195 out of 291. The success rate was 67.01%. The best two classification results with the new texture2 features are shown in Table 6.20.

Seventh Set: The steps of this experiment were exactly same as that of the third set of the experiments. The experimental result with all features of the fifth experiment, CVIP-FEPC with old texture features, had been used here. So, Partek's discriminant analysis with no-cross validation was performed. 43 features were used in this experiment. And like the third set of experiments only the original data had been used. The overall classification result with no cross-validation is shown in Table 6.21.

Table 6.20: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	Data normalization method	Number of images per class	Number/ Percent correct	Number of experiments with the success rate
Histogram Std. Dev Histogram entropy Histogram energy	SoftMax1	Present:195 Absent:96	195/291 67.01%	1/2046
Histogram entropy	SoftMax1	Present:195 Absent:96	194/291 66.67%	1/2046

Table 6.21: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	96	38	58	39.58%
Present	195	195	0	100%
Total	291	233	58	80.07%

Then to improve the success rate, since it was only 80.07%, the variable selection with backward search method was used and found that eight features were not useful for quadratic discriminant analysis model. So, those eight features were removed and the discriminant analysis with no cross-validation was performed again with 35 features. And the success rate was increased to 81.44%. But after this experiment, two images of *Present* class were misclassified and the individual success rate of this class decreased from 100% to 98.97%. However, the overall classification result was increased, shown in Table 6.22.

Table 6.22: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	96	44	52	45.83%
Present	195	193	2	98.97%
Total	291	237	54	81.44%

After obtaining 81.44% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 64.60%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.23.

Table 6.23: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	96	3	93	3.13%
Present	195	185	10	94.87%
Total	291	188	103	64.60%

Eighth Set: This experiment was a repetition of the seventh set of experiments. The only difference was that here the experiment result with all features of the sixth set of experiments, CVIP-FEPC with new texture2 features, had been used. The discriminant analysis with no cross-validation was performed with 43 features and the success rate was 80.07%. The overall classification result with no cross-validation is shown in Table 6.24.

Table 6.24: Classification Results: Discriminant Analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	96	38	58	39.58%
Present	195	195	0	100%
Total	291	233	58	80.07%

After using the variable selection with backward search, it was found that the same five features, removed in the seventh set of the experiments, were not useful for quadratic discriminant analysis model. So, after removing these features the discriminant analysis was performed again with 35 features and the success rate became 81.44%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.25.

After obtaining 81.44% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 64.60%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.26.

Table 6.25: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	96	44	52	45.83%
Present	195	193	2	98.97%
Total	291	237	54	81.44%

Table 6.26: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	96	3	93	3.13%
Present	195	185	10	94.87%
Total	291	188	103	64.60%

6.1.2.1.1.3. Summary of the results

With the front view of the heads' sedated and unsedated thermographic images, it was found (Fig. 6.1) that the maximum success rate was 63.88% and 67.01% respectively which indicates that there may be a difference between the *Present* and *Absent* classes. The most effective classification method for both group of images was the K-nearest neighbor algorithm. However, for the sedated group both the old texture and new texture2 features of CVIP-FEPC provided almost similar classification results 61.1% and 63.88% respectively. And for the unsedated group both the old texture and new texture2 features of CVIP-FEPC provided exactly the same classification results.

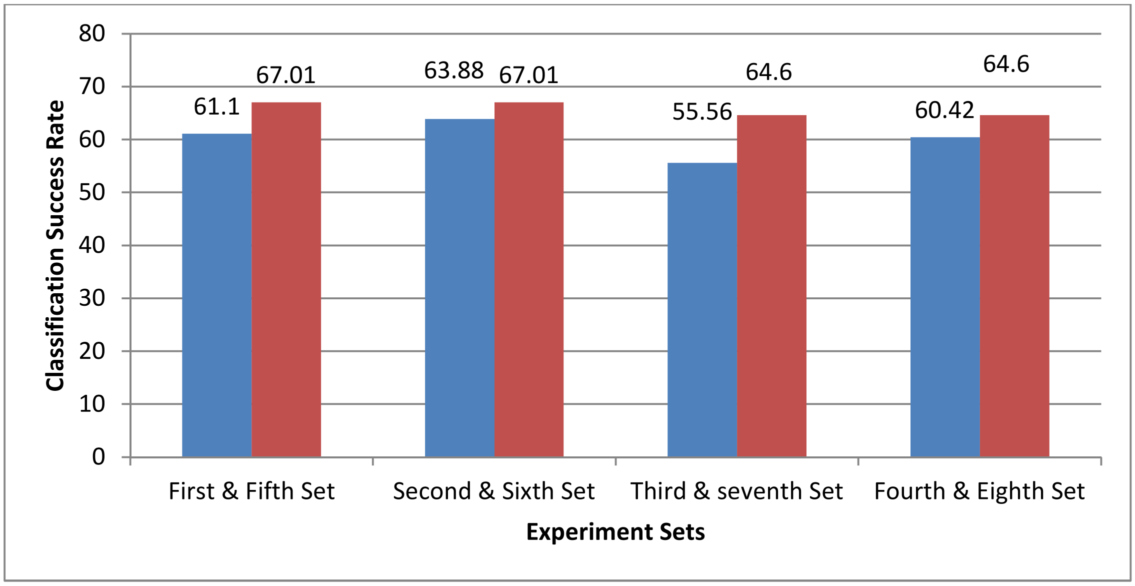


Figure 6.1. Classification success rate comparison chart for the head front view images with different classification methods.

After finishing all the experiments with front view of sedated and unsedated images of the heads of the canines, it was found that the unsedated images (67.01%) provided better classification results than the sedated images (63.88%).

6.1.2.1.2. Top view

With the top view of images also total eight sets of experiments were performed. With CVIP-FEPC four sets of experiments were performed, with each set having 2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. Another four sets of experiments were performed with the Partek Discovery Suite, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.1.2.1. Experiments with sedated images

For the experiments with the sedated group, 152 images were used of which 93 were in *Present* class and 53 were in *Absent* class. A total of four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: CVIP-FEPC was run with old texture features to classify the thermograms. The best two classification results with old texture features are shown in Table 6.27. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with only histogram standard deviation provided the best classification result, 96 out of 152. The success rate was 63.15%.

Table 6.27: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Histogram Std. Dev	Standard Normal Density	Present:93 Absent:59	96/152 63.15%	3/2046
Histogram Std. Dev Histogram energy Histogram entropy	SoftMax1	Present:93 Absent:59	94/152 61.84%	2/2046

Second Set: CVIP-FEPC was run with the new texture2 features to classify the images. The best two classification results with the new texture2 features are shown in Table 6.28. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy and texture entropy provided the best classification result, 99 out of 152. The success rate was 65.13%.

Table 6.28: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture correlation Histogram skew Histogram entropy	SoftMax1	Present:93 Absent:59	99/152 65.13%	2/2046
Texture inv-diff Histogram skew Histogram energy Histogram entropy	SoftMax1	Present:93 Absent:59	98/152 64.47%	5/2046

Third Set: The success rates of the classification experiments with CVIP-FEPC were not good enough, the Partek was used with the same images here. In this experiment, discriminant analysis with no cross-validation was performed. All the features (43 features) were used to predict in this experiment. The feature set from the first experiment, CVIP-FEPC with old texture features, had been used for the Partek Discovery Suite. And only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.29. Similar to the front view experiment, the discriminant analysis was performed with quadratic discriminant functions and equal prior probability and the success rate was 96.05%.

Table 6.29: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	53	6	89.83%
Present	93	93	0	100%
Total	152	146	6	96.05%

The next step was to use the variable selection modeling method with quadratic discriminant analysis model to determine the best features. Using the backward search method it was found that three features among 43 features were not useful for quadratic discriminant analysis model to get the minimum best score. So, those features were discarded and only 39 features were used to run Partek. After removing these features the discriminant analysis with no cross-validation was performed again. And the success rate became 97.37%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.30.

Table 6.30: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	55	4	93.22%
Present	93	93	0	100%
Total	152	148	4	97.37%

After obtaining 97.37% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 55.92%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.31.

Table 6.31: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	59	2	57	3.39%
Present	93	83	10	89.25%
Total	152	85	67	55.92%

Fourth Set: This experiment is same as the third set of the experiments. The only difference was that here the features of the second set of experiments, CVIP-FEPC with new texture2 features, were used. And the rest of the experiment procedure was exactly same as the third set of the experiments that means at first the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 96.71%. The overall classification result with no cross-validation is shown in Table 6.32.

Then after using the variable selection with backward search, it was found that five features were not useful for quadratic discriminant analysis model. After removing these features the discriminant analysis was performed again with 38 features and the success rate became 97.37%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.33.

Table 6.32: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	54	5	91.53%
Present	93	93	0	100%
Total	152	147	5	96.71%

Table 6.33: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	56	3	94.92%
Present	93	92	1	98.92%
Total	152	148	4	97.37%

After obtaining 97.37% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 59.87%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.34.

6.1.2.1.2.2. Experiments with unsedated images

For the experiments with unsedated group, 274 images were used of which 175 were in *Present* class and 99 were in *Absent* class. Again four sets of experiments were done with this group as sedated group. And for these experiments original thermographic images were used.

Table 6.34: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	59	8	51	13.56%
Present	93	83	10	89.25%
Total	152	91	61	59.87%

Fifth set: In this set of experiment CVIP-FEPC was run with old texture features to classify the unsedated thermographic images of top view. The best two classification results with old texture features are shown in Table 6.35. However, for this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture energy, texture correlation and histogram standard deviation provided the best classification result, 174 out of 274. The success rate was 63.5%.

Sixth Set: This experiment was a repetition of the fifth set of experiments. The only difference was CVIP-FEPC was run with the new texture2 features to classify the same images, used in fifth set. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy, texture correlation, texture inverse difference and texture inertia provided the best classification result, 171 out of 274. The success rate was 62.4%. The best two classification results with the new texture2 features are shown in Table 6.36.

Table 6.35: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture correlation Histogram Std. Dev	SoftMax1	Present:175 Absent:99	174/274 63.5%	1/2046
Texture energy Texture correlation Texture entropy Histogram skew	Standard Normal Density	Present:175 Absent:99	172/274 62.77%	2/2046

Table 6.36: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture correlation Texture inv-diff Texture inertia	SoftMax1	Present:175 Absent:99	171/274 62.4%	1/2046
Texture correlation Texture entropy	SoftMax1	Present:175 Absent:99	170/274 62%	3/2046

Seventh Set: This experiment was a repetition of the third set of the experiments. The feature set from the fifth experiment, CVIP-FEPC with old texture features, was used here. Then the discriminant analysis with no cross-validation was performed. Again all the features that means 43 features were used in this experiment. And like the third set of experiments only the original data had been used. The overall classification result with no-cross validation is shown in Table 6.37.

Table 6.37: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	99	63	36	63.64%
Present	175	171	4	97.71%
Total	274	234	40	85.40%

The success rate was only 85.40%, so to improve the classification rate the variable selection with backward search method was used for quadratic discriminant analysis model and found that four features were not useful for this model. Those four features were removed and the discriminant analysis with no cross-validation was performed again with 39 features. And the success rate was increased to 87.96%. But after this experiment, one more image of Present class were misclassified and the individual success rate of this class decreased from 97.71% to 97.14% but eight more images of Absent class were classified correctly so the individual success rate of this class increased from 63.64% to 71.72%. The overall classification result with no cross-validation but with appropriate features was increased, shown in Table 6.38.

After obtaining 87.96% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And

the success rate became 60.58%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.39.

Table 6.38: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	71	28	71.72%
Present	175	170	5	97.14%
Total	274	241	33	87.96%

Table 6.39: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	12	87	12.12%
Present	175	154	21	88.00%
Total	274	166	108	60.58%

Eighth Set: This experiment is same as seventh set of experiments. The experimental result with all features of the sixth set of experiments, CVIP-FEPC with new texture2 features, was used. The discriminant analysis with no cross-validation was performed with 43 features and the success rate was 88.32%. The overall classification result is shown in Table 6.40.

