**Classification of level of severity of Rheumatoid Arthritis using Machine Learning
(Decision Tree)**

By

Abiola Ogungbemile

B.Sc. Electrical Engineering, Clark Atlanta University

A thesis submitted to the Faculty of Graduate Studies and Research

In partial fulfilment of the requirements for the degree of

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Carleton University

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Abiola Ogungbemile,
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Chair, Dr. Howard Schwartz, Department of Systems and Computer Engineering

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Thesis Supervisor, Dr. Monique Frize

Carleton University

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ABSTRACT

This research is a continuation of earlier work, which assessed the use of thermal infrared (TIR) imaging systems as a potential tool for physicians to diagnose and manage Rheumatoid Arthritis (RA). From that work, TIR images were taken of 18 control subjects and 13 patients diagnosed with RA by a rheumatologist. However, in order to further explore and better improve classification 10 additional control subjects and 13 additional patients were recruited. Temperature measurements were extracted from all the joints in the hand, wrist, elbow, ankle, feet and knee images and statistical tests were done to show which joints were the best indicators of RA and good discriminators between the patients and the control subjects. It was established that the 2nd metacarpophalangeal (MCP), the 3rd metacarpophalangeal (MCP), the ankle and the knee were the joints that showed the greatest statistical difference between control subjects and patients. The dataset series were submitted to the C.5 software to generate a classifier (decision tree). The Min and Max datasets were the best in classifying RA with a sensitivity of 96% and a specificity of 92%. The 2nd and 3rd MCPs proved to be the best joints to classify RA using the Min and Max dataset series confirming the statistical results from earlier work; where these same joints were concluded to be the best indicators of RA. The classifier was used to classify the level of severity of the patient group into LOW, MEDIUM and HIGH classes' successfully.

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LIST OF ACRONYMS

ANN	Artificial Neural Network
AUC	Area Under the Curve
ATR	Automated Target Recognition
CCR	Correct Classification Rate
DIP	Distal InterPhalangeal
DMARDs	Disease-Modifying Anti-Rheumatic Drugs
DT	Decision Tree
FN	False Negative
FP	False Positive
HDI	Heat Distribution Index
HRUS	High Resolution Ultra Sound
IR	InfraRed
MCP	MetaCarpoPhalangeal
MIRG	Medical Information-technologies Research Group
MRI	Magnetic Resonance Imaging
MTP	MetaTarsal Phalangeal
NPV	Negative Predictive Value
NSAIDs	NonSteroidal Anti-Inflammatory Drugs
OHREB	Ottawa Hospital Research Ethics Board
PPV	Positive Predictive Value
RA	Rheumatoid Arthritis
ROC	Receiver Operating Characteristic

STD	Standard Deviation
TI	Thermal Index
TIR	Thermal InfraRed
TN	True Negative
TP	True Positive
WHO	World Health Organization

CHAPTER ONE

1. INTRODUCTION

This chapter gives background information on the motivation behind this thesis; it also gives an introductory look into Rheumatoid Arthritis and discusses the disease, its causes, the signs & symptoms and also available/current treatment & therapy options. This detailed introduction is necessary in order to stress the importance of using thermal imaging as a potentially established diagnostic tool.

1.1. Motivation

From previous work (Adéa 2009), the use of thermal imaging as a tool to aid in the diagnosis and measurement of the severity of RA has proven to be effective. This is why the continuation of research work in this area is important. During flare up periods with this disease, there is always inflammation, which sometimes makes clinical assessment almost always impossible because the patient is in too much pain. But with the use of thermal imaging, this is a non-invasive tool that has shown potential to make assessment and diagnosis of RA easier and possibly earlier in the evolution of the condition. The progress that is continually made by the use of the technique makes it a viable diagnostic tool in the foreseeable future in Canada, the US and elsewhere. RA has a significant impact on health-related quality of life, and is associated with increased health-care costs and an increased mortality rate when affected patients are compared with the general population.

Rheumatoid arthritis is a debilitating disease that, if diagnosed early can be properly managed, controlling the disease activity, which is the only prevention strategy against

permanent joint damage or severe deformity available at the moment. There are available modern treatment methods which are effective at controlling disease activity and reducing long term disability (Woolf & Pfleger, 2003). It is imperative to identify patients early so that control of inflammation can prevent joint destruction and disability (Mody & Cardiel, 2008). The etiology of this disease currently still remains unknown, which makes anyone from different walks of life susceptible to the disease. Therefore developing a diagnostic tool that is easy to use, non-invasive and cost effective bridges the gap and makes early diagnosis possible for everybody. There are limitless potentials and upsides to the development of this technology; it can also be used as a potential Telemedicine tool, and thereby offering diagnostic options to those who live in remote areas where the community cannot afford sophisticated equipments such as magnetic resonance imaging (MRI) and high resolution ultrasound (HRUS). Due to the inexpensive nature of this technology, its use can also be extended to developing countries, where there are currently no diagnostic tools for RA due to the expensive nature of some of the current imaging tests being used such as MRI and HRUS.

The successful implementation of this technique as a potential diagnostic tool would help to reduce the wait times for the current gold standard methods of diagnosing of RA and allow these tools to be used for the diagnosis of other diseases. This technology has a potential to aid rheumatologists in the diagnosis of RA in cases where they are confronted with limited to no physical manifestation of the disease. One of the major limitations rheumatologists face is the inability to diagnose RA in cases where there are no physical manifestations such as swelling, or inflammation. TIR imaging could make a diagnosis possible without physical symptoms because this is a measure of temperature readings over specific joints that have been shown to be indicators of RA (Adea, 2009). One characteristic of RA is inflammation in the affected joints,

and these inflammations manifest themselves as abnormal increases in the temperature around these joints, which could be easily seen by the thermal imaging but not by the naked eye.

1.2. Rheumatoid Arthritis

This is an autoimmune disease associated with a chronic, inflammatory, systemic effect, which affects the musculoskeletal system. This disease is often progressive in nature and results in reduced physical function, pain, fatigue and joint damage (Uhlig et al, 2010). It is also characterized by a distinctive pattern of bone and joint destruction. The disease is manifested when the immune system, which is normally supposed to protect by fighting infections and diseases combats the body. During the flare-up, the immune system attacks the tissue that lines the joints, which causes pain, swelling, stiffness in those joints and affects their proper functioning. Over a period of time, RA begins to cause damage to bone and cartilage within the joints and weakens muscles and tendons that support the joints, and ultimately leads to joint destruction (NCBI, 2009).

It often begins in between the ages of 25 and 55 years old, however older people are more prone to this disease. It is also more prominent in women than in men, the statistic shows that it occurs in twice as many women as men. RA tends to run in families; research has been able to establish a genetic connection, showing that the genetic contribution to susceptibility is an estimated 60%. There has also been a link to shared human leukocyte antigen- DRBI alleles, which is associated with RA and has been shown to probably play a role in determining the severity of the disease than susceptibility to it (Woolf & Pfleger, 2003). All the joints in the body are susceptible to RA, but previous studies have shown that it is most common in the wrists and finger. It usually occurs in a symmetric pattern, where if it is present in one hand, it also affects

the other. This is one of the distinctive differences between RA and osteoarthritis, the latter occurring in an asymmetric pattern.

RA usually begins in smaller joints of the hands and the feet, then later spreads to larger joints. It is marked by persistent systemic inflammation and tissue damage (Costenbader et al, 2010). The inflamed joint lining or synovium extends and then erodes the articular cartilage and bone, causing joint deformity and progressive physical disability (Symmons et al, 2006). Due to the progressive nature of this disease, research has shown that it can place a substantial burden on those afflicted and their families. There is no cure for RA currently, so patients are subjected to living their lives around the disease, which has shown to have detrimental effects on the quality of life of those affected. Though there are modern treatment options available and there has been a reduction in the mortality rate due to RA, treatment options and therapy can be sometimes painful and there have been reported complications that affect areas of normal living such as physical, psychological and social functioning (Marra et al, 2005).

1.3. Epidemiology of RA

Past research has shown that there was no evidence of RA in Europe, Asia, or Africa before the 17th century, supporting the ideology that RA is a “modern disease” that can be attributed to an environmental (infectious) factor as its cause. It is believed by many that RA originated from North America, and then spread to Europe and other parts of the world (Abdel-Nasser et al, 1997), due to its high incidence rate among North Americans. Recent reports support this theory because till date, the highest occurrence rate can be found in Native Americans. 300 000 Canadians, 2.1 million Americans and approximately 260 000 French citizens are currently diagnosed with RA (Adea, 2009). There is no doubt about the worldwide

impact of this disease on the population. The disease is known to occur in all populations, although much of the work on the impact of the disease on functional disability and mortality has been done in the industrialized world (Kalla & Tikly, 2003)

According to reports, the rates of incidence in North America and Northern Europe ranges from 20 – 50 cases per 100,000 population, and the prevalence at 0.5 – 1.1%. In Southern Europe, however, the range is between 9 - 24 cases per 100, 000, with a lower prevalence at 0.3 – 0.7% (Toban et al, 2010). The prevalence of RA is estimated to be 0.5–1.0% worldwide. However, considerable variation exists among ethnicities, with a higher prevalence in populations of European ancestry than those of Asian ancestry (Kochi et al, 2009). The numbers for the specific incidence rate in developing countries are not known at this time. However, there have been epidemiological studies done in developing countries that have shown a lower but still important prevalence in different regions when compared to that in Caucasians, it is also suspected that RA probably starts at a younger age in developing countries. The incidence and prevalence of RA generally rises with increasing age until about age 70, then patients start to decline.

1.4. Causes of RA

The etiology of RA is still unknown, however there are several factors believed to be involved in the development of RA, which includes but are not limited to environmental (infectious), genetic and hormonal factors. Some studies have also shown that smoking, obesity, an adverse pregnancy outcome, age and also sex, with the female gender twice as susceptible to the disease as the male gender, are contributing factors. Environmental and immunogenetic

factors play a leading role in these multi-causal and often autoimmune disorders. Several amongst them are lifestyle disorders (Chopra & Abdel-Nasser, 2008).

1.5. Signs & Symptoms

During the early stages of rheumatoid arthritis, the disease tends to affect smaller joints first, the wrists, hands, ankles and feet, as the disease progresses and spreads, larger joints become affected- the shoulders, elbows, knees, hips, and neck. In the case of RA, symptoms occur symmetrically, in the same joints on both sides of your body. This is the most important distinguishing factor between Osteoarthritis and RA. The signs and symptoms may sometimes vary in the level of severity and may even come and go depending on the individual. Some of the signs and symptoms of RA may include, but are not limited to, joint pain, joint swelling, joint tenderness, red and puffy hands, firm bumps of tissue under the skin of the arms (rheumatoid nodules), fatigue, morning stiffness, which may last for hours, fever and weight loss. There are also periods of increased disease activity -called flare-ups or flares, alternate with periods of relative remission, during which the swelling, pain, difficulty sleeping and weakness fade or disappear.

There is a classification method which is the gold stand for diagnosing RA, which was established in 1987, by the American college of Rheumatology (ACR), Table 1 shows the classification criteria

Table 1-1: American College of Rheumatology's Criteria for the Classification of Rheumatoid Arthritis (Arnett 1998, 315-324)

Criterion		Definition
(1)	Morning stiffness	Morning stiffness in and around the joints, lasting at least 1 hour before maximal improvement
(2)	Arthritis of three or more joint areas	At least three joint areas simultaneously have had soft-tissue swelling or fluid (not overgrowth alone) observed by a physician. The 14 possible areas are right or left PIP, MCP, wrist, elbow, knee, ankle and MTP joints.
(3)	Arthritis of hand joints	At least one area swollen (as defined above) in a wrist, MCP or PIP joint
(4)	Symmetric arthritis	Simultaneous involvement of the same joint areas (as defined in 2) on both sides of the body (bilateral involvement of PIPs, MCPs or MTPs is acceptable without absolute symmetry).
(5)	Rheumatoid nodules	Subcutaneous nodules, over bony prominences, or extensor or juxta-articular regions, observed by a physician.
(6)	Serum rheumatoid factor	Demonstration of abnormal amounts of serum rheumatoid factor by any method for which the result has been positive in <5% of normal control subjects.
(7)	Radiographic changes	Radiographic changes typical of rheumatoid arthritis on postero-anterior hand and wrist radiographs, which must include erosions or unequivocal bony decalcification localized in or most marked adjacent to the involved joints (osteoarthritis changes alone do not qualify).

1.6. Treatment & Therapy Options

A cure for RA has been elusive; however there has been an improvement in treatment and therapy option over the last 50 years. Treatment options have evolved with improving medical advances, and have been able to successfully reduce the rate of mortality due to RA. Though a number of agents have proved useful in treating the disease, individual response to treatment is variable (Marra et al, 2005). Due to the aggressive nature of RA, it usually requires a lifelong treatment plan, which includes but is not limited to various intensive options, such as, medications, physical therapy, education, and in severe cases surgical intervention to relieve the

symptoms and progressiveness of the disease. If diagnosed in the early onset of the disease, aggressive treatment options can delay and effectively manage further joint destruction. In addition to rest, strengthening exercises, and anti-inflammatory drugs, the current standard of care is to begin aggressive therapy with disease-modifying anti-rheumatic drugs (DMARDs), once the diagnosis is confirmed.

DMARDs, commonly used to initiate therapy, include methotrexate, hydroxychloroquine, and sulfasalazine. Minocycline may be as effective as or more effective than hydroxychloroquine. Methotrexate is the most commonly used initial DMARD agent. Increasingly, combination therapy is being used for added effectiveness. The idea of "triple therapy," using methotrexate, hydroxychloroquine, and sulfasalazine together, has been found to be more effective than any one of the drugs alone. Combining methotrexate with a variety of other individual drugs may add benefit as well.

1.7. Thesis Objectives

The primary objective for this thesis was to combine and incorporate statistical datasets collected by a previous student into a classifier. The method selected was a decision tree, to help classify the datasets of temperature measurements of two groups: patients and control subjects, in order to distinguish between the two groups. After that has been satisfied, we wish to be able to determine the level of severity of the illness in each patient and also determine the varying degree of severity in each specified joint. Even though RA is a bilateral disease and affects both sides of the body, the degree of joint degeneration varies from joint to joint. For example, the smaller joints of the hands and feet are where RA first manifests itself in the early onset of the disease before progressing to larger joints in the knees, elbows, ankles and neck regions. Supervised learning helps to make the task of classifying images of patients easier, because it

takes an input variable (prior know parametric values) and from those variables predicts an output variable (e.g. presence or absence of RA). The goal was to find a function that best discriminates between the patients and the participants, and help eliminate factors that are not necessary in the assessment of RA. Future work would develop a prototype that is fully automated in order to assist physicians in diagnosing and assessing the disease status of their RA patients. Decision-tree learning is a common classification method (Ishii et al, 2010); it combines several binary tests in a tree like structure. The goal is to create a simple tree with a good predictive performance on the learning sample (Geurts et al, 2009). There are four specific - objectives to be completed in this thesis:

1. The first objective was to complete statistical analysis of the various joints (Feet, Ankles and Elbows) for which data were collected but not analyzed (Adéa, 2009, Frize *et al.* 2009, Frize *et al.* 2010). From that earlier work, the scope of the analysis was limited to the joints of the knees and the joints in the hand of 13 patients (patient 1 through 13) and 18 control subjects (participants 1 through 18); it was established in that work that the knees, 2nd and 3rd MCPs (hand joints) were statistically good indicators of RA. So for this thesis, after the recruitment of additional patients and control subjects (13 patients and 10 control subjects), the first objective here was to complete statistical analysis on the remaining joints in the feet, ankles and elbows to determine whether among these joints, any one(s) could also be good indicators of RA and to also complete analysis of the knee and hand joints of the patients and control subjects.
2. The second objective was to determine the presence of RA (discriminate between patients and control subjects). Using the various statistical dataset series (Min and Max temp, Min/Max and Median/Max, Mode/Min and Median/Min, Mode/Min and Mean/Min,

Mode/Max and Median/Max, Mode/Max and Mean/Max, Min/Max and Median/Min, Min/Max and Mean/Min, Min/Max and Mean/Min, Median/Max and Mode/Min, Mean/Max and Min/Max, Min/Max and Mode/Min and Mode/Min and Median/Max) to discriminate between the patient and control subject groups. These datasets were inputted into the decision tree to determine which of the datasets generated a classifier that could discriminate between the patient and control subject groups. To create this classifier, the dataset of all the joints (knee, 2nd MCP, 3rd MCP, and ankle) that statistically discriminated successfully between the patient and control subject groups were inputted all together in the decision tree.

3. The third objective was to determine which joints were more affected than others, because the progress of the disease varies from joint to joint depending on individuals. Even though the early onset of the disease manifests itself in smaller joints and progresses to larger joints, the rate of progress is not dependent on where the disease manifested itself; for example, the joint in the knee may deteriorate faster than those in the hands and might need more focused therapy option or surgical intervention than the joints in the hands even though the disease first manifests itself universally in the joints in the hands. This determination is necessary and important in order to help target certain joints in terms of a diagnosis, because each person's degree of severity in certain joint varies from one another. This was done by a process of elimination of variables (joints), where a combination of joints were inputted into the decision tree to determine which combination of joints generated the best classifier, indicating which joints were the best indicators of RA; and then the joints were further separated individually to determine which specific joints could on their own generate an excellent classifier. The results of the various dataset series were also compared to determine which combination helped improve the classification in terms of sensitivity and specificity.

4. The fourth objective, after successfully separating the patient and control groups efficiently, was to determine the level of RA activity in the patient groups into LOW, MEDIUM and HIGH, using the same dataset series used to satisfy the previous objectives. From the patient group, the individual patients are at varying stages of the disease; in some patients the disease is at an early onset and in others the disease is in its advanced stages with visible deformities, and in others the disease is at an intermediate stage. The goal here was to generate a classifier that could classify these patients into these three groups. It is important to note that the classifier's discriminatory value in separating this patient group was established in terms of its specificity and sensitivity and the area under the Receiver operator characteristic curve as well as compared to the qualitative assessment of the rheumatologist.

1.8. Thesis Outline

Chapter 2 provides a technical literature review of the science behind the technology that is used in this thesis. It gives a medical evaluation of the patients by the Rheumatologist and their current disease status, and then it discusses the science behind thermal imaging – Stephan Boltzmann law, Planck's law & electromagnetism. The chapter also looks at some of the other clinical applications of Infrared Thermography. And lastly, the chapter looks at classification techniques, decision trees and some of its performance measures.

Chapter 3 discusses the methodology. It takes a look, briefly, at the ethical review & clearance process, the recruitment of patients & participants for this project, and also the data collection process. Then the chapter concludes with a discussion on the classification of images and the testing using Decision Trees.

Chapter 4 begins with an analysis of the thermal images, and then discusses the resulting statistical data. It then shows the classification of the thermal images using decision trees and compares the best dataset series that help improve classification. The chapter concludes with a discussion of the results and discussion of whether the thesis objectives were met or not.