Table 6.40: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	72	27	72.73%
Present	175	172	5	97.14%
Total	274	242	32	88.32%

After using the variable selection with backward search, it was found that three features were not useful for quadratic discriminant analysis model. So, these features were discarded and the discriminant analysis with no cross-validation was performed again with 40 features and the success rate became 89.78%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.41.

Table 6.41: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	75	24	75.76%
Present	175	171	4	97.71%
Total	274	246	28	89.78%

After obtaining 89.78% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And

the success rate became 60.22%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.42.

Table 6.42: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	99	9	90	9.09%
Present	175	156	19	89.14%
Total	274	165	109	60.22%

6.1.2.1.2.3. Summary of the results

With heads' sedated and unsedated top view thermographic images, it was found (Fig. 6.2) that the maximum success rate was 65.13% and 63.5% respectively which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for both groups of images was K-nearest neighbor algorithm. For the sedated image group, both the old texture and new texture2 features of CVIP-FEPC provided almost the similar classification results 63.15% and 65.13% respectively. And for the unsedated group of images both the old texture and new texture2 features of CVIP-FEPC also provided almost the similar classification results 55.92% and 59.87% respectively.

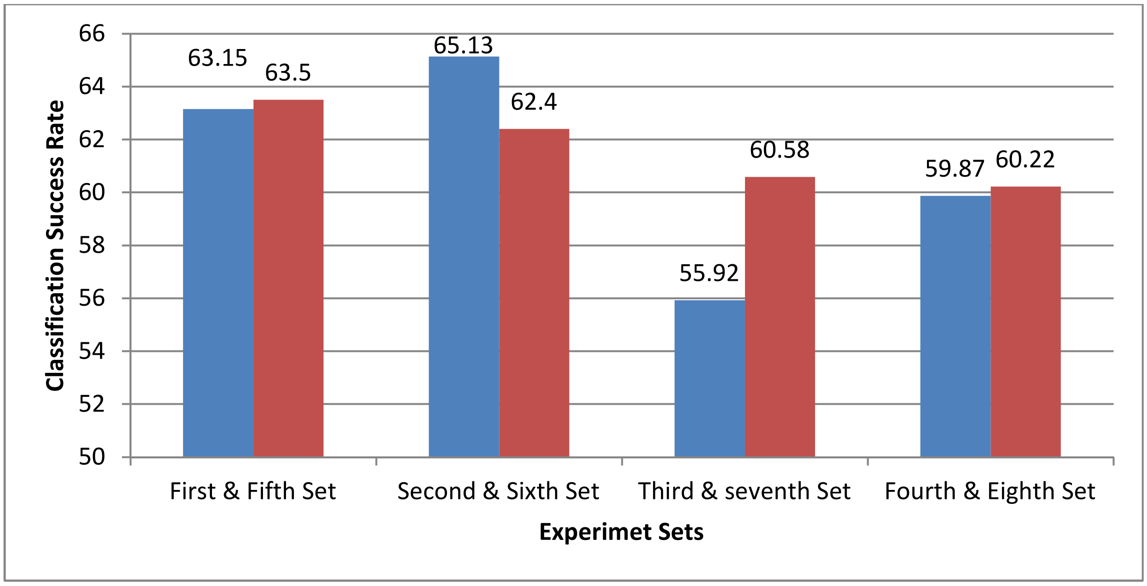


Figure 6.2. Classification success rate comparison chart for the head top view images with different classification methods.

After finishing all the experiments with top view of sedated and unsedated images of the heads of the canines, it was found that sedated images (65.13%) provided better classification results than the unsedated images (63.5%).

6.1.2.1.3. Left lateral view

Eight sets of experiments were performed with the left lateral view of images. With CVIP-FEPC four sets of experiments were performed, with each set having 2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. Another four sets of experiments were performed with Partek, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.1.3.1. Experiments with sedated images

For the experiments with sedated group, 156 images were used of which 95 were in *Present* class and 61 were in *Absent* class. Four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: CVIP-FEPC was run with old texture features to classify the thermograms. The best two classification results with old texture features are shown in Table 6.43. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with spectral 3x3, texture energy, texture correlation, histogram entropy and histogram standard deviation provided the best classification result, 101 out of 156. The success rate was 64.74%.

Table 6.43: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Spectral 3x3 Texture energy Texture correlation Histogram entropy Histogram Std. Dev	Standard Normal Density	Present:95 Absent:61	101/156 64.74%	8/2046
Texture entropy Histogram Std. Dev	SoftMax1	Present:95 Absent:61	100/156 64.1%	9/2046

Second Set: This experiment was also done to classify the images by CVIP-FEPC but with the new texture2 features. The best two classification results with the new texture2 features are shown in Table 6.44. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture correlation, texture entropy and histogram energy provided the best classification result, 107 out of 156. The success rate was 68.59%.

Table 6.44: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture correlation Texture entropy Histogram energy	SoftMax1	Present:95 Absent:61	107/156 68.59%	1/2046
Texture correlation Texture entropy Histogram energy Histogram entropy	SoftMax1	Present:95 Absent:61	105/156 67.3%	3/2046

Third Set: To improve the success rates of the classification, Partek was used with same images here. In this experiment, discriminant analysis with no cross-validation was performed. All the features (43 features) were used to predict in this experiment. The experimental result with all features of the first experiment, CVIP-FEPC with old texture features, was used for Partek Discovery Suite. And only the original data had been used as the original data provided better result than normalized data. The overall classification with no cross-validation result is shown in Table 6.45. Discriminant analysis was performed with quadratic discriminant functions and equal prior probability and the success rate was 96.05%.

Table 6.45: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	54	7	88.52%
Present	95	95	0	100%
Total	156	149	7	95.51%

The next step was to use variable selection modeling with quadratic discriminant analysis model to determine the best features. Using the backward search method for this experiment it was found that six features were not useful for quadratic discriminant analysis model to get the minimum best score. So, after removing those features Partek was run with 37 features again. And the success rate became 96.79%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.46.

Table 6.46: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	56	5	91.80%
Present	95	95	0	100%
Total	156	151	5	96.79%

After obtaining 96.79% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And

the success rate became 64.74%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.47.

Table 6.47: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	12	49	19.67%
Present	95	89	6	93.68%
Total	156	101	55	64.74%

Fourth Set: This experiment is same as the third set of the experiments but in this experiment, the feature set from the second set of experiments, CVIP-FEPC with new texture2 features, was used. First, the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 96.71%. The overall classification result with no cross-validation is shown in Table 6.48.

Table 6.48: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	52	9	85.25%
Present	95	95	0	100%
Total	156	147	9	94.25%

Next, the variable selection with backward search was done; it was found that two features were not useful for quadratic discriminant analysis model. After removing these features the discriminant analysis was performed second time with same parameters and 41 features. And the success rate became 95.51%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.49.

Table 6.49: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	55	6	90.16%
Present	95	94	1	98.95%
Total	156	149	7	95.51%

After obtaining 95.51% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 58.97%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.50.

6.1.2.1.3.2. Experiments with unsedated images

For the experiments with unsedated group, 275 images were used of which 175 were in *Present* class and 100 were in *Absent* class. Again four sets of experiments were done with this group as sedated group. And for these experiments the original thermographic images were used.

Table 6.50: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	61	6	55	9.84%
Present	95	86	9	90.53%
Total	156	92	64	58.97%

Fifth Set: In this set of experiments CVIP-FEPC was run with old texture features to classify the unsedated thermographic images of this view. The best two classification results with old texture features are shown in Table 6.51. However, for this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with histogram energy and histogram standard deviation provided the best classification result, 177 out of 275. The success rate was 64.36%.

Table 6.51: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	Data normalization method	Number of images per class	Number/ Percent correct	Number of experiments with the success rate
Histogram energy Histogram Std. Dev	Standard Normal Density	Present:175 Absent:100	177/275 64.36%	1/2046
Spectral 3x3 Texture energy Texture inertia Histogram skew Histogram energy	Standard Normal Density	Present:175 Absent:100	173/275 62.9%	1/2046

Sixth Set: This experiment was a repetition of the fifth set of experiments. The only difference was CVIP-FEPC was run with the new texture2 features to classify the same images. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and standard normal density data normalization with histogram energy and histogram standard deviation provided the best classification result, 177 out of 275. The success rate was same as of fifth set of experiments 64.36% with same 2 features. The best two classification results with the new texture2 features are shown in Table 6.52. So the classification results with both old texture and new texture2 features were same.

Table 6.52: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Histogram energy Histogram Std. Dev	Standard Normal Density	Present:175 Absent:100	177/275 64.36%	1/2046
Texture energy Texture inertia Histogram skew Histogram energy	Standard Normal Density	Present:175 Absent:100	176/275 649%	1/2046

Seventh Set: This experiment was a repetition of the third set of the experiments. The experimental result with all features of the fifth experiment, CVIP-FEPC with old texture features, was used here. Then the discriminant analysis with no cross-validation was performed. All the features (43 features) were used in this experiment. And like the third set of experiments only the original data had been used. The overall classification result with no cross-validation is shown in Table 6.53.

Table 6.53: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	100	60	40	60.00%
Present	175	173	2	98.86%
Total	275	233	42	83.73%

The success rate was only 83.73% after using discriminant analysis. To improve the classification rate the variable selection with backward search method was used for quadratic discriminant analysis model and found that three features were not useful for this model. So, after removing those three features the discriminant analysis with no cross-validation was performed again with 40 features. Then it was found that the success rate was increased to 86.91%. So after using the variable selection not only the overall classification result was increased but also the individual classification rate for both classes was increased. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.54.

After obtaining 86.91% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 62.55%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.55.

Table 6.54: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	100	65	35	65.00%
Present	175	174	1	99.45%
Total	275	239	36	86.91%

Table 6.55: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	100	7	93	7.00%
Present	175	165	10	94.29%
Total	275	172	103	62.55%

Eight Set: This experiment is the repetition of the seventh set of experiments. The experimental result with all features of the sixth set of experiments, CVIP-FEPC with new texture2 features, was used. Then discriminant analysis with no cross-validation was performed with 43 features and the success rate was 82.55%. The overall classification result with no cross-validation is shown in Table 6.56.

After using the variable selection with backward search, it was found that three features were not useful for quadratic discriminant analysis model. So, these features were removed and the discriminant analysis with no cross-validation was performed again with 40 features and the success rate became 83.64%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.57.

Table 6.56: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	100	53	47	53.00%
Present	175	174	1	99.43%
Total	275	227	48	82.55%

Table 6.57: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	100	57	43	57.00%
Present	175	173	2	98.66%
Total	275	230	45	83.64%

After obtaining 83.64% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 61.86%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.58.

Table 6.58: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	100	3	97	3.00%
Present	175	166	9	94.86%
Total	275	169	106	61.86%

6.1.2.1.3.3. Summary of the results

With heads' sedated and unsedated left lateral view thermographic images, the maximum success rate was 68.59% and 64.36% respectively which indicates that there may be a difference between the *Present* and *Absent* classes (Fig. 6.3). Again the most effective classification method for both group of images was the K-nearest neighbor algorithm. For the sedated image group both the old texture and new texture2 features of CVIP-FEPC provided approximately similar classification results 64.74% and 68.59% respectively. And for unsedated group both the old texture and new texture2 features of CVIP-FEPC provided exactly the same classification result, 64.36%.

The classification results of all the experiments with top view sedated and unsedated images of the heads of the canines indicates that sedated images (68.59%) provided better classification results than the unsedated images (64.36%), same as the top view images.