Chapter 5 provides the conclusion of this work and contributions to new knowledge, to the previous works done. It also proposes some new research objectives for future works in this study.

CHAPTER TWO

2. LITERATURE REVIEW

This chapter provides a medical evaluation of patient joints (the hands, elbows, ankles, knees and feet) by a rheumatologist, from previous work (Adéa, 2009), to give a better understanding of the level of illness severity, as this differs from patient to patient. It also gives a brief history and it also delves into some of the past clinical applications of Infrared Imaging. And then the chapter looks at classification techniques, decision trees and some of its performance measures.

2.1. *Medical Evaluation of Patient joints*

This medical evaluation was necessary in order to determine the level of severity in each patient and determine the joints that were most affected by RA, because each patient has particular joints that are more affected than others. In order to complete this session, the patients were asked to fill out a questionnaire (Appendix A) asking them a brief medical history of their RA and also of any other joint issues that are not RA specific that could also be attributed to inflammation in the joints or that could cause an increase in temperature. The purpose of this is to eliminate any other factors that could contribute to false temperature readings or an increase in the temperature, because so much of this work is based on extracting as accurate as possible temperature measurements from the specified joints. The questionnaire contained questions about their age, number of years with the disease and also a ranking of the disease on a scale of 1 to 10, where on the ranking scale 1 to 4 is LOW, 4 to 7 is MEDIUM, and 7 to 10 is HIGH, to

determine from the patient's perspective a disease level in terms of pain during inflammation. This medical evaluation provided us with pertinent information to help satisfy the fourth objective of this thesis. An assessment was also done by the rheumatologist (Appendix F)

2.2. *Infrared Imaging*

Infrared imaging is a technique that uses a thermographic camera to capture invisible infrared images; those images are converted to normal images that are visible to the human eye. For over five decades now, this imaging technique has had vast applications in many fields ranging from the military, to veterinary, to electronic maintenance applications, to food inspections. Thermography follows two principles: the mathematical model of Planck's law which states that any object whose temperature is above absolute zero Kelvin emits radiation at a specific rate and with a distribution of wavelengths. This wavelength distribution is dependent on the temperature of the object and its spectral emissivity, $\varepsilon(\lambda)$. The spectral emissivity, which may also be considered as the radiation efficiency at a given wavelength, is in turn characterized by the radiation emission efficiency based on whether the body is a blackbody, grey body or selective radiators. The blackbody is an ideal body. It is a perfect absorber that absorbs all incident radiation and is conversely a perfect radiator, this implies that a blackbody absorbs and emits energy of the maximum theoretically possible at a given temperature (Ng, 2009) and the Stephan-Boltzmann law, which defines the relation between radiated energy and temperature by stating that the total radiation emitted by an object is directly proportional to the object's area and emissivity and the fourth power of its absolute temperature. Due to the emissivity of human skin being extremely high (within 1% of that of a black body), measurements of infrared radiation emitted by the skin can be converted directly into accurate temperature values. This makes infrared imaging an ideal procedure to evaluate surface temperatures of the body (Amalu,

2003). The underlying idea of thermography is based on temperature changes in the human skin (see Appendix G for further details).

2.3. *Past Clinical Applications*

The use of infrared imaging as a medical diagnostic tool started in the early 1960's. The father of thermography as a screening technique was Lawson, who discovered in 1956 that the skin temperature over a cancer in the breast was higher than that of normal tissue. He also showed that the venous blood draining the cancer is often warmer than its arterial supply (Amalu *et al.*, 2006). After this ground breaking discovery, there were other published works from other researchers such as, Lloyd-Williams *et al.*, Gershon-Cohen *et al.*, Swearingen and Connell *et al.* all confirming Lawson's findings on thermography as a clinical screening method (Dodd *et al.*, 1969). However, the fall of thermography came in the 1970's after the sensitivity and specificity of infrared imaging was being questioned; its physical limitations (size, weight and cooling requirement), subjectivity in thermographic interpretation, and the expensive cost of IR systems were other factors.

But since the early discoveries of Lawson, and vast improvements made to the thermal IR cameras, there has been renewed interest in its medical application. These improvements include, the development of IR cameras with focal-plane arrays not requiring cooling, new detector materials with improved thermal sensitivity, and the development of smart image processing algorithms to enhance the interpretation of thermal signatures. The application of thermal infrared (TIR) imaging in medicine ranges from breast cancer screening, as earlier stated, to open heart surgery to image processing (Diakides, 2000).

2.4. *Application of TIR imaging in RA*

The application of TIR imaging from past research has been limited to its use as an assessment tool (Collins 1974 and Ring 1974) and effective evaluation tool (Bird *et al.* 1979) in its application in RA. It has never been explored as a potential stand-alone diagnostic tool until now. In their research, Collins and Ring used a Thermal Index (TI) calculation based on the isothermal temperature difference to quantify the measurement of synovitis.

$$\text{Thermal Index} = \frac{\sum (\Delta t \times a)}{A} \quad (2.1)$$

where Δt is the difference between the measured isothermal temperature and the lowest common isotherm recorded, a is the area occupied by isotherm (cm^2) and A is the total area of the thermogram (cm^2).

This TI reflected the mean temperature of a specified ROI. They established that TIR images of the hands, feet and knees can be used to identify patients with RA and as an assessment tool for the disease. In their work there was a decrease in the TI with treatment and therapy, and an increase in TI during periods of flare up. Their findings were confirmed by the research of Bird *et al.*, where they also showed that “thermography can be used to assess inflammation of the synovial membrane and to evaluate the effectiveness of an RA treatment” (Bird *et al.*, 1979).

However, in 1983, a new method of interpreting the thermal properties of TIR images of RA was suggested in the work of Salisbury to detect RA abnormalities in the knee, wrist, elbow and ankle joints (Salisbury 1983). He demonstrated that the quantification of synovitis by TIR imaging should be based on dysfunctional thermal patterns rather than by indexes, such as the

TI, that are based on absolute skin temperature values. However, it has been shown that, various external factors can affect the skin's surface temperature such as hot/cold beverages consumption, emotional state, circadian variation, physical activity, environment temperature and humidity, etc. (Reinberg 1976). Salisbury *et al.* introduced a Heat Distribution Index (HDI) that show the pattern and spread of the temperature distribution over the surface of a joint. They went on to prove that the HDI correlated better with joint inflammation and synovitis than Collins and Ring's TI. The TI proved to be less significant in identifying the presence of inflammation and was even less significant in identifying inflammation in afternoon TIR readings. The TI is more variable and less reproducible than the HDI, since it is greatly affected by the patient's circadian rhythm and the environment in which the images are taken. The HDI was able to identify a normal thermal distribution in the absence of inflammation in the knee, ankle, wrist and elbow joints. Alternatively, inflammation of the synovial membrane was repeatedly detected by the HDI analysis and these results were not affected by the time of day of the TIR readings (Adéa, 2009).

Salisbury *et al.*'s HDI is calculated based on the relative frequency distribution of the thermogram via a 256 grey level TIR image. A ROI of interest is delimited to cover the joint to be analysed. A pixel count is made at each grey level within the ROI and each resulting number is divided by the number of pixels in the ROI. Normal joints present a narrower relative frequency distribution (lower standard deviation) than a diseased joint. Salisbury *et al.* also added that the distribution of heat over a normal joint results in a positive temperature gradient from the centre to the periphery of the joint. They also noted that normal joints do not have localized areas of increased temperature, hot spots. An abnormal joint with synovitis can

therefore be described as a joint presenting with a negative thermal gradient with localized hot spots within the joint's ROI; this was also confirmed by Adéa in the earlier research.

In this thesis, TIR image analysis of the joints, the hands, elbows, feet, ankles and knees were all based on the temperature distribution methodology introduced by Salisbury, supported by many others and implemented by Adéa and myself. The temperature distribution pattern was analysed to see if abnormal localized regions of increased or decreased temperatures can be used to classify participants with RA.

2.5. *Pattern Classification techniques*

Pattern classification is the method of exploring the model that generated the patterns explored. Depending on different information over the model or the exploratory method used, pattern classification techniques can be further organized in different taxonomies. An example of such taxonomy can be seen in a model of statistical versus syntactical, parametric versus nonparametric dichotomies. For the statistical technique, the focus is on statistical properties of patterns, as was done in earlier work. Whereas a syntactical (or structural) like a decision tree uses models with some logical rules, as was done in this thesis. On the other hand, class-conditional densities of the model are assumed to be known in parametric techniques and not known in nonparametric ones. Examples of other taxonomies are deterministic versus stochastic (randomness is present during model search or learning for the latter), supervised versus unsupervised (learning is guided through target labels in the former), and metric versus nonmetric (relative to feature values) (Unay 2006).

2.5.1. *Decision Tree*

In the medical field, there are often times situations, where the medical decision maker will be faced with a sequential decision problem involving decisions that lead to different outcomes depending on chance. If the decision process involves many sequential decisions, then the decision problem becomes difficult to visualize and to implement. Decision trees are indispensable graphical tools in such settings. They allow for intuitive understanding of the problem and can aid in decision making (Ishwaran and Rao).

A decision tree is a graphical model describing decisions and their possible outcomes. Decision trees consist of three types of nodes (figure 2-3)

1. Decision node: This node often represents the decisions that can be made, and shows all the distinct options available at a node.
2. Chance node: This node shows chance outcomes. These are events that can occur but are outside the ability of the decision maker to control.
3. Terminal node: These are end nodes, where there are no further decision nodes or chance nodes. These nodes depict the final outcomes of the decision making process.