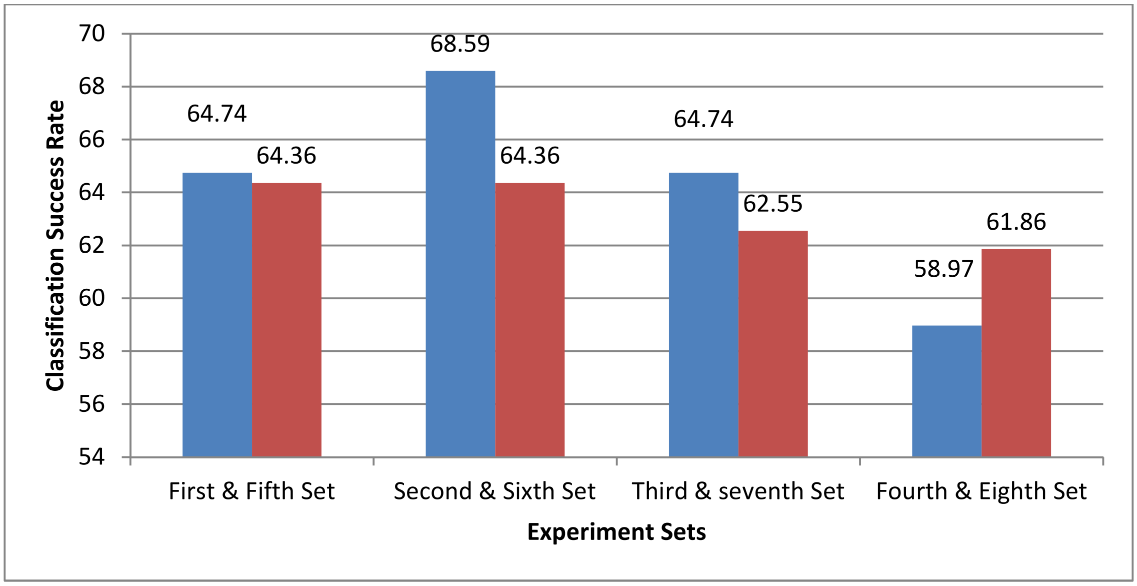


Figure 6.3. Classification success rate comparison chart for the head left lateral view images with different classification methods.

6.1.2.1.4. Right lateral view

With the right lateral view of the images also total eight sets of experiments were performed. Among them with CVIP-FEPC four sets of experiments were performed, with each set having 2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. And another four sets of experiments were performed with Partek, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.1.4.1. Experiments with sedated images

For the experiments with sedated group, 152 images were used of which 93 were in *Present* class and 59 were in *Absent* class. four set of experiments were done with this group. For these experiments original thermographic images were used.

First Set: Similar to the other experiments of different views of the images CVIP-FEPC was run with old texture features to classify the images. And the best two classification results with old texture features are shown in Table 6.59. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture energy, texture inertia, texture inverse difference, texture correlation, histogram entropy and histogram standard deviation provided the best classification result, 98 out of 152. The success rate was 64.47%.

Table 6.59: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia Texture inv-diff Texture correlation Histogram entropy Histogram Std. Dev	SoftMax1	Present:93 Absent:59	98/152 64.47%	1/2046
Texture energy Texture inv-diff Texture correlation Histogram entropy	SoftMax1	Present:93 Absent:59	95/152 62.5%	4/2046

Second Set: This experiment was done by CVIP-FEPC again but with the new texture2 features. The best two classification results with the new texture2 features are shown in Table 6.60. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture inertia and texture inverse difference provided the best classification result, 99 out of 152. The success rate was 65.13%. The second best result also used the same two features to classify the images but because of the different data normalization method it misclassified one image.

Table 6.60: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture inertia Texture inv-diff	SoftMax1	Present:93 Absent:59	99/152 65.13%	1/2046
Texture inertia Texture inv-diff	Standard Normal Density	Present:93 Absent:59	98/152 64.47%	1/2046

Third Set: To improve the success rates of the classification, Partek was used with same images here. In this experiment, discriminant analysis with cross-validation was performed. 43variables (features) were used to predict in this experiment. The feature set from the first experiment, CVIP-FEPC with old texture features, was used for Partek. And only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.61. Discriminant analysis was performed with quadratic discriminant functions and equal prior probability and the success rate was 92.76%.

The next step was to use variable selection modeling with quadratic discriminant analysis model to determine the best features. Using the backward search method for this experiment it was found that six features were not useful for quadratic discriminant analysis model to get the minimum best score. So, after removing those features Partek was run with 37 features again. And the success rate became 94.08%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.62.

Table 6.61: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	48	11	81.36%
Present	93	93	0	100%
Total	152	141	11	92.76%

Table 6.62: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	50	9	84.75%
Present	93	93	0	100%
Total	152	144	9	94.08%

After obtaining 94.08% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 61.18%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.63.

Table 6.63: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	1	58	1.69%
Present	93	92	1	98.92%
Total	152	93	59	61.18%

Fourth Set: This experiment was a repetition of the third set of the experiments. But the only difference in this experiment was that the feature set from the second set of experiments, CVIP-FEPC with new texture2 features, was used. So, at first the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 94.74%. The overall classification result with no cross-validation is shown in Table 6.64.

Table 6.64: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	59	51	8	86.44%
Present	93	93	0	100%
Total	152	144	8	94.74%

Next, the variable selection with backward search was done; it was found that eight features were not useful for quadratic discriminant analysis model. After removing these eight features the discriminant analysis was performed again with same parameters and 35 features. And the success rate became 97.37%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.65.

Table 6.65: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	59	55	4	93.22%
Present	93	93	0	100%
Total	152	148	4	97.37%

After obtaining 97.37% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 59.21%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.66.

Table 6.66: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	59	7	52	11.86%
Present	93	83	10	89.25%
Total	152	90	62	59.21%

6.1.2.1.4.2. Experiments with unsedated images

For the experiments with unsedated group, 1555 images were used of which 105 were in *Present* class and 50 were in *Absent* class. Again four sets of experiments were done with this group as sedated group. And for these experiments the original thermographic images were used.

Fifth Set: CVIP-FEPC was run with old texture features to classify the unsedated thermographic images of this view. The best two classification results with old texture features are shown in Table 6.67. However, for this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture energy, texture correlation and texture inverse difference provided the best classification result, 105 out of 155. The success rate was 67.74%.

Table 6.67: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture correlation Texture inv-diff	SoftMax1	Present:105 Absent:50	105/155 67.74%	1/2046
Texture correlation	Standard Normal Density	Present:105 Absent:50	104/155 67.09%	8/2046

Sixth Set: This experiment was a repetition of the fifth set of experiments. The only difference was CVIP-FEPC was run with the new texture2 features to classify the same images. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and standard normal density data normalization with texture energy, texture inverse difference, histogram skew, histogram energy and histogram standard deviation provided the best classification result, 106 out of 155. So the success rate was same as of fifth set of experiments 68.38% with same 2 features. The best two classification results with the new texture2 features are shown in Table 6.68.

Table 6.68: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inv-diff Histogram skew Histogram energy Histogram Std. Dev	SoftMax1	Present:105 Absent:50	106/155 68.38%	2/2046
Texture energy Texture correlation	SoftMax1/Standard Normal Density	Present:105 Absent:50	104/155 67.09%	3/2046

Seventh Set: This experiment was a repetition of the third set of the experiments. The experimental result with all features of the fifth experiment, CVIP-FEPC with old texture features, was used here. Then the discriminant analysis with no cross-validation was performed. All the features (43 features) were used in this experiment. And like the third set of experiments only the original data had been used. The overall classification result with no cross-validation is shown in Table 6.69.

Table 6.69: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	50	33	17	66.00%
Present	105	105	0	100%
Total	155	138	17	89.03%

The success rate was 89.03% after using discriminant analysis. To improve the classification rate the variable selection with backward search method was used for quadratic discriminant analysis model and found that five features were not useful for this model. So, after removing those five features the discriminant analysis was performed again with 38 features. Then it was found that the success rate was increased to 90.97%. So after using the variable selection three more images in *Absent* class were classified correctly. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.70.

Table 6.70: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	50	36	14	72.00%
Present	105	105	0	100%
Total	155	138	14	90.97%

After obtaining 90.97% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 67.74% but this experiment could not classify any of the images correctly from *Absent* class. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.71.

Table 6.71: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	50	0	50	0%
Present	105	105	0	100%
Total	155	105	50	67.74%

Eighth Set: This experiment is the repetition of the seventh set of experiments. The experimental result with all features of the sixth set of experiments, CVIP-FEPC with new texture2 features, was used. Then discriminant analysis with no cross-validation was performed with 43 features and the success rate was 88.39%. The overall classification result with no cross-validation is shown in Table 6.72.

After using the variable selection with backward search, it was found that eight features were not useful for quadratic discriminant analysis model. So, these features were removed and the discriminant analysis was performed again with 35 features and the success rate became 91.61%. The overall classification result with no cross-validation and with appropriate features is shown in Table 6.73.

Table 6.72: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	50	32	18	64.00%
Present	105	105	0	100%
Total	155	137	18	88.39%

Table 6.73: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	50	37	13	74.00%
Present	105	105	0	100%
Total	155	138	13	91.61%

After obtaining 91.61% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 66.45% but this experiment could not classify any of the images correctly from *Absent* class. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.74.

Table 6.74: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	50	0	50	0%
Present	105	103	2	98.10%
Total	155	103	52	66.45%

6.1.2.1.4.3. Summary of the results

With heads' sedated and unsedated right lateral view thermographic images it was found (Fig. 6.4) that the maximum success rate was 65.13% and 68.38% respectively which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for both groups of images was the K-nearest neighbor algorithm. For sedated image group both the old texture and new texture2 features of CVIP-FEPC provided approximately similar classification results 64.74% and 65.13% respectively. And for unsedated group both the old texture and new texture2 features of CVIP-FEPC provided also almost similar classification results 67.74% and 68.38% respectively.

The classification results of all the experiments with right lateral view of sedated and unsedated images of the heads of the canines indicates that unsedated images (68.38%) provided better classification results than the sedated images (65.13%), same as front view images. Even though for the unsedated images discriminant analysis with 1-level cross-validation provided more than 66% success rate but it misclassified all the images of *Absent* class.

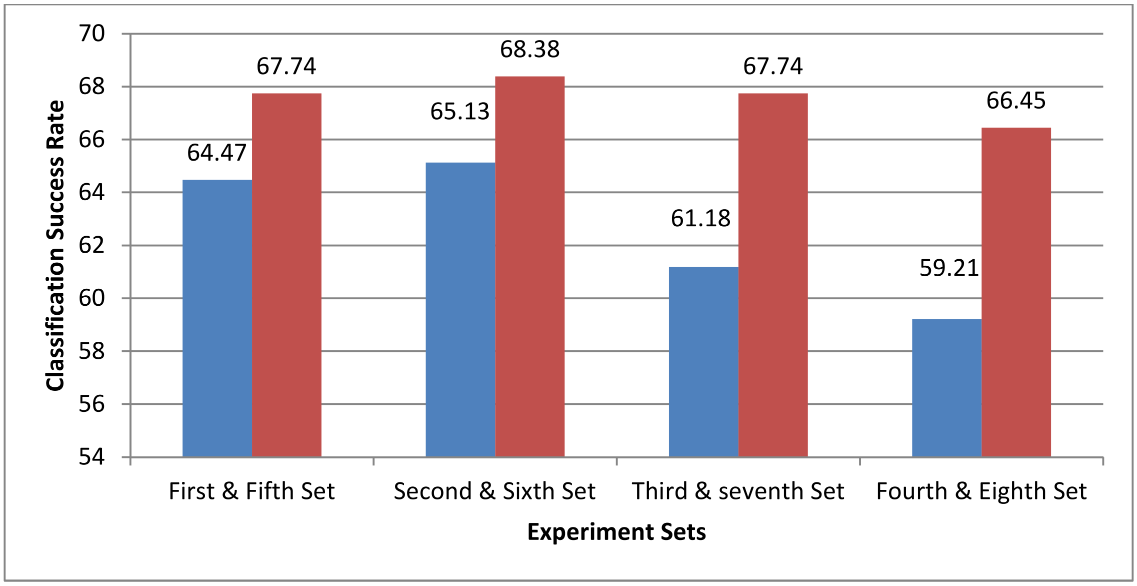


Figure 6.4. Classification success rate comparison chart for the head right lateral view images with different classification methods.

6.1.2.2. Thermographic Images – Body of the Canines

There were five different views of the thermographic images of the canines' bodies; dorsal, front, back, left lateral and right lateral. Dorsal, front and back view images were of only unsedated group but left lateral and right lateral views images were of both sedated and unsedated group. To detect the presence and absence of syrinx, two software were used CVIP-FEPC with both old texture and new texture2 features and Partek for all of the views.

6.1.2.2.1. *Dorsal view*

With the dorsal view of the images total four sets of experiments were performed. Among them with CVIP-FEPC two sets of experiments were performed, with each set having 2046 permutations, with the unsedated images. And another two sets of experiments were performed with the Partek Discovery Suite with the same images.

6.1.2.2.1.1. Experiments with unsedated images

For the experiments, 276 images were used of which 177 were in *Present* class and 99 were in *Absent* class. Four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: In this experiment CVIP-FEPC was run with old texture features to classify the images. And the best two classification results with old texture features are shown in Table 6.75. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture energy and texture inertia provided the best classification result, 173 out of 276. The success rate was 62.68%.

Table 6.75: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia	SoftMax1	Present:177 Absent:99	173/276 62.68%	2/2046
Texture entropy Texture inv-diff Texture correlation	SoftMax1	Present:177 Absent:99	172/276 62.31%	1/2046

Second Set: This experiment was performed using CVIP-FEPC again but with the new texture2 features. The best two classification results with the new texture2 features are shown in Table 6.76. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and standard normal density data normalization with texture energy and texture entropy provided the best classification result, 178 out of 276. The success rate was 64.49%.

The second best result also used the same two features to classify the images but because of the different data normalization method it misclassified four images.

Table 6.76: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture entropy	Standard Normal Density	Present:177 Absent:99	178/276 64.49%	1/2046
Texture energy Texture entropy	SoftMax1	Present:177 Absent:99	174/276 63.04%	1/2046

Third Set: To improve the success rates of the classification, Partek was used with same images in this experiment. Discriminant analysis with no cross-validation was performed. 43variables (features) were used to predict in this experiment. The experimental result with all features of the first experiment, CVIP-FEPC with old texture features, was used for Partek. And here also only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.77. Discriminant analysis was performed with quadratic discriminant function and equal prior probability and the success rate was 84.42%.

Since the success rate was not good enough, the next step was to use variable selection modeling with quadratic discriminant analysis model to find out the appropriate features. Using the backward search method for this experiment it was found that three features were not useful for quadratic discriminant analysis model to get the minimum best score. So, after removing those features Partek was run with 40 features again. And the success rate became 86.23%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.78.

Table 6.77: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	61	33	61.62%
Present	177	172	5	97.18%
Total	276	233	43	84.42%

Table 6.78: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	68	31	68.69%
Present	177	170	7	96.05%
Total	276	238	38	86.23%

After obtaining 86.23% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 57.97%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.79.

Table 6.79: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	2	97	2.02%
Present	177	158	19	89.27%
Total	276	160	116	57.97%

Fourth Set: This experiment was a repetition of the third set of the experiments. But the only difference in this experiment was that the feature set from the second set of experiments, CVIP-FEPC with new texture2 features, was used. First, the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 82.61%. The overall classification result with no cross-validation is shown in Table 6.80.

Table 6.80: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	52	47	52.53%
Present	177	176	1	99.44%
Total	276	228	48	82.61%

Next, the variable selection with backward search was done; it was found that only two features were not useful for quadratic discriminant analysis model. After removing these two features the discriminant analysis with no cross-validation was performed again with same parameters and 41 features. And the success rate became 87.68%. But after this experiment, 11 more images of *Present* class were misclassified and the individual success rate of this class decreased from 99.44% to 93.22% but 25 more images of *Absent* class were classified correctly so the individual success rate of this class increased from 52.53% to 77.78%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.81.

Table 6.81: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	99	77	22	77.78%
Present	177	165	12	93.22%
Total	276	242	34	87.68%

After obtaining 87.68% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 59.42%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.82.

6.1.2.2.1.2. Summary of the results

With the dorsal view unsedated thermographic images of the body it was found (Fig. 6.5) that the maximum success rate was 64.49% which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for these images was the K-nearest neighbor algorithm. And both the old texture and new texture2 features of CVIP-FEPC provided almost similar classification results 62.68% and 64.49% respectively.

Table 6.82: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	99	3	96	3.03%
Present	177	161	16	90.96%
Total	276	164	112	59.42%

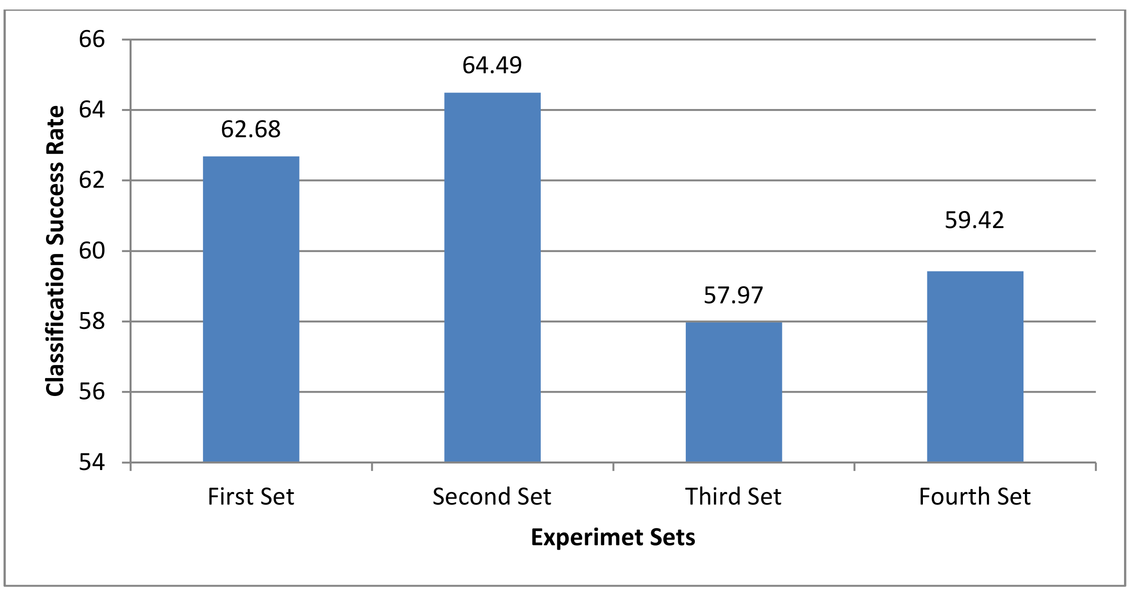


Figure 6.5. Classification success rate comparison chart for the dorsal view images with different classification methods.

6.1.2.2.2. Front view

With the front view of the thermographic images also total four sets of experiments were performed. Among them with CVIP-FEPC two sets of experiments were performed, with each set having 2046 permutations, with the unsedated images. And another two sets of experiments were performed with the Partek Discovery Suite with the same images.

6.1.2.2.2.1. Experiments with unsedated images

For the experiments, 277 images were used of which 180 were in *Present* class and 97 were in *Absent* class. Four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: In this experiment CVIP-FEPC was run with old texture features to classify the images. And the best two classification results with old texture features are shown in Table 6.83. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with texture energy, texture inertia, texture inverse difference, texture correlation, histogram skew and histogram entropy provided the best classification result, 185 out of 277. The success rate was 66.78%.

Second Set: This experiment was performed using CVIP-FEPC again but with the new texture2 features. The best two classification results with the new texture2 features are shown in Table 6.84. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with texture entropy, texture inverse difference, texture correlation and histogram entropy provided the best classification result, 179 out of 277. The success rate was 64.62%.

Table 6.83: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia Texture inv-diff Texture correlation Histogram skew Histogram entropy	Standard Normal Density	Present:180 Absent:97	185/277 66.78%	1/2046
Texture inertia Texture inv-diff Histogram energy Histogram entropy	Standard Normal Density	Present:180 Absent:97	182/277 65.7%	1/2046

Table 6.84: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture entropy Texture inv-diff Texture correlation Histogram entropy	Standard Normal Density	Present:180 Absent:97	179/277 64.62%	1/2046
Texture inertia Texture inv-diff Texture correlation Histogram energy	SoftMax1	Present:180 Absent:97	178/277 64.26%	2/2046

Third Set: The Partek Discovery Suite was used with same images in this experiment. Discriminant analysis with no cross-validation was performed. 43 variables (features) were used to predict in this experiment. The experimental result with all features of the first experiment, CVIP-FEPC with old texture features, was used for Partek. And here also only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.85. Discriminant analysis was performed with quadratic discriminant function and equal prior probability and the success rate was 81.95%.

Table 6.85: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	48	49	49.48%
Present	180	179	1	99.44%
Total	277	227	50	81.95%

The next step was to use the variable selection modeling method with quadratic discriminant analysis model to determine the best features to improve the classification rate. Using the backward search method for this experiment it was found that 10 features were not useful for quadratic discriminant analysis model to get the minimum best score. So, after removing those features Partek was run with 33 features again. And the success rate became 85.92%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.86.

Table 6.86: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	59	38	60.82%
Present	180	179	1	99.44%
Total	277	238	39	85.92%

After obtaining 85.92% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 64.62%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.87.

Table 6.87: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	9	88	9.28%
Present	180	170	10	94.44%
Total	277	179	98	64.62%

Fourth Set: This experiment was a repetition of the third set of the experiments. But the only difference in this experiment was that the experimental result with all features of the second set of experiments, CVIP-FEPC with new texture2 features, was used. First, the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 81.95%. The overall classification result with no cross-validation is shown in Table 6.88.

Table 6.88: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	47	50	48.45%
Present	180	180	0	100%
Total	277	227	50	81.95%

Next, the variable selection with backward search was done; it was found that 10 features were not useful for quadratic discriminant analysis model. After removing these 10 features the discriminant analysis with no cross-validation was performed again with same parameters and 33 features. And the success rate became 86.28%. But after this experiment, one image of *Present* class was misclassified and the individual success rate of this class decreased from 100% to 99.44% but 13 more images of *Absent* class were classified correctly so the individual success rate of this class increased from 48.45% to 61.86%. The overall classification result with no cross validation but with appropriate features is shown in Table 6.89.

After obtaining 86.28% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 64.26%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.90.

Table 6.89: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	60	37	61.86%
Present	180	179	1	99.44%
Total	277	239	38	86.28%

Table 6.90: Classification Results: Discriminant Analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	97	7	90	7.22%
Present	180	171	9	95.00%
Total	277	178	99	64.26%

6.1.2.2.2.2. Summary of the results

With the front view unsedated thermographic images of the body, the maximum success rate was 66.78% (Fig. 6.6) which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for these images was the K-nearest neighbor algorithm. And both the old texture and new texture2 features of CVIP-FEPC provided almost similar classification results 66.78% and 64.62% respectively.

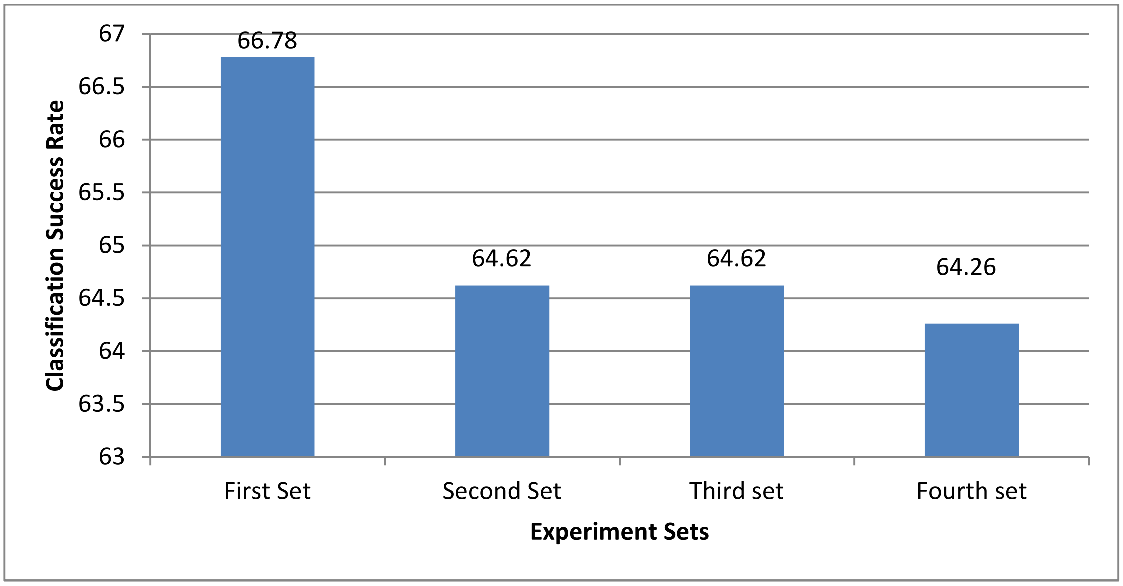


Figure 6.6. Classification success rate comparison chart for the body front view images with different classification methods.