In this thesis, Rulequest's See5 software was used to generate the classifier used as a tool in the decision making process of the diagnosis of RA (1) determine the presence of RA from two distinct groups; (2) determine the joints that best indicate the presence of RA; and (3) determine the level of severity in the presence of RA.

Fig. 2-1: Preliminary sample model of the proposed decision tree for RA diagnosis.

2.5.1.1. Bootstrapping

Bootstrapping in its simplest form, simply means, instead of repeatedly analyzing subsets of the data, you repeatedly analyze subsamples of the data. Where each subsample, is a random sample with replacement from the full sample. Depending on the needs of the user, this method can be implemented on anywhere from 50 to 2000 subsamples. However, there are also various sophisticated bootstrap methods that can be used not only for estimating generalization error but also for estimating confidence bounds for network outputs (Efron and Tibshirani 1993).

2.5.2. Ensemble Decision Tree Classifier

An ensemble decision tree classifier is simply the creation of numerous decision trees for classification purposes. This is necessary because, single trees are known to be fairly unstable

especially with smaller databases; since the designing of a tree depends greatly on the dataset and variables used for training and testing. Therefore, relying on the creation and results of only one tree is inadequate. To avoid the instability of using single trees and also maintain robustness in the performance of the decision tree (DT) classifier, an ensemble method was used. The ensemble classifiers were created by bootstrapping the original training sets and allocating these into bootstrapped training subsamples (bTRAIN). In this method, the DT classifier created a tree from each training subset and tested each tree on the test set. A typical tree is created using the best split among all variables; however, another issue with DTs is that they choose variables according to local optima. This does not necessarily guarantee a global optimum (Mitra and Acharya, 2003). Once a tree is created in See5, the variables are ranked according to usage where some variables are not used at all. In order to optimize the DT classification once an initial tree was created, a variable used in the split was removed, and a new tree was created from the remaining variables. The performance of the new tree was monitored to observe the changes caused by the removal of the variable, if the removal had an adverse effect on the performance of the tree, then the removed variable was re-introduced back and another variable removed to create a new tree. These steps were repeated until the best performing tree was found. This tree was then used as one of the trees of the ensemble classifier. This same process was repeated for each bootstrapped training subset in the DT classifier.

2.6. Performance measures of Classification Techniques

2.6.1. Confusion Matrix (Contingency Table)

The confusion matrix is a matrix that displays the number of scores that are correctly predicted and incorrectly predicted by the model. The figure below shows the confusion datasets

for a two-class problem. Although it is worth noting that a confusion matrix can be extended to an n-class problem (Tan *et al.*, 2006).

Table 2-1: A 2 x 2 Contingency Table

	Positives	Negatives
Positives	TP	FP
Negatives	FN	TN

2.6.2. Correct Classification Rate (CCR)

This simply refers to the number of correctly predicted scores by the classifier. It is also known as the accuracy of the classifier:

$$CCR = \frac{\text{\textit{\# of correct prediction}}}{\text{\textit{Total \# of prediction}}} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2.4)$$

2.6.3. Error Rate

This simply refers to the number of incorrect predictions. The prediction model for the training data gives the apparent error which is usually lower than that of the true error found using the test data.

$$\text{Error rate} = \frac{\text{\textit{\# of wrong predictions}}}{\text{\textit{Total \# of predictions}}} = \frac{FP+FN}{FP+FN+TN+TP} \quad (2.5)$$

2.6.4. Sensitivity

The sensitivity, also known as, the true positive rate (TPR) of the classifier – given that the actual value is positive, is the fraction of value that is actually classified as true positive. In medical informatics such rates would be the positive result when the outcome is abnormal (Prince and Links, 2006).

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2.6)$$

2.6.5. Specificity

The specificity, also known as, the True Negative Rate (TNR) of the classifier – given that the actual value is negative, is the fraction of value classified as true negative. In medical informatics, such rates would be the negative result when the outcome is normal (Prince and Links, 2006).

$$\text{TNR} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (2.7)$$

Can also be expressed as,

$$\text{TNR} = 1 - \text{FP} \quad (2.8)$$

2.6.6. Prevalence

Prevalence is the prior probability that the subject has the disease before the test is applied; while the posterior probability is the probability of the disease after a test has been

applied. Rare outcomes have low prior probability. In order to assess the usefulness of the test, a comparison between the prior and posterior probability can be made. Predictive values are used for medical diagnostics evaluation to determine the probability that the diagnosis is correct. This is highly dependent on the patient population that the test is used for (Altman and Bland, 1994).

2.6.7. Positive Predictive Value

The PPV is the probability of the actual disease (positive outcome) given that the prediction is positive. PPV is proportional to prevalence therefore if prevalence of disease is low, PPV will not be close to 1 (even with high specificity and sensitivity). A disease with low prevalence would have a sharp decrease in the PPV. The PPV can be calculated using the following equations (Kelly *et al.*, 2008).

$$PPV = \frac{Sensitivity \times Prevalence}{Sensitivity \times Prevalence + (1 - Specificity) \times (1 - Prevalence)} \quad (2.9)$$

Can also be expressed as,

$$PPV = \frac{TP}{TP + FP} \quad (2.10)$$

2.6.8. Negative Predictive Value

The NPV is the probability of a non-disease or negative outcome given that the prediction is negative. A high NPV indicates a greater chance that a negative test has no abnormality. A rare outcome (low prevalence) would indicate a greater assurance that a patient with a negative test is correctly diagnosed (Altman and Bland, 1994). The NPV can be calculated using the following equations (Kelly *et al.*, 2008):

$$NPV = \frac{Specificity \times (1 - Prevalence)}{Specificity \times (1 - Prevalence) + (1 - Sensitivity) \times Prevalence} \quad (2.11)$$

Can also be expressed as,

$$NPV = \frac{TN}{TN + FN} \quad (2.12)$$

2.6.9. Receiver Operating Characteristic (ROC) Curves

ROC curves provide a visual model that displays the trade-off between sensitivity and specificity. The ROC curve is produced by graphing the false positive rate (FPR) which is the same as “1-Specificity” against the true positive rate (TPR). The visual model, in figure 2-4 presents points that are of importance as noted by Fawcett (2006).

Fig. 2-4: An ROC curve and the different points of significance (created from Fawcett 2006).

1. The coordinate (0,0) is located where no positive classification is given therefore no false positive classification exists. The opposite point is (1,1) where the classifier assigns a positive class label to all points, therefore the FPR is at a maximum.

2. **Point a** is a point, where most points are correctly classified.
3. At **point b**, the TPR is higher than a, but the FPR has increased as well.
4. **Point c** has a low FPR; however, its true positive rate is almost at 60%.
5. The diagonal line, **point d**, indicates random guessing. A point on the linear mark indicates that TPR and FPR are equal and the classifier performance is random. This classifier does not contain useful information.
6. The **point e** is below the random line and is worse than random guessing. Having a classifier performance in this area may indicate that useful information is contained in the classifier, but the application is incorrect.

Various operating points under different threshold values of the model provide the ROC curve. Though the curve assesses the performance of the model at each individual point, the area under the curve (AUC) presents an assessment of the whole model. The AUC is a scalar value of the ROC curve and is used to compare the performance of different models (Yuu, 2010).

2.6.10. Area Under the Curve

The AUC of the diagonal line has a value of 0.5 while the AUC containing point a, has a value closer to 1. Values less than 0.5 are worse than random guessing. The AUC is used to compare the performance between classifiers and will always have a value between 0 and 1. The AUC contains statistical property as it is the probability that the “the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance (Fawcett, 2006).” The AUC is a measurement of the model’s effectiveness in discriminating outcomes as shown in the Table 2-2 (Ambrosius 2007).

Table 2-2: AUC index and its effectiveness for discrimination

Min	Max	Effectiveness
	≤ 0.500	No discrimination (Random)
0.500	< 0.700	Poor discrimination
0.700	< 0.800	Acceptable discrimination
0.800	< 0.900	Excellent discrimination
0.900	1.000	Outstanding discrimination

CHAPTER THREE

3. METHODOLOGY

This chapter discusses the ethical review and clearance process, the recruitment of patients and control subjects for this project, the protocol to which the participant (patients and control subjects) had to adhere to for participation in the research, and the data collection process. The chapter concludes with a discussion of the classification of the datasets using Decision-Trees.

3.1. *Ethics Review*

For this research, the original proposal (submitted by Adéa) was approved by the Ethics board at the three institutions involved in the research, The Ottawa Hospital Riverside Campus, Carleton University and The University of Ottawa. Initial ethical clearance was given by the three ethics boards under the title of “Severity of illness measures in rheumatoid arthritis from multi-spectral imaging”. The principal investigator for the Ottawa Hospital for this research was Dr. Jacob Karsh, a rheumatologist from the Riverside Campus, where the patients were recruited. The two Principal investigators at Carleton University and University of Ottawa were professors from the Faculty of Engineering and Design at Carleton University and the School of Information Technology and Engineering at the University of Ottawa and students from the two institutions. The ethics clearance was requested from the Ottawa Hospital Research Ethics Board (OHREB), since the patients were recruited from the hospital. Also Ethics clearance was requested from the Carleton Research Ethics Committee and The University of Ottawa Research Ethics Board since the research involved the use of physical resources and equipment’s at both institutions. This thesis is the second phase and continuation of the objectives outlined in the

original proposal submitted , which was to explore the effectiveness of thermal Infrared imaging as a viable diagnostic tool to aid in the early detection and effective monitoring of RA. The continuation of this study has added valuable knowledge to Dr. Frize's Medical Information-technologies Research Group (MIRG) at Carleton University and has also raised other budding research questions that would aid in gearing the research towards the next phase.