6.1.2.2.3. Back view

With the back view of the thermographic images also total four sets of experiments were performed. Among them with CVIP-FEPC two sets of experiments were performed, with each set having 2046 permutations, with the unsedated images. And another two sets of experiments were performed with the Partek Discovery Suite with the same images.

6.1.2.2.3.1. Experiments with unsedated images

For the experiments, 251 images were used of which 164 were in *Present* class and 87 were in *Absent* class. Four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: In this experiment CVIP-FEPC was run with old texture features to classify the images. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture energy, texture entropy and texture inverse difference provided the best classification result, 166 out of 251. The success rate was 66.13%. And the best two classification results with old texture features are shown in Table 6.91.

Table 6.91: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture entropy Texture inv-diff Texture energy	SoftMax1	Present:164 Absent:87	166/251 66.13%	1/2046
Texture energy Texture entropy Histogram entropy	Standard Normal Density	Present:164 Absent:87	163/251 64.94%	4/2046

Second Set: This experiment was performed using CVIP-FEPC again but with the new texture2 features. The best two classification results with the new texture2 features are shown in Table 6.92. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with texture entropy, texture inverse difference, texture correlation and histogram entropy provided the best classification result, 165 out of 251. The success rate was 65.73%.

Third Set: To improve the classification rate Partek was used with same images in this experiment. Discriminant analysis with no cross-validation was performed. 43variables (features) were used to predict in this experiment. The feature set from the first experiment, CVIP-FEPC with old texture features, was used for Partek. And here also only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.93. And the success rate was 87.25%.

Table 6.92: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture entropy Texture energy Texture inertia Histogram entropy Histogram skew Histogram Std. Dev	SoftMax1	Present:164 Absent:87	165/251 65.73%	1/2046
Texture entropy	Standard Normal Density	Present:164 Absent:87	162/251 64.54%	2/2046

Table 6.93: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	87	56	31	64.37%
Present	164	163	1	99.39%
Total	251	219	32	87.25%

To improve the classification rate, the next step was to use variable selection modeling with quadratic discriminant analysis model to determine the best features. Using the backward search method for this experiment it was found that only one feature was not useful for quadratic discriminant analysis model to get the minimum best score. So, these features were discarded and Partek was run with 42 features again. And the success rate was decreased and became 86.06%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.94. So, the feature cannot be discarded.

Table 6.94: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	87	54	33	62.07%
Present	164	162	2	98.78%
Total	251	216	35	86.06%

After obtaining 87.25% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as all features. And the success rate became 64.54%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.95.

Fourth Set: This experiment was a repetition of the third set of the experiments. But the only difference in this experiment was that the experimental result with all features of the second set of experiments, CVIP-FEPC with new texture2 features, was used. First, the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 82.87%. The overall classification result with no cross-validation is shown in Table 6.96.

Table 6.95: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	87	3	84	3.45%
Present	164	159	5	96.95%
Total	251	162	89	64.54%

Table 6.96: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	87	46	41	52.87%
Present	164	162	2	98.78%
Total	251	208	43	82.87%

Next, the variable selection with backward search was done; it was found that only two features were not useful for quadratic discriminant analysis model. After removing these two features the discriminant analysis with no cross-validation was performed again with same parameters and 41 features. And the success rate became 84.86%. But after this experiment, two more images of Present class was misclassified and the individual success rate of this class decreased from 98.78% to 97.56% but seven more images of Absent class were classified correctly so the individual success rate of this class increased from 52.87% to 60.92%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.97.

Table 6.97: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	97	60	37	60.92%
Present	180	179	1	97.56%
Total	277	239	38	84.86%

After obtaining 84.86% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 62.95%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.98.

Table 6.98: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	87	4	83	4.60%
Present	164	154	10	93.90%
Total	251	158	93	62.95%

6.1.2.2.3.2. Summary of the results

With the front view unsedated thermographic images of the body, the maximum success rate was 66.13% (Fig. 6.7) which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for these images was the K-nearest neighbor algorithm. And both the old texture and new texture2 features of CVIP-FEPC provided almost similar classification results 66.13% and 65.73% respectively.

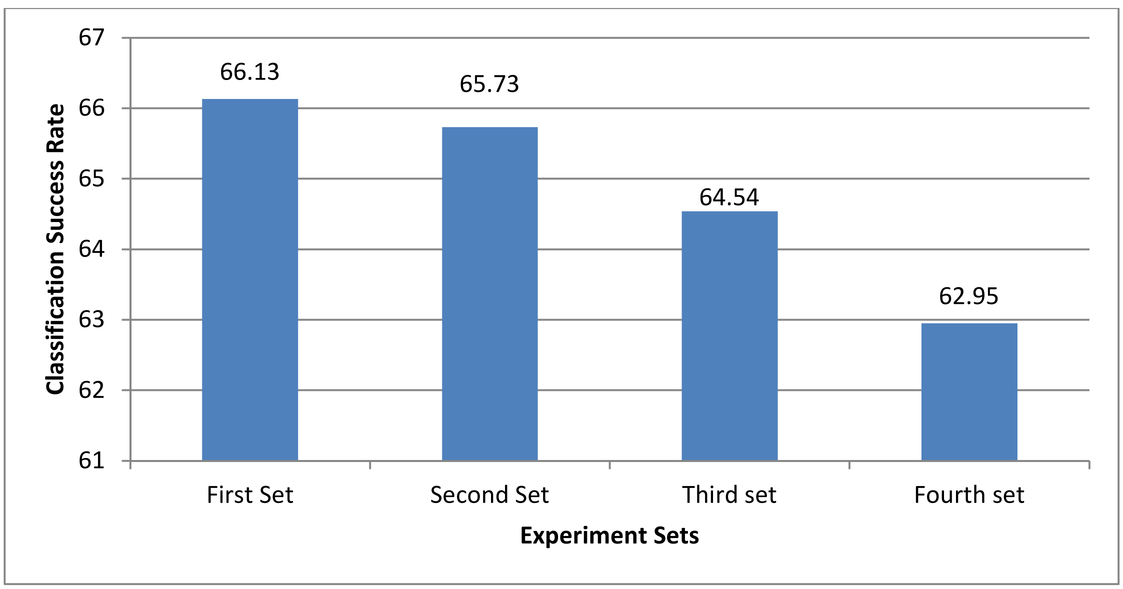


Figure 6.7. Classification success rate comparison chart for the body back view images with different classification methods.

6.1.2.2.4. Left lateral view

With the left lateral view of the images total eight sets of experiments were performed. With CVIP-FEPC four sets of experiments were performed, with each set having

2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. Another two sets of experiments were performed with Partek, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.2.4.1. Experiments with sedated images

For the experiments with sedated group, 146 images were used of which 89 were in *Present* class and 57 were in *Absent* class. A total of four sets of experiments were done with this group. For these experiments original thermographic images were used.

First Set: In this experiment CVIP-FEPC was run with old texture features to classify the images. The best two classification results with old texture features are shown in Table 6.99. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with only texture correlation provided the best classification result, 94 out of 146. The success rate was 64.38%.

Table 6.99: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture correlation	SoftMax1	Present:89 Absent:57	94/146 64.38%	2/2046
Texture inertia Histogram energy Histogram skew	SoftMax1	Present:89 Absent:57	93/146 63.69%	3/2046

Second Set: CVIP-FEPC was run again but with the new texture2 features to classify the images. The best two classification results with the new texture2 features are shown in Table 6.100. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy, texture entropy and histogram energy provided the best classification result, 91 out of 146. The success rate was 62.33%.

Table 6.100: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture entropy Histogram energy	SoftMax1	Present:89 Absent:57	91/146 62.33%	2/2046
Spectral 3x3 Texture correlation	Standard Normal Density	Present:89 Absent:57	90/146 61.64%	6/2046

Third Set: Since the success rates of the classification experiments with CVIP-FEPC were not good enough, so Partek was used with same images. In this experiment, discriminant analysis with no cross-validation was performed. 43 variables (features) were used to predict in this experiment. The experimental result with all features of the first experiment, CVIP-FEPC with old texture features, had been used for Partek. And only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.101. Similar to the other views experiments, discriminant analysis was performed with quadratic discriminant functions and equal prior probability and the success rate was 95.21%.

Table 6.101: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	57	50	7	87.72%
Present	89	89	0	100%
Total	146	139	7	95.21%

Even though the success rate was good enough, seven images were misclassified; the variable selection modeling with quadratic discriminant analysis model was used thereafter to determine the best features. Using the backward search method it was found that two features among 43 features were not useful for quadratic discriminant analysis model to get the minimum best score. So, after removing these features 41 features were used to run Partek again. And the success rate became 96.58%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.102.

Table 6.102: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	57	52	5	91.23%
Present	89	89	0	100%
Total	146	141	5	96.58%

After obtaining 96.58% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 63.01%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.103.

Table 6.103: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	57	8	49	14.04%
Present	89	84	5	94.38%
Total	146	92	54	63.01%

Fourth Set: This experiment is same as the third set of the experiments. The only difference was that here the feature set from the second set of experiments, CVIP-FEPC with new texture2 features, was used. And the rest of the experimental procedure was exactly same as the third set of the experiments that means at first the discriminant analysis with no cross validation was performed with 43 features and the success rate was 95.21%. The overall classification result with no cross-validation is shown in Table 6.104, which is exactly same as that of third set of experiments.

Then after using the variable selection with backward search, it was found that same two features were not useful for quadratic discriminant analysis model in the third experiment, also were not important here. So, after removing these features the discriminant analysis with no cross-validation was performed again with 41 features and the success rate became again 96.58% as of third set. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.105.

Table 6.104: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	57	50	7	87.72%
Present	89	89	0	100%
Total	146	139	7	95.21%

Table 6.105: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	57	52	5	91.23%
Present	89	89	0	100%
Total	146	141	5	96.58%

After obtaining 96.58% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 63.01%, same as of third set. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.106.

Table 6.106: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	57	8	49	14.04%
Present	89	84	5	94.38%
Total	146	92	54	63.01%

6.1.2.2.4.2. Experiments with unsedated images

For the experiments with unsedated group, 285 images were used of which 182 were in *Present* class and 103 were in *Absent* class. Again four sets of experiments were done with this group as sedated group. And for these experiments original thermographic images were used.

Fifth Set: In this set of experiment CVIP-FEPC was run with old texture features to classify the unsedated thermographic images. The best two classification results with old texture features are shown in Table 6.107. However, for this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with texture energy, texture inertia and histogram energy provided the best classification result, 185 out of 285. The success rate was 64.91%.

Sixth Set: This experiment was a repetition of the fifth set of experiments. The only difference was CVIP-FEPC was run with the new texture2 features to classify the same images, used in fifth set. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy, texture correlation, texture entropy, texture inertia, histogram energy and histogram entropy provided the best classification result, 190 out of 285. The success rate was 66.66%. The best two classification results with the new texture2 features are shown in Table 6.108.

Table 6.107: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture inertia Histogram energy	Standard Normal Density	Present:182 Absent:103	185/285 64.91%	1/2046
Texture inv-diff Texture correlation Histogram energy Histogram entropy	SoftMax1	Present:182 Absent:103	184/285 64.56%	2/2046

Table 6.108: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture correlation Texture entropy Texture inertia Histogram energy Histogram entropy	SoftMax1	Present:182 Absent:103	190/285 66.66%	1/2046
Texture inv-diff Texture energy Texture correlation Texture entropy Texture inertia	SoftMax1	Present:182 Absent:103	188/285 65.96%	1/2046

Seventh Set: This experiment was a repetition of the third set of the experiments. The experimental result with all features of the fifth experiment, CVIP-FEPC with old texture features, was used here. Then the discriminant analysis with no cross-validation was performed.43 variables (features) were used in this experiment. And as the third set of experiments only the original data had been used. The overall classification result with no cross-validation is shown in Table 6.109.

Table 6.109: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	103	74	29	71.84%
Present	182	176	6	96.70%
Total	285	250	35	87.72%

The success rate was only 87.72%, so to improve the classification rate the variable selection with backward search method was used for quadratic discriminant analysis model and found that four features were not useful for this model. So, those four features were removed and the discriminant analysis with no cross-validation was performed again with 39 features. And the success rate was exactly same as of the previous experiment with all features, 87.72%. But after this experiment, three more images of *Presen*t class were misclassified and the individual success rate of this class decreased from 96.70% to 95.05% but three more images of *Absent* class were classified correctly so the individual success rate of this class increased from 71.84% to 74.76%. So, the overall classification with no cross-validation but with appropriate features result was same of the experiment with all features, shown in Table 6.110.

Table 6.110: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	103	77	26	74.76%
Present	182	173	9	95.05%
Total	285	250	35	87.72%

After obtaining 87.72% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 60%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.111.

Table 6.111: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	103	20	83	19.42%
Present	182	151	31	82.97%
Total	285	171	114	60.00%

Eighth Set: This experiment is same as seventh set of experiments. The feature set from the sixth set of experiments, CVIP-FEPC with new texture2 features, was used. So, the discriminant analysis with no cross-validation was performed with 43 features and the success rate was 86.67%. The overall classification result with no cross-validation is shown in Table 6.112.

Table 6.112: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	103	72	31	69.90%
Present	182	175	7	96.15%
Total	285	247	38	86.67%

After using the variable selection with backward search, it was found that two features were not useful for quadratic discriminant analysis model. So, these features were discarded and the discriminant analysis was performed again with 41 features and the success rate was decreased and became 85.61%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.113. So, these two features cannot be discarded.

After obtaining 86.67% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as all features. And the success rate became 61.75%. The overall classification result with 1-level cross validation (Full “leave-one-out”) is shown in Table 6.114.

Table 6.113: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	103	66	37	64.08%
Present	182	178	4	97.80%
Total	285	244	41	85.61%

Table 6.114: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	Number of Images Correct	Number of Images Error	Percent Correct
Absent	103	18	85	17.48%
Present	182	158	24	86.81%
Total	285	176	109	61.75%

6.1.2.2.4.3. Summary of the results

With the sedated and unsedated left lateral view thermographic images of body, it was found that the maximum success rate was 64.38% and 66.66% respectively (Fig. 6.8) which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for both groups of images was the K-nearest neighbor algorithm. For the sedated image group both the old texture and new texture2 features of CVIP-FEPC provided approximately similar classification results 64.38% and 62.33% respectively. And for the unsedated group both the old texture and new texture2 features of CVIP-FEPC also provided almost similar classification results 64.91% and 66.66% respectively.

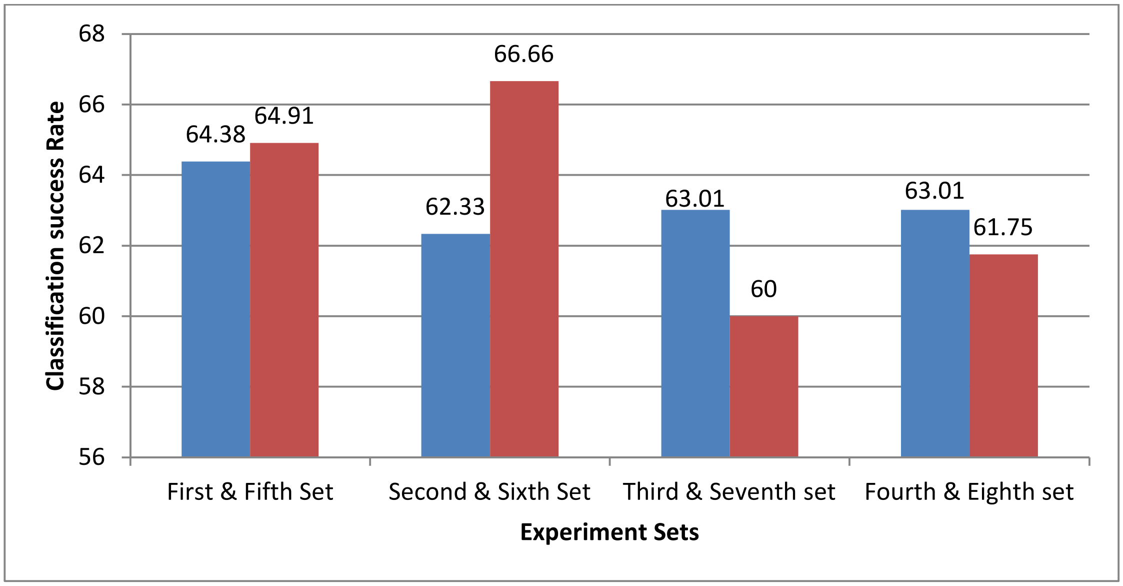


Figure 6.8. Classification success rate comparison chart for the body left lateral view images with different classification methods.

After finishing all the experiments with this view for sedated and unsedated images of the bodies of the canines, it was found that unsedated images (66.66%) provided better classification results than the sedated images (64.38%), same as the head front view images.

6.1.2.2.5. Right lateral view

With the right lateral view of images total eight sets of experiments were performed. With CVIP-FEPC four sets of experiments were performed, with each set having 2046 permutations, of which two sets of experiments were with sedated images and another two were with unsedated images. Another two sets of experiments were performed with Partek, of which two sets of experiments were with sedated images and another two were with unsedated images.

6.1.2.2.5.1. Experiments with sedated images

For the experiments with the sedated group, 143 images were used of which 85 were in *Present* class and 58 were in *Absent* class. A total of four sets of experiments were done with this group. For these experiments the original thermographic images were used.

First Set: CVIP-FEPC was run with old texture features to classify the thermograms. The best two classification results with old texture features are shown in Table 6.115. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture inertia and histogram standard deviation provided the best classification result, 95 out of 143. The success rate was 66.43%.

Table 6.115: Classification Results: Sedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture inertia Histogram Std. Dev	SoftMax1	Present:85 Absent:58	95/143 66.43%	1/2046
Texture energy Texture inertia Texture inv-diff Texture entropy Histogram Std. Dev	SoftMax1	Present:85 Absent:58	93/143 65.03%	2/2046

Second Set: In this experiment CVIP-FEPC was run with new texture2 features to classify the thermograms. The best two classification results with new texture2 features are shown in Table 6.116. For this experiment, K-nearest neighbor where K = 5; Euclidean distance, and softmax scaling data normalization with texture entropy and texture inertia provided the best classification result, 97 out of 143. The success rate was 67.83%.

Table 6.116: Classification Results: Sedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture entropy Texture inertia	SoftMax1	Present:85 Absent:58	97/143 67.83%	1/2046
Texture entropy Texture inertia Texture energy Histogram Std. Dev	Standard Normal Density	Present:85 Absent:58	95/143 66.43%	2/2046

Third Set: The success rates of the classification experiments with CVIP-FEPC were not good enough, so Partek was used with same images here. In this experiment, discriminant analysis with no cross-validation was performed. All the features (43 features) were used to predict in this experiment. The feature set from the first experiment, CVIP-FEPC with old texture features, had been used for Partek. And only the original data had been used as the original data provided better result than normalized data. The overall classification result with no cross-validation is shown in Table 6.117. Similar to the other views experiments, discriminant analysis was performed with quadratic discriminant function and equal prior probability and the success rate was 95.10%.

Table 6.117: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	51	7	87.93%
Present	85	85	0	100%
Total	143	156	7	95.10%

The next step was to use variable selection modeling with quadratic discriminant analysis model to determine the best features. Using the backward search method it was found that four features among 43 features were not useful for quadratic discriminant analysis model to get the minimum best score. So, those features were discarded and only 39 features were used to run Partek. After removing these features the discriminant analysis was performed again. And the success rate was decreased and became 94.41%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.118.

After obtaining 95.10% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as all features. And the success rate became 53.85%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.119.

Table 6.118: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	50	8	86.21%
Present	85	85	0	100%
Total	143	135	8	94.41%

Table 6.119: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	3	58	5.17%
Present	85	74	11	87.06%
Total	143	77	66	53.85%

Fourth Set: This experiment is same as the third set of the experiments. The only difference was that here the experimental result with all features of the second set of experiments, CVIP-FEPC with new texture2 features, was used. And the rest of the experiment procedure was exactly same as the third set of the experiments that means at first the discriminant analysis with no cross validation was performed with 43 features and the success rate was 96.71%. The overall classification result with no cross-validation is shown in Table 6.120.

Table 6.120: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	48	10	82.76%
Present	85	85	0	100%
Total	143	133	10	93.01%

Then after using the variable selection with backward search, it was found that three features were not useful for quadratic discriminant analysis model. After removing these features the discriminant analysis was performed again with 40 features and the success rate became 93.71%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.121.

Table 6.121: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	50	8	86.21%
Present	85	84	1	98.82%
Total	143	134	9	93.71%

After obtaining 93.71% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And

the success rate became 58.74%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.122.

Table 6.122: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	58	6	52	10.34%
Present	85	78	7	91.76%
Total	143	84	59	58.74%

6.1.2.2.5.2. Experiments with unsedated images

For the experiments with unsedated group, 274 images were used of which 176 were in *Present* class and 98 were in *Absent* class. Again four sets of experiments were done with this group as sedated group. And for these experiments the original thermographic images were used.

Fifth Set: In this set of experiment CVIP-FEPC was run with old texture features to classify the unsedated thermographic images of right lateral body view. The best two classification results with old texture features are shown in Table 6.123. However, for this experiment, K-nearest neighbor where K = 5; Euclidean distance, and standard normal density data normalization with spectral 3x3, texture inertia, texture correlation and histogram skew provided the best classification result, 185 out of 274. The success rate was 67.5%.

Table 6.123: Classification Results: Unsedated images with old texture features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Spectral 3x3 Texture inertia Texture correlation Histogram skew	Standard Normal Density	Present:176 Absent:98	185/274 67.5%	2/2046
Spectral 3x3 Texture inv-diff Texture correlation Histogram skew	SoftMax1	Present:176 Absent:98	184/274 67.15%	2/2046

Sixth Set: This experiment was a repetition of the fifth set of experiments. The only difference was CVIP-FEPC was run with the new texture2 features to classify the same images, used in fifth set. For this experiment, K-nearest neighbor where K = 5, Euclidean distance, and softmax scaling data normalization with texture energy, texture entropy and texture inertia provided the best classification result, 181 out of 274. The success rate was 66.06%. The best two classification results with the new texture2 features are shown in Table 6.124.

Seventh Set: This experiment was a repetition of the third set of the experiments. The experimental result with all features of the fifth experiment, CVIP-FEPC with old texture features, was used here. Then the discriminant analysis with no cross-validation was performed. Again all the features that means 43 features were used in this experiment. And like the third set of experiments only the original data had been used. The overall classification result with no cross-validation is shown in Table 6.125.