3.2. Recruitment of Patients

Following the same recruitment protocol as was in the previous study (Adéa, 2009), the research participants were patients already diagnosed with RA from the Ottawa Hospital-Riverside Campus aged 19 years old and above. These patients were recruited by their Rheumatologist, Dr. Jacob Karsh, who informed them of the ongoing project and if they were interested in participating in it. Since RA is a disease that affects both sexes, patients of both sexes and of any age from 19 and above were asked to participate in the study. Dr. Karsh provided the patients with information about the study. If the patients were interested in participating in the research, the doctor provided them with the participation package, which contained the information and consent forms, and providing further information about the study and the consent form to sign (Appendix B). Once they had read and understood the information letter and still wanted to be a part of the research study, they directly contacted the co-investigator's student at Carleton University or the University of Ottawa to further discuss participation and to ask any further questions. After signing the consent form and discussing the expectation for the imaging session, an imaging session is scheduled. Those patients, who consented and completed the consent form, permitted the usage and storage of the digital IR images of their limbs and joints. No images of participants' faces were taken and no personal information was shared with Carleton University or the University of Ottawa's research teams.

The only criteria for exclusion from the study was whether the patients were diagnosed with joint issues not attributed to RA, patients who had recently suffered any kind of trauma that affected their joints, or patients with joint sepsis. The patients who participated in the study were not given any research incentives to participate in the study, and were not coerced into participating neither was there any adverse effect to their quality of care.

The control group participants, like the patients recruited, followed the same protocol and were subjects aged 19 years and above from both University Campuses, and had not been diagnosed with RA, or had any joint issues or recent trauma's; they were generally in good health and without pain or symptoms resembling RA. These control subjects were recruited to establish a range of temperature distributions for normal subjects and to provide a baseline for what was to be identified as normal. There were no incentives to participate in the study or were there any coercion of the control participants. They were given the same participation package as the RA patients (see Appendix B) and signed the same consent form which permitted the usage and storage of the digital IR images of their limbs and joints. No images of control subjects' faces were taken and no personal information was shared with Carleton University or the University of Ottawa's research teams.

In the first study by Cynthia Adéa, thirteen patients diagnosed with RA were recruited from the Ottawa Hospital-Riverside Campus and eighteen control subjects were recruited from Carleton University, the University of Ottawa and a few from outside the campuses that participated in the original research study. However, while furthering the project, for the purposes of classification, it was necessary to recruit more patients and control subjects to help improve the classification, so an additional thirteen patients were recruited again from the Ottawa Hospital-Riverside Campus and ten additional control subjects were recruited.

3.3. Collection of Data

3.3.1. Infrared Camera Specification

The FLIR A320 Researcher Infrared Camera from FLIR Systems was used to capture the TIR images. This IR camera uses an uncooled microbolometer focal plane array of 320×240 pixels at a refresh rate of 50/60 Hz. It operates in the $7.5\mu\text{m}$ to $13\mu\text{m}$ of the far IR spectral range of the electromagnetic spectrum. The A320 has a 24 mm germanium lens with an anti-reflective coating. The germanium lens renders a field of view that is $25^\circ \times 18.8^\circ$ with a minimum focus distance of 0.3 m. The camera's spatial resolution is 1.3 mrad, which means that at a distance of 1 m each pixel represents a square of $1.3\text{mm} \times 1.3\text{mm}$. The A320 has a thermal sensitivity of 0.07°C at 30°C and can measure temperature ranges from -20°C to $+120^\circ\text{C}$. The camera was connected to a laptop via an Ethernet cable, thereby capturing sequences of 14 bit digital thermal images at a maximum speed of 60 frames per seconds (FLIR Systems 2007).

3.3.2. Infrared Camera and recording settings

The software used during the imaging sessions was the ThermaCAM Researcher Pro 2.9 from FLIR Systems. It was via this software that measurement corrections were inputted by the user, the emissivity, the camera distance, the ambient temperature and the relative humidity. The A320 radiometric camera outputted emissivity measurements to the ThermaCAM software which converted the measurements into absolute temperatures while taking into consideration all the inputted corrections. The camera settings used for this thesis were as follows. The emissivity was kept constant at 0.98 for the skin. The camera distance ranged from 0.5 m to 1 m and was manually adjusted for every image captured via the settings options of the software. The ambient temperature and relative humidity of the environment were measured for each session

and were 23 ± 1 °C and 40 ± 2 % respectively for all the sessions. The image intervals for the recording conditions were set at 2, which means 30 images were taken per second during each recording time. The image presentation box was enabled to allow the user to view the images live and make manual adjustments to the camera for the best image captured (Adéa, 2009).

Fig. 3-1: A320 Infrared Camera from FLIR Systems (FLIR Systems, 2007)

Images were recorded in *.seq format for sequences of images and were subsequently exported into Matlab as *.mat files. The *.mat files contained the temperatures of each pixel of the image and information about the environmental settings.

3.3.3. Medical Thermal Infrared Imaging Protocol

Prior to the imaging session, each participant was given these guidelines to follow (adapted from Herry, 2007):

- Do not consume alcoholic beverages twenty-four hours prior to the session.
- Do not consume hot beverages at least one hour prior to the session.
- Do not wear rings, necklaces, anklets and/or bracelets during the session.

- Do not use talcum powder, lotion, drug or deodorant on the skin on the day of the session.
- Avoid prolonged sun exposure at least one week prior to the session.
- Avoid smoking at least two hours prior to the session.
- Avoid any intense physical exercise at least four hours prior to the session.
- Avoid procedures such as electromyography, acupuncture, myelography, transcutaneous electrical stimulation, hot or cold patches, or any other form of physiotherapy at least twenty-four hours prior to the session.

3.3.4. *Recording Procedures*

There were certain protocols that needed to be followed for the room to be conducive for an IR thermographic session. These sessions took place in a room that had no windows to avoid any reflective effects of light captured by the camera. There were no shiny or plastic floors and the only lights used were fluorescent lights. The temperature and humidity were measured before and after every session. They were uniform throughout the room and were kept constant throughout the entire session. The patients and control subjects were asked to adhere strictly to the medical thermal infrared protocol prior to the session. They were also asked to wear or bring along a sleeveless shirt and shorts to the session and to remove their socks and shoes to facilitate the imaging of different views of the feet and ankles (Adéa, 2009).

Before the recording session, the participants (patients and control subjects) were seated in a chair with their arms resting on the chair arms to the side with no contact to their body's and their bare feet relaxed on the floor for a cooling down period of 15 minutes to adjust their body temperature to reflect the ambient room temperature. During this time, the participants' surface body temperature was cooled sufficiently in a room remaining constant around 23 °C. The participants remained seated without any body parts in contact with one another and without

removing their feet from the bench to ensure that the surface temperature of their skin correctly reflected the internal temperature of the joints and limbs.

During the imaging session, the joints of interest were the elbows, wrist and hand joints, knees, ankles and feet joints. Each joint was captured from different anatomical views.

For the elbows, the first image was of the extended elbow and the images captured were of the posterior and anterior view of the frontal anatomical plane. Then the participants (patients and controls) were asked to flex their elbows at 90 degrees and images captured in the frontal plane. The flexed elbows were also imaged in the right and left sides. The images of the different anatomical views are shown below in grey level TIR images of the images that were captured of the elbows.

Table 3-1: Grey Level Thermal Infrared Views of the Elbow (Adéa, 2009)

For the wrist and hand joints, wrists and palm were extended and the joints were imaged in a single capture in the posterior and anterior view of the frontal anatomical plane. The images

of the different anatomical views are shown below in grey level of TIR images that were captured of the wrist and hand joints.

Table 3-2: Grey Level Thermal Infrared Views of the Wrist and Hand (Adéa, 2009)

The images of the knees were first from an extended straight standing up position and were captured in the posterior and anterior view of the frontal anatomical plane. The images of both extended knees were captured at the same time and then that of individual extended knees separately taken also. Also images were captured while the participants were in the sitting position (knees flexed at 90 degrees) in the anterior frontal view. The images of both flexed knees were captured at the same time and then that of individual flexed knees separately captured. The individual's flexed knees were also imaged in the right and left sides. The images of the different anatomical views of the knees are shown below in grey level TIR images.

Table 3-3: Grey Level Thermal Infrared Views of the Knee (Adéa, 2009)

For the ankles and feet joints, the images were captured in the posterior view of the frontal anatomical plane. For the posterior view, images were captured of both ankles at the same time and then that of individual ankles separately. Also, images were captured in the right and left sides of the ankles and feet joints. The top and the bottom view of the feet were also captured. For the top of the feet, images were captured at two distances - 0.5 m and 1m respectively. The top views were captured of both feet at the same time and then that of individual feet separately. The bottoms of the feet were captured at the end of the session in two

rounds. The first round was captured immediately after the imaging session and the second round was captured after a 5 minute resting and cooling period. During this cooling period, the feet remained propped up and relaxed on a stool to allow the skin surface of the feet to efficiently represent the intra-articular temperature of all the feet joints (Adéa, 2009). The images of the different anatomical views of the ankles and feet are shown below in grey level TIR images.

Table 3-4: Grey Level Thermal Infrared Views of the Feet (Adea, 2009)

3.4. Data Analysis

In order to be able to process the TIR images and perform the necessary statistical tests and subsequently classify the images, it is important to first review the aforementioned objectives of the thesis. The first objective was to complete statistical analysis on the remaining joints (elbows, ankles and feet) that were not analyzed in earlier work by Adéa which was limited to the analysis of the joints in the hands and knees, to determine if other joints could discriminate statistically between the patients and control subjects datasets. The second objective, after establishing the joints that could statistically discriminate between the patients and control subjects, was to use these temperature measurements as inputs into a decision tree to discriminate between the patients and control subjects. The third objective was to use these statistical datasets in a decision tree to determine (1) the combination of joints that could generate a classifier that determined the joints that were good indicators of RA, (2) the specific joints of the four joints (knee, 2nd MCP, 3rd MCP and ankle) that best indicated the presence of RA and also compared the various datasets series to determine which series combination generated the best classifier with the highest specificity and sensitivity. The fourth and last objective was to determine the level of RA activity in the patient groups and separate them into three group classes: LOW, MEDIUM and HIGH, using the same dataset series that successfully satisfied the second objective and then the results from the classification were compared with the rheumatologist's evaluation of RA activity in those patients.

3.4.1. *Conversion of TIR images to Grey Scale*

The first step to accomplishing the objectives specified in this thesis, was the conversion of the *.seq FLIR file into a *.mat MATLAB file using the FLIR software (ThermaCAM Researcher Pro 2.9). The images, now a matrix of temperatures in Kelvin, using the mat2gray function in MATLAB were converted into a normalized matrix ranging from 0 to 1. Then these normalized matrix were displayed via MATLAB's imshow function, displaying a gray scale image. The reason for this transformation to gray scale was in an effort to eliminate any biases that a pseudo-colour image may create when the image was being reviewed subjectively (by the researcher). This method, is corroborated by past research that has shown that pseudo-colours when interpreting TIR images is not a good practice given that humans are subject to psychological effect of hot and cold colours (Anbar 1991).

The next step after converting these images to gray scale was selecting the region of interest to be analyzed. In this thesis, the Regions of Interests (ROIs) were manually selected from the gray scale images using anatomical reference points with the aid of MATLAB's roipoly function. The selection of the region of interest played a significant role in the analysis of the images. However there were some drawbacks to this method because of its susceptibility to human error; there is no standard method of selection, which leaves the selection of the ROI to the interpreter's discretion. Therefore it was important to carry out the selection process with as much accuracy as possible. This meant that for each joint, the anatomical reference points were determined by determining the location of the synovial membrane (Moore, 2007). This determination was made through careful assessment and studying of the various anatomical reference point of each joint analysed. The rheumatologist in this study gave an assessment of where this reference points were located in the joints, however was unavailable to review the

images; this determination was also made from studying literature on where this reference points are located in the joint. The determination of the ROI was selected using a combination of this two methods. The joints analysed were those in the hands, the elbows, the feet, the ankles and the knees. For instance, in the joint of the knee, anatomical reference point used in the selection of the region of interest was the patella. The patella was used as the main anatomical reference point, because the synovial joint is found underneath it. The anatomical reference points used for the MCP, PIP and MTP joints are the articulations of these joints themselves. The MCP and PIP joints were identified by their ovoid surface. The synovial joint is found directly under the ovoid surface. The images shown below show the gray scale datasets of the original TIR image with the manually selected ROIs.

Table 3-5: Regions of Interests Manually Selected for the 2nd and 3rd MCPS, the 2nd and 3rd PIPs, the Wrist and the Knee (Adéa, 2009)

Once the joints were identified, MATLAB outputted an array of temperature values which represented the temperature of every pixel within the selected region of interest of the TIR image. The resulting array was a probability distribution of a real-valued random variable.

Measurements extracted from these arrays to be analysed were: max, min, mean, median, mode, standard deviation, skewness and kurtosis. The max and min measurements refer to the maximum and minimum temperatures within the array of the joint. The mean is the average temperature value of the elements of the array. The median is the temperature value of the middle element of the joint's array when all the elements of the array are arranged in either ascending or descending order according to their temperature values. The mode is the temperature value that occurs most frequently in the array of the joint. The mean, median and mode are measures of central tendency, the location of a distribution. The standard deviation is a measure of dispersion and refers to the variability of the array distribution around the mean value. The skewness and the kurtosis describe the shape of the distribution. The skewness is a measure of the asymmetry of an array's distribution. The kurtosis is a description of the peak of the array's distribution (Salvatore 2002).

From the literature review it has been established that certain measurements (such as max, min, mean, median, and mode) extracted from the TIR images are subject to inter-participant variation and many other factors (such as time of day, vascular distribution of the patient, environment, etc.). Therefore, in order to eliminate the possibility that a person might have warmer or colder temperatures than another, these measurements were slightly modified. This measurement modification was inspired by the Heat Distribution Index and Salisbury's research, where ratios, differences and dispersion measurements (variance) were used to compare the measurements of the control subjects and the patients. These modified measurements were based on the thermal distribution of the surface of the skin rather than the exact temperature reading, thus eliminating inter-participant differences (Salisbury 1983). Thus the modified datasets used for the analysis were:

Skewness	Max-Min
Kurtosis	(Mode – Mean)²
Variance	Mode/Min
Mode/Max	Median/Min
Median/Max	Mean/Min
Min/Max	

Salisbury's HDI is based on the dispersion (the variance) of the distribution of the thermal surface over the joint. In this thesis, many other measures of dispersion are used to characterize different dispersion aspects of the datasets. For instance, the skewness and kurtosis are direct representations of the temperature distribution's shape and thus indirectly represents the dispersion. The variance is the standard deviation (STD) squared and is the typical measurement of dispersion. The (Mode-Mean)² is the mode temperature minus the mean temperature squared. It represents the dispersion range between the mode temperature and the mean temperature.

To further explore datasets that eliminate inter-participant variation, ratios were also explored: Mode/Max, Median/Max, Mode/Min, Median/Min and Mean/Min are calculated by dividing the numerator temperature (by the mode, median or mean) by the denominator temperature (by either max or min). These ratios normalize the exact temperature value with the participant's own maximum or minimum temperature value. These ratios eliminated the variations caused by a naturally colder or warmer participant.

The Max-Min datasets is the maximum temperature minus the minimum temperature and represents the temperature range of the joint region. This range is explored to see if the datasets can be used to correctly represent the temperature range of control subjects and RA patients (Adéa, 2009).

The hypothesis is that the dispersion, ratio and difference datasets may be a better representation of the presence or absence of RA in participants.

3.4.2. *Lilliefors Test*

To complete the statistical analysis, the first step involved testing the distribution of the datasets for normality. If the datasets are not distributed normally, then the use of statistical tests derived from the normal distribution such as the t-test and ANOVA are invalid (Salvatore, 2002). In this current analysis, the Lilliefors Test of normality was used (Matlab, 2009, Adéa 2009). It was applied to the dataset series to determine if they were Gaussian. The result from this analysis helped in determining if the null hypothesis tests were applicable to the dataset. In order to accomplish the first objective stated, these hypothesis tests should show that the patients datasets were statistically different from the control subjects datasets at a significant level of at least 5% ($\alpha = 0.05$) and with a p-value lower than 0.05. The values selected for α and p are the generally accepted values for statistical significance in hypothesis testing (Salvatore, 2002). This is used to test the null hypothesis that the datasets samples come from a normal distribution against the alternative that they do not come from a distribution in the normal family. It is a 2-sided goodness-of-fit test used when the parameters of the distribution are unknown and must be estimated. The Lilliefors test statistic is:

$$KS = \max_x |SCDF(x) - CDF(x)| \quad (3.1)$$

where SCDF is the cumulative distribution function taken from the datasets samples and CDF is the normal cumulative distribution function with the same mean and standard deviation as the sample datasets (Matlab, 2009).

The `lillietest` function in MATLAB uses a table of critical values computed using Monte Carlo simulation for sample sizes less than 1000 and significance levels between 0.001 and 0.50. The significance level (α) is used to determine the region of rejection of the statistical test (critical value). If Lilliefors test statistic $>$ critical value, then the null hypothesis is rejected. If Lilliefors test statistic $<$ critical value, then the null hypothesis cannot be rejected (Salvatore, 2002). MATLAB outputs four results: h value, p value, KS value and critical value. The test returns the logic value $h = 1$ if the null hypothesis is rejected and 0 if it cannot be rejected at the 5% significance level. The significance level was always set to 0.05 in this thesis, to establish the same significance level used in previous work. The p value is the probability of observing an element from the datasets distribution if the null hypothesis is true. The KS value is the Lilliefors test statistic retrieved from the equation stated above. The critical value is the value that determines the rejection region of the test based on α and the degrees of freedom.

3.4.3. *Kruskal-Wallis Test and Ranksum Test*

After the normality test had been completed, the second step of the statistical analysis was applying hypothesis tests to the datasets. If the datasets were distributed normally, then parametric hypothesis tests such as the Student t-Test and the Anova test were be used to prove the statistical significance of the results. If the datasets were not distributed normally, then parametric hypothesis test were not applicable, then non-parametric hypothesis tests, such as the Kruskal-Wallis Test (Salvatore, 2002; Matlab, 2009) and the Ranksum Test (Matlab, 2009), were used to prove the statistical significance of the results. Every dataset from the control group was compared to every dataset from the patient group for every joint using MATLAB'S ranksum test, and then the results were confirmed with the Kruskal-Wallis test. This test performed a two-sided non-parametric test of the null hypothesis that data in the two samples were independent

samples from identical continuous distributions with equal medians, against the alternative that they do not have equal medians.

3.5. Classification Methodology

After the first objective of the thesis was accomplished, the next step was to use these dataset series from the established joints that showed statistical difference in the datasets of the control subjects and patient groups as input variables into a classifier. The goal behind this, was to create a data mining approach that would generate a classifier that improved recognition of both positive cases; presence of RA (sensitivity) and negative cases; no RA (specificity) and also showed the effect of the sample size on the classifier; and generated a classifier that showed which joints were good indicators of RA and compared the combination of 12 dataset series to determine which combination were the best discriminator. And lastly, the determination of the level of activity of RA in each patient, where they were classified into three classes: LOW, MEDIUM and HIGH.