Table 6.124: Classification Results: Unsedated images with new texture2 features

Best two classification results of 2046 experiments Minimum Features (texture pixel dist=6)	**Data normalization method**	**Number of images per class**	**Number/ Percent correct**	**Number of experiments with the success rate**
Texture energy Texture entropy Texture inertia	SoftMax1	Present:176 Absent:98	181/274 66.06%	2/2046
Texture energy Texture entropy Texture inertia Texture correlation	Standard Normal Density	Present:176 Absent:98	180/274 65.69%	2/2046

Table 6.125: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	81	17	82.65%
Present	176	169	7	96.02%
Total	274	250	24	91.24%

The success rate was 91.24%, so to improve the classification rate the variable selection with backward search method was used for quadratic discriminant analysis model and found that four features were not useful for this model. So, those four features were removed and the discriminant analysis with no cross-validation was performed again with 39 features. And the success rate was increased to 92.70%. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.126.

Table 6.126: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	86	12	87.76%
Present	176	168	8	95.45%
Total	274	254	20	92.70%

After obtaining 92.70% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 58.76%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.127.

Table 6.127: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	26	72	26.53%
Present	176	135	41	76.70%
Total	274	161	113	58.76%

Eighth Set: This experiment is same as seventh set of experiments. The feature set from the sixth set of experiments, CVIP-FEPC with new texture2 features, was used. So, the discriminant analysis with no cross validation was performed with 43 features and the success rate was 91.24%, same as of seventh set experiment (Table 6.125). But the individual success rates of each class are different. The overall classification result with no cross-validation is shown in Table 6.128.

Table 6.128: Classification Results: Discriminant analysis with no cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	84	14	85.71%
Present	176	166	10	94.32%
Total	274	250	24	91.24%

After using the variable selection with backward search, it was found that four features were not useful for quadratic discriminant analysis model. So, these features were discarded and the discriminant analysis with no cross-validation was performed again with 39 features and the success rate became 92.70%, same as of seventh set experiment (Table 6.126). But the individual success rates of each class are different. The overall classification result with no cross-validation but with appropriate features is shown in Table 6.129.

Table 6.129: Classification Results: Discriminant analysis after using variable selection

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	87	11	88.78%
Present	176	167	9	94.89%
Total	274	254	20	92.70%

After obtaining 92.70% success rate with no cross-validation, discriminant analysis was performed again but with 1-level cross-validation as well as appropriate features. And the success rate became 58.03%. The overall classification result with 1-level cross validation (Full "leave-one-out") is shown in Table 6.130.

Table 6.130: Classification Results: Discriminant analysis with 1-level cross-validation

	Number of Images per Class	**Number of Images Correct**	**Number of Images Error**	**Percent Correct**
Absent	98	25	73	25.51%
Present	176	134	42	76.14%
Total	274	159	115	58.03%

6.1.2.2.5.3. Summary of the results

With the sedated and unsedated right lateral view thermographic images of body, it was found that the maximum success rate was 67.83% and 67.5% respectively (Fig. 6.9) which indicates that there may be a difference between the *Present* and *Absent* classes. Again the most effective classification method for both groups of images was the K-nearest neighbor algorithm. For the sedated image group both the old texture and new texture2 features of CVIP-FEPC provided approximately similar classification results 66.43% and 67.83% respectively. And for the unsedated group both the old texture and new texture2 features of CVIP-FEPC also provided almost similar classification results 67.5% and 66.06% respectively.

After finishing all the experiments with right lateral view sedated and unsedated body images of the canines, it was found that sedated images (67.83%) provided better classification results than the unsedated images (67.5%), same as the top and left lateral head view images.

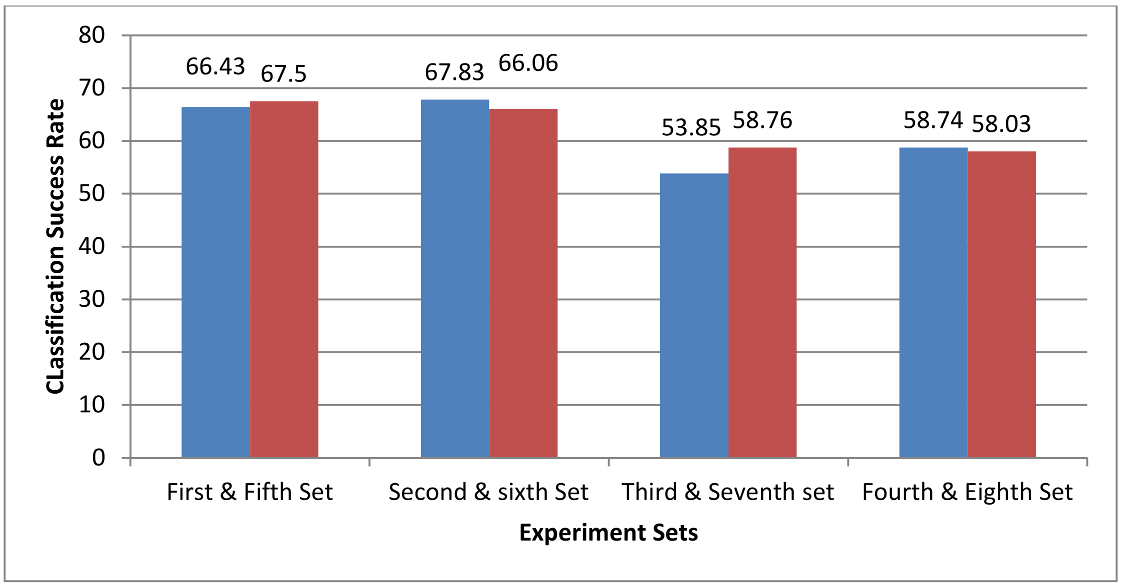


Figure 6.9. Classification success rate comparison chart for the body right lateral view images with different classification methods.

6.2. The Algorithm for Automated Masks Creation

To create the automated masks, using the algorithm described in Chapter 4, CVIP-ATAT was run three times for three different views: dorsal, left lateral and right lateral. The masks were selected from CVIP-ATAT using subtraction energy. The highest valued images were picked. The automated masks of corresponding images of Fig 3.1, in Chapter 3, are shown in Fig. 6.10.

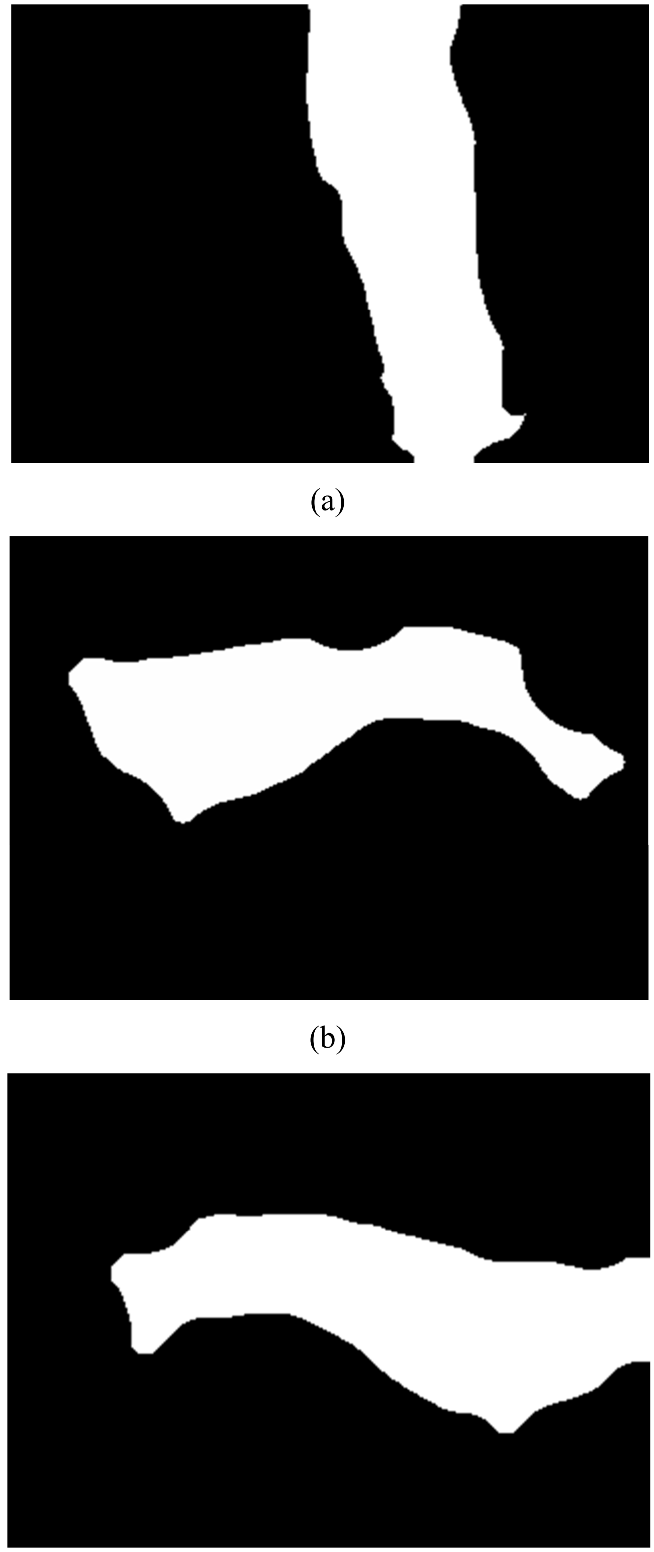
After selecting the automated masks the energy of the masks were obtained using the CVIPtools function *Utilities->Stats->Image Statistics*. The energy of the manually created masks also were found same way. Then the energy difference between the automated masks and manually created masks were calculated. If this difference is positive, it implies that the automatic mask is better. The results are shown in Fig. 6.11, Fig. 6.12 and Fig. 6.13 for dorsal, left lateral and right lateral view respectively. From the graph bars it can be seen that better masks were obtained using the automatic mask creation algorithm.

Now again after running the CVIP-FEPC on these images it was found that, as shown in Fig. 6.14, the automated masks for the dorsal, left and right lateral views produced the best classification result. However, the manually created mask is also very close to it.

For the dorsal automated mask, nearest neighbor, vector inner product, and standard normalization with texture correlation, histogram standard deviation and histogram energy provided the best result, 85 out of 96 were correct.

For the left lateral automated mask, K-nearest neighbor where K = 3, Euclidean distance, and standard normalization with texture inertia, texture entropy and histogram standard deviation provide the best classification result, 79 out of 88 were correct.

For the right lateral automated mask, K-nearest neighbor where K = 3, Euclidean distance, and standard normalization with texture inertia, texture energy and texture correlation provide the best classification result, 79 out of 88 were correct.