3.5.1. Accomplishing Objective #2

The second objective was to discriminate between patients and control subjects. The goal was, using the various statistical dataset series (Min and Max temp, Min/Max and Median/Max, Mode/Min and Median/Min, Mode/Min and Mean/Min, Mode/Max and Median/Max, Mode/Max and Mean/Max, Min/Max and Median/Min, Min/Max and Mean/Min, Min/Max and Mean/Min, Median/Max and Mode/Min, Mean/Max and Min/Max, Min/Max and Mode/Min and Mode/Min and Median/Max) to establish which of the datasets, if any, were able to generate a classifier that could discriminate with a high enough specificity and sensitivity (over 85%

respectively) between the patient and control subject groups, and to also determine the effect of increase in the sample size on the classifier generated. To accomplish this task, the following steps were followed for each dataset series combination.

Step 1 Separate datasets into different dataset combination series. Establish the risk model.

Step 2 Input variables into the DT.

Step 3 Determine results of the DT

- Split each database into a train set (TRAIN) and test set (TEST). Bootstrap the TRAIN set to create five bootstrapped datasets b_TRAIN.
- Classify Patients and Control subjects using DTs.

3.5.2. *Accomplishing Objective #3*

The third objective was to assess which joints were more affected than others, in order to help target certain joints in terms of diagnosis, because each person's degree of severity in certain joint vary from one another. This was done in two ways, first the combination of joints that generated the best classifier was determined by a process of elimination of variables (joints) and alternations; the second step was to separate these joints individually to determine which joints created the best classifier indicating the presence of RA. Then the various dataset series were compared to determine which combination helped improve the classifications sensitivity and specificity.

Step 1 Separate datasets into different dataset combination series. Establish the risk model.

Step 2 Input variables into the DT.

Step 3 Determine results of the DT

- Split each database into a train set (TRAIN) and test set (TEST). Bootstrap the TRAIN set to create five bootstrapped datasets b_TRAIN.
- Classify Patients Joints DTs.

3.5.3. *Accomplishing Objective #4*

The fourth objective was to classify the level of severity of RA. After successfully being able to discriminate between the patients and the control subjects, the next step was generating a classifier that could determine the level of severity in the patient groups and separate them into three classes: LOW, MEDIUM and HIGH, using the same dataset series previously used to satisfy the second objective. However, it is important to note that only those dataset series established to be the best discriminators from the second objective were used to generate the classifiers. As in the previous objectives, the following steps were followed:

Step 1 Separate datasets into different dataset combination series. Establish the risk model.

Step 2 Input variables into the DT.

Step 3 Determine results of the DT

- Split each database into a train set (TRAIN) and test set (TEST). Bootstrap the TRAIN set to create five bootstrapped datasets b_TRAIN.
- Classify Patients into LOW, MEDIUM, HIGH levels of severity using DTs.

3.6. *Creating DT Input Variables*

3.6.1. *Input Variables for DT*

The initial variable list, as shown in the table below (Table 3-6), pertains to variables that were submitted to the See5 Decision Tree for feature selection. Additional predictor variables discovered during initial data processing steps and suspected to improve classification were also included. The degree of importance of these variables varied according to their attribute usage: Some of the most prominent variables were the mobility, in terms of range of motion that could be comfortably reached, the number of years the disease has been present and race. Race proved

to be an important aspect of the classification process, as it was observed during temperature measurement extraction that the participants with black ethnic backgrounds had a slightly higher temperature measurement than those from other races (Caucasian or Asian descent). Some of these variables were extracted from the questionnaire (Appendix A).

Table 3-6: Shows the variables submitted to the See5 software and their description

VARIABLE	DESCRIPTION
PART	Participant #
SEX	Gender (Male or Female)
AGE	Age (Years)
FRP	Flare up period (True or False)
MEDS	Medications on
SURG	Surgical Intervention (True or False)
ALT_THER	Alternative therapy
ACT_LEV	Activity level (lifestyle)
MOB	Level of mobility
MORN_STIFF	Morning stiffness
YEARS	Years with diseases
TIME	Time of day of imaging session
KNEE	Knee joint
MCP2	2nd Metacarpophalangeal joint
MCP3	3rd Metacarpophalangeal joint
ANK	Ankle Joint
BLACK	Black
WHITE	White
ASIAN	Asian
OTH_ISS	Other (Any) joint issues

3.6.2. *Dividing the Dataset*

The whole dataset was split into a training and test set: 70% of the data was allocated for the training (TRAIN) portion and tree generation and 30% of the data was used for the testing portion (TEST) of the tree classifier. The training set was bootstrapped three times (using about 90%), creating the bootstrapped training subsamples (bTRAIN).

3.6.3. *Ensemble Decision Tree*

Redundant or similar data that came from the statistical analysis were used for the initial DT classifier. All these variables were used to generate the first DT. See5 displays which attributes have the most contribution to the classifier in terms of percentage. The steps used in the creation of each of the three DT were as follows:

1. Create a DT using all the predictor variables found in Table including confounding variables.
2. Attributes that contribute to less than 1% to the classifier are not displayed in the attribute usage list. We ignore these variables when creating the next tree – ignoring the variable with the least contribution according to the attribute usage.
3. Re-generate a new tree using the modified variable subset list.
4. Remove each variable iteratively before regenerating a tree until the tree has optimal sensitivity, specificity and minimal error.

CHAPTER FOUR

4. RESULTS AND DISCUSSION

This chapter begins with an analysis of the thermal images, and then discusses the resulting statistical data. It then shows the classification of the thermal images using decision trees and comparing the best dataset series that helps improve classification. The chapter concludes with a discussion of the results and discussion of whether the thesis objectives stated were rejected or confirmed.

4.1. Results

In this chapter, all raw data measurements extracted from the original Thermal InfraRed (TIR) images can be found in Appendix D. The datasets used for analysis and classification purposes are all calculated from the raw measurements. All the classification decision tree results for the datasets can be found in Appendix E.

The table below shows the average value for each dataset of every joint for the control and patient groups.

Table 4-1: Average values for each dataset of each joint for the patient and control groups

Average Values for:										
Joints		Variance	Mode/Max	Median/Max	Min/Max	Max-Min	(Mode-Mean) ²	Mode/Min	Median/Min	Mean/Min
Ankle	Controls	0.6397	0.9950	0.9951	0.9891	3.3049	0.3933	1.0059	1.0060	1.0060
	Patients	0.7559	0.9944	0.9947	0.9875	3.8072	0.5447	1.0070	1.0072	1.0070
Knee	Controls	0.3594	0.9889	0.9958	0.9896	3.1589	0.1298	1.0067	1.0062	1.0060
	Patients	0.4650	0.9893	0.9964	0.9911	2.6986	0.2694	1.0054	1.0054	1.0051
2nd MCP	Controls	0.1400	0.9964	0.9968	0.9943	1.7248	0.0492	1.0022	1.0025	1.0026
	Patients	0.1421	0.9972	0.9971	0.9938	1.8992	0.0435	1.0035	1.0034	1.0033
3rd MCP	Controls	0.0883	0.9911	0.9974	0.9955	1.3563	0.0442	1.0015	1.0019	1.0019
	Patients	0.0628	0.9933	0.9978	0.9962	1.1577	0.0288	1.0016	1.0016	1.0017
2nd PIP	Controls	0.0762	0.9977	0.9979	0.9958	1.2555	0.0495	1.0019	1.0021	1.0021
	Patients	0.0707	0.9978	0.9980	0.9955	1.3603	0.1521	1.0022	1.0025	1.0025
3rd PIP	Controls	0.0794	0.9982	0.9983	0.9956	1.3230	0.1320	1.0026	1.0027	1.0026
	Patients	0.0750	0.9983	0.9982	0.9952	1.4747	0.0209	1.0031	1.0030	1.0030
Wrist	Controls	0.1376	0.9974	0.9973	0.9941	1.8068	0.0538	1.0033	1.0033	1.0032
	Patients	0.1619	0.9971	0.9969	0.9934	2.0290	0.0507	1.0038	1.0036	1.0035
1st MTP	Controls	0.1041	0.9979	0.9978	0.9955	1.3599	0.0526	1.0024	1.0023	1.0023
	Patients	0.0963	0.9978	0.9978	0.9958	1.2687	0.0633	1.0022	1.0024	1.0021
5th MTP	Controls	0.0690	0.9979	0.9980	0.9961	1.1570	0.0494	1.0018	1.0019	1.0019
	Patients	0.0681	0.9981	0.9982	0.9961	1.1607	0.0225	1.0020	1.0021	1.0020
Elbow	Controls	0.4018	0.9955	0.9973	0.9906	2.8615	0.2110	1.0049	1.0067	1.0048
	Patients	0.4428	0.9954	0.9953	0.9902	3.0029	0.2201	1.0053	1.0052	1.0051

*Participants 9 & 10 (control subjects) data were excluded from the group

From the above table, it is important to note that for the control group's averages the calculation from 52 datasets values (26 control subjects x 2), because each control subject presented two TIR images per joint – the left joint and the right joint. Also for the patient group's averages, the same approach was used; they were calculated from 52 datasets values (26 RA patients x 2). This is important to note, because as with the nature of RA, it is an auto-immune disease that affects the joints bilaterally – meaning the disease is present in the joints on both sides of the body. For instance, if the right wrist is affected by RA, the left wrist would also be affected by RA.