(a)

(b)

(c)

Figure 6.10. The automated masks of the images in Fig. 3.1

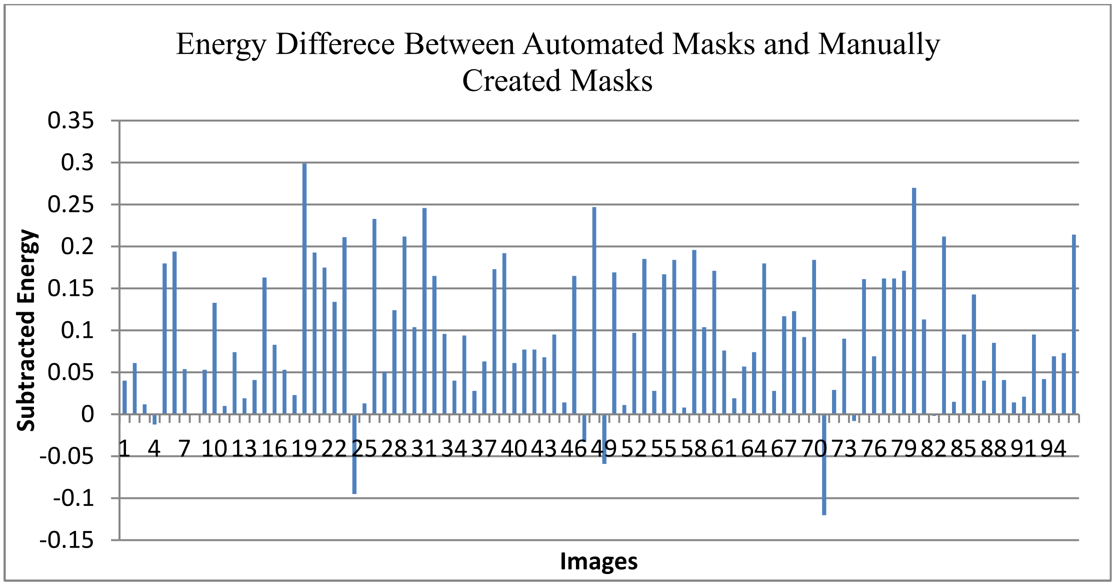


Figure 6.11. Subtracted Energy versus Images for dorsal view images

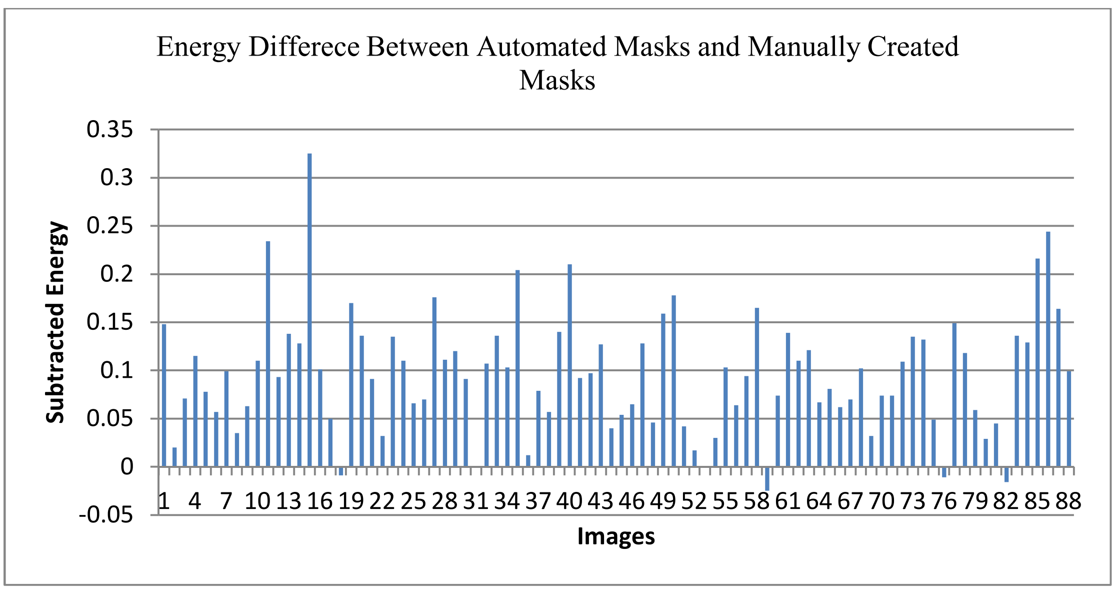


Figure 6.12. Subtracted Energy versus Images for left lateral view images

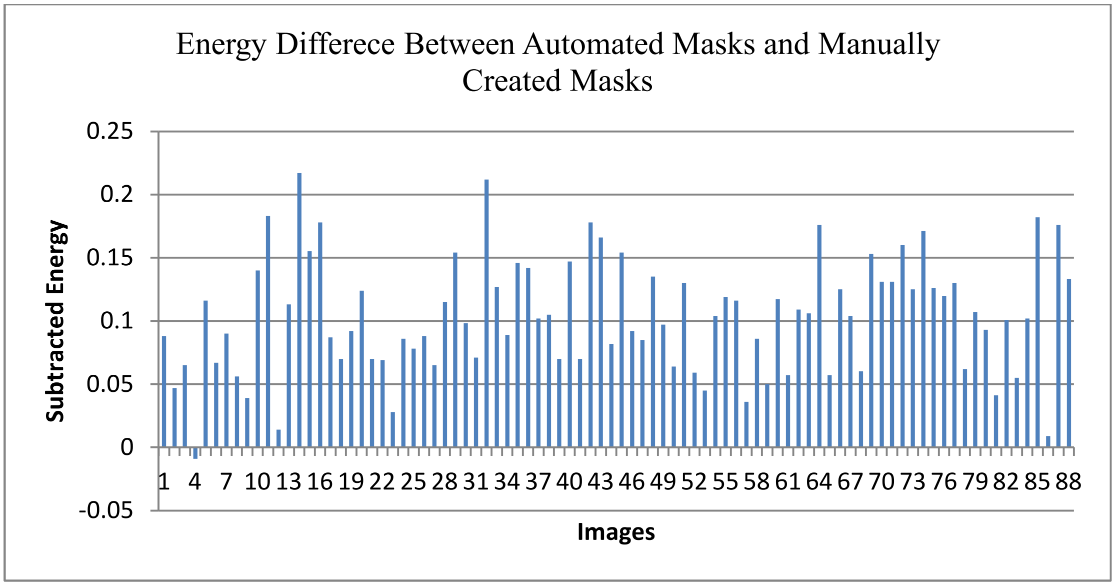


Figure 6.13. Subtracted Energy versus Images for right lateral view images

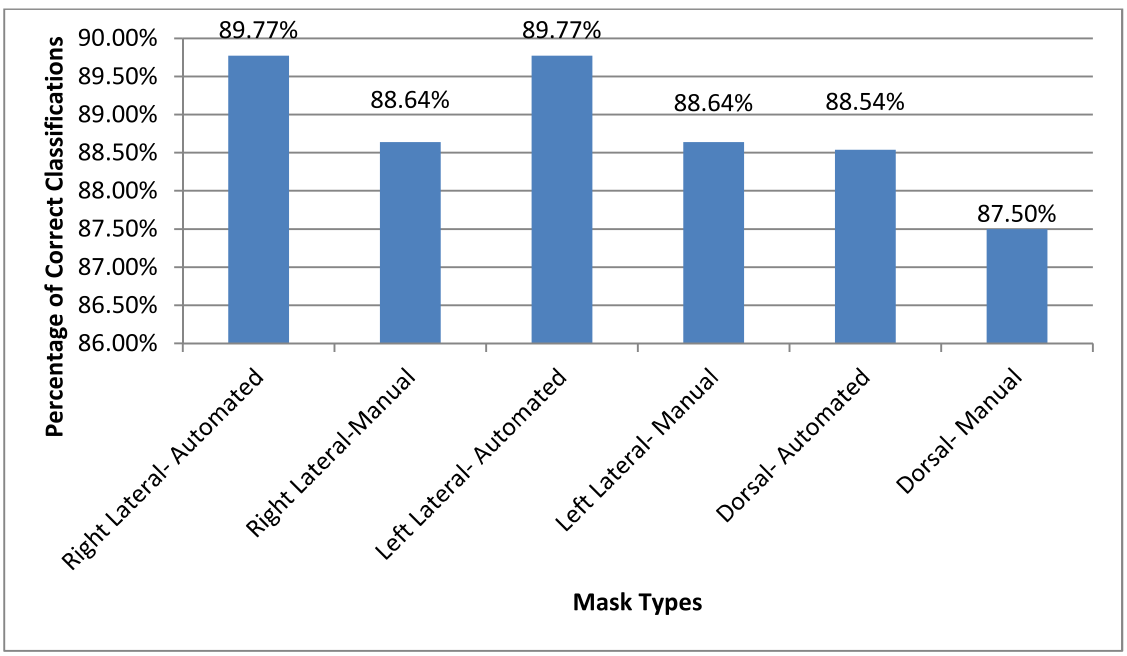


Figure 6.14. Comparison chart of classification success rate with automated and manually created masks

CHAPTER 7

CONCLUSION

A total of 73 sets of experiments were performed, where each set corresponds to a particular view of images with a particular pathology. Among all of the experiments only the best results are summarized in this Chapter.

With the pathological condition Intervertebral Disc Disease (IVDD) there are 13 sets of experiments performed. At first, three sets of experiments were performed with manually created masks for dorsal, left lateral and right lateral view images of canines and classified them as *IVDD* and *Normal*. The maximum classification success rates for dorsal, left lateral and right lateral images were 87.50%, 88.64% and 88.64% respectively. Next, another three sets of experiments were performed with automated masks for the three different views of images and found the classification success rate for dorsal, left lateral and right lateral images were 88.54%, 89.77% and 89.77% respectively. The left/right lateral view images provided highest classification rate, 89.77% with K-nearest neighbor, where K=3. So, it is obvious that the automatic mask creation algorithm provided marginally better masks than those created manually.

Intervertebral disc disease is a disease that is expensive to diagnose with current standard methods. Therefore, it is beneficial to find alternative diagnostic methods that are cheaper and easy to use. From this research it is found that thermographic images are useful as a diagnostic method for IVDD. An accurate classification for at least 87.5% of the images was obtained.

But for the surgery or further treatment of IVDD it is essential to identify the specific herniated disc space. A total of seven sets of experiments were performed to identify the herniated disc space in the vertebrae. Experiments with Multilayer Perceptron (MLP) neural network provided a 97% success rate which indicates that it is possible to classify the herniated intervertebral disc space from the normal disc spaces and correlates with the MRI findings. So, from this research it is found that thermographic images are useful as a diagnostic method for IVDD because it not only could classify the clinical canines but also identify the specific herniated disc space among total 32 disc spaces in the vertebrae.

With the pathological condition Syringomyelia there are 60 sets of experiments that were performed with nine different views of images. At first, eight sets of experiments were performed with the front of head images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With sedated and unsedated images, a classification success rate of 63.88% and 67.01%, respectively, was achieved.

Eight sets of experiments used the top of head images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With sedated and unsedated images, a classification success rate of 65.13% and 63.5%, respectively, was achieved.

Eight sets of experiments used the left lateral of head images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With Sedated and unsedated images, a classification success rate of 68.59% and 64.36%, respectively, was achieved.

Eight sets of experiments used the right of head images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With sedated and unsedated images, a classification success rate 65.13% and 68.38%, respectively, was achieved.

Four sets of experiments used the dorsal images that were classified as *Present* and *Absent* classes of the pathology. Here, only unsedated images were used and a classification success rate of 64.49% was achieved.

Four sets of experiments used the front of body images that were classified as *Present* and *Absent* classes of the pathology. Here, only unsedated images were used and a classification success rate of 66.78% was achieved.

Four sets of experiments used the back of body images that were classified as *Present* and *Absent* classes of the pathology. Here, only unsedated images were used and a classification success rate of 66.13% was achieved.

Eight sets of experiments used the left lateral of body images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With sedated and unsedated images, a classification success rate 64.38% and 66.66%, respectively, was achieved.

Eight sets of experiments used the right lateral of body images that were classified as *Present* and *Absent* classes of the pathology. Here, sedated and unsedated images were used. With sedated and unsedated images, a classification success rate of 67.83% and 67.5%, respectively, was achieved.

Comparing the results from all sets of experiments of Syringomyelia it is found that the left/right lateral of head images provide the highest classification rates. But it is difficult to say which type of images provides better classification rate, sedated or unsedated. Since experiments with unsedated images had a larger training set than with the sedated images these experiments provided a slightly higher success rate. Overall, the classes for the MRI findings of syrinx are differentiable with the thermographic images. But to get an ultimate decision about using thermographic images as a diagnostic tool for Syringomyelia a higher success rate should be achieved.

So, at the end of this research, it is found that thermographic images can be used as a diagnostic tool for the pathological condition Intervertebral Disc Disease (IVDD) and further experiments are required to improve the classification success rate for Syringomyelia.

CHAPTER 8

FUTURE SCOPE

Since the training set for the sedated images and unsedated images were not equal in size, it was difficult to compare results. So, experiments can be performed with equal sized training set for both types of images. Also, the classification success rate for the pathological condition Syringomyelia was not high enough. In most of the cases, the experiments were unable to classify the *Absent* class of images. That is why, the classification success rates were only around 65%. Maybe the feature sets were not adequate for the classification. So different feature sets can be used for further experiments. Color normalization methods were used for IVDD but were not used for Syringomyelia. So, color normalization may be a good option to improve the success rate with this pathological condition of Syringomyelia.

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