The reason for the exclusion of participants 9 and 10 (control subjects) from the research was because those participants showed exceedingly higher temperatures than those observed in the normals. This led to their exclusion because, from their results, even though they were not diagnosed with RA, these abnormally high temperature ranges could possibly be attributed to potential joint issues that were yet to be diagnosed at the time of the study or it could also be attributed to the fact that these participants did not strictly adhere to the infrared imaging protocol (see section 3.3.3), with various environmental factors influencing their temperature measurements. It is also important to note that their results were excluded from both the statistical analysis and the classification for the purpose of consistency.

4.2. *Statistical Analysis*

To complete the statistical analysis described in chapter 3, Lilliefors test and Ranksum test were performed on the datasets. All the statistical explanations and equations provided in this chapter were derived from MathWork's MATLAB Help files and from D. Salvatore and D. Reagle's "Statistics and Econometrics" book from the Schaum's Outline Series of McGraw-Hill Companies (2002).

4.2.1. *FIRST OBJECTIVE – determining the joints that statistically discriminate best between the patients and control subjects*

To accomplish this first objective, the first step was determining whether the data samples calculated from the TIR measurements came from a normal distribution. This was determined by using the Lillietest function in MATLAB. So, random datasets for random joints were selected to test for normality using MATLAB's *lillietest* function. The table below shows MATLAB's four outputs obtained by the normality test. From this table we can conclude that the

datasets distribution is not from a normal family, the table shows that $h = 1$ and the p values are lower than α ($\alpha = 0.05$); therefore rejecting the null hypothesis.

Table 4-2: MATLAB Lilliefors Test Results for Randomly Selected Datasets

Matlab Lilliefors test for randomly selected joints						
Participant Type	Joint	Dataset	MATLAB Outputs			
			h Value	P Value	KS Value	Critical Value
Control Subjects	Ankle	Skewness	1	0.0010	0.1456	0.1620
	1st MTP	Kurtosis	1	0.0216	0.3777	0.1620
	3rd MTP	Kurtosis	1	0.0031	0.2146	0.1620
	Elbow	Max Temperature	1	0.0150	0.1952	0.1620
	1st PIP	Min Temperature	1	0.0002	0.1927	0.1620
	3rd PIP	Variance	1	0.0024	0.1771	0.1620
	2nd MCP	Variance	1	0.0121	0.2399	0.1620
	3rd MCP	Max Temperature	1	0.0056	0.1990	0.1620
	Knee	Skewness	1	0.0198	0.1782	0.1620
Patients	Ankle	Kurtosis	1	0.0515	0.3110	0.2132
	1st MTP	Variance	1	0.0037	0.2654	0.2132
	3rd MTP	Kurtosis	1	0.0451	0.4142	0.2132
	Elbow	Min Temperature	1	0.0040	0.1664	0.2132
	1st PIP	Max Temperature	1	0.0379	0.1999	0.2132
	3rd PIP	Skewness	1	0.0606	0.1846	0.2132
	2nd MCP	Max Temperature	1	0.0210	0.4005	0.2132
	3rd MCP	Skewness	1	0.0111	0.3792	0.2132
	Knee	Kurtosis	1	0.0001	0.2444	0.2132

The results from above are of the Lilliefors test performed on eighteen datasets representing the thermal distribution of the joints, and they were shown not to be normally distributed (since $h = 1$ in all datasets) at a 5% significance level ($\alpha = 0.05$). The KS values were all superior to the critical values and the p -values are all lower than α ; from this it can be confirmed and concluded that the datasets are not from the normal Gaussian family. Therefore, for the purposes of this thesis, it would be assumed from here on that all the datasets are not

normally distributed, since the eighteen randomly selected datasets do not show normality. As a result, as stated earlier, parametric hypothesis tests cannot be used for the statistical analysis. Instead of the Student t-Test and the Anova Test, the Kruskal-Wallis Test and the Ranksum Test are applied to the datasets.

The next step was to show that the control group's datasets were statistically different from the patient's datasets, in essence, showing that TIR images could be used to discriminate between the control and patient groups. Since it had been established that the datasets were not normally distributed, non-parametric hypothesis test were used to show this. The Kruskal-Wallis test and the Ranksum test were implemented for this purpose. The Kruskal-Wallis test is a nonparametric version of the classical one-way ANOVA, and an extension of the Wilcoxon ranksum test for more than two groups. This test is based on the standard Anova table using ranks rather than the numeric values of individual sample points. The function compares the medians of the samples, and returns the p -value for the null hypothesis that all samples are drawn from the same population (or equivalently, from different populations with the same distribution) (Matlab 2009).

MATLAB's ranksum test, also a non-parametric test, is equivalent to a Mann-Whitney U -test, and is also similar to the Kruskal-Wallis test. It is a two sided non-parametric test with the null hypothesis that two datasets are independent samples from identical continuous distributions with equal medians, against the alternative that they do not have equal medians. If the null hypothesis of the Kruskal-Wallis and the Ranksum tests are rejected at a significance level of 5% with a p -value lower than 0.05, it is fair to say that the two compared datasets are not from the same distribution and are statistically different (Matlab, 2009).

MATLAB's ranksum test outputs two results: h value, p value. The h value is 1 if the null hypothesis is rejected and 0 if it cannot be rejected at the 5% significance level. The p value is the probability of observing an element from the datasets distribution if the null hypothesis is true. If the h value is 1, with a p -value lower than 0.05, it is possible to conclude that the datasets of the control group are statistically different from the datasets of the patient group (Matlab, 2009). The table below demonstrates the two MATLAB outputs from the ranksum test performed on the two groups (control subjects and patients) datasets distribution.

Table 4-3: MATLAB's Ranksum Test Results Comparing the Datasets of the Control and the Patient Group

MATLAB Ranksum Test Results comparing the Datasets of the control and patients							
Joint	Datasets	P Value	h value	Joint	Datasets	P Value	h value
Ankle	STD	0.7562	0	1st MTP	STD	0.0235	1
	Skewness	0.3411	0		Skewness	0.0113	1
	Kurtosis	0.2453	0		Kurtosis	0.7654	0
	Mode/Max	0.9842	0		Mode/Max	0.6752	0
	Median/Max	0.0011	1		Median/Max	0.7550	0
	Min/Max	0.0034	1		Min/Max	0.3511	0
	Variance	0.0167	1		Variance	0.0253	1
	Max- Min	0.0451	1		Max- Min	0.0026	1
	(Mode - Mean)2	0.2451	0		(Mode - Mean)2	0.9880	0
	Mode/Min	0.1675	0		Mode/Min	0.2227	0
	Median/Min	0.0063	1		Median/Min	0.4710	0
	Mean/Min	0.0411	1		Mean/Min	0.5634	0
Joint	Datasets	P Value	h value	Joint	Datasets	P Value	h value
1st PIP	STD	0.2349	0	2nd PIP	STD	0.7217	0
	Skewness	0.1154	0		Skewness	0.5622	0
	Kurtosis	0.6799	0		Kurtosis	0.5001	0
	Mode/Max	0.1000	0		Mode/Max	0.3461	0
	Median/Max	0.5644	0		Median/Max	0.1286	0
	Min/Max	0.9888	0		Min/Max	0.5627	0
	Variance	0.3423	0		Variance	0.0631	0
	Max- Min	0.7787	0		Max- Min	0.1117	0
	(Mode - Mean)2	0.3212	0		(Mode - Mean)2	0.9451	0

	Mode/Min	0.4467	0		Mode/Min	0.5400	0
	Median/Min	0.0654	0		Median/Min	0.1005	0
	Mean/Min	0.2354	0		Mean/Min	0.2911	0
Joint	Datasets	P Value	h value	Joint	Datasets	P Value	h value
3rd PIP	STD	0.7511	0	2nd MCP	STD	0.5644	0
	Skewness	0.3981	0		Skewness	0.0033	1
	Kurtosis	0.0047	1		Kurtosis	0.8722	0
	Mode/Max	0.7770	0		Mode/Max	0.0176	1
	Median/Max	0.3344	0		Median/Max	0.3429	0
	Min/Max	0.3961	0		Min/Max	0.2277	0
	Variance	0.4859	0		Variance	0.1058	0
	Max- Min	0.7216	0		Max- Min	0.2592	0
	(Mode - Mean)2	0.0782	0		(Mode - Mean)2	0.3366	0
	Mode/Min	0.4455	0		Mode/Min	0.0097	1
	Median/Min	0.2786	0		Median/Min	0.2145	0
	Mean/Min	0.0882	0		Mean/Min	0.2365	0
Joint	Datasets	P Value	h value	Joint	Datasets	P Value	h value
3rd MCP	STD	0.0175	1	Knee	STD	0.0235	1
	Skewness	0.3586	0		Skewness	0.4555	0
	Kurtosis	0.7091	0		Kurtosis	0.4120	0
	Mode/Max	0.0312	1		Mode/Max	0.7231	0
	Median/Max	0.0101	1		Median/Max	0.6666	0
	Min/Max	0.0345	1		Min/Max	0.0035	1
	Variance	0.0175	1		Variance	0.0253	1
	Max- Min	0.0008	1		Max- Min	0.0145	1
	(Mode - Mean)2	0.0245	1		(Mode - Mean)2	0.8971	0
	Mode/Min	0.2019	0		Mode/Min	0.0222	1
	Median/Min	0.0400	1		Median/Min	0.0147	1
	Mean/Min	0.0115	1		Mean/Min	0.0045	1
Joint	Datasets	P Value	h value	Joint	Datasets	P Value	h value
Elbow	STD	0.2260	0	Wrist	STD	0.3684	0
	Skewness	0.3922	0		Skewness	0.2112	0
	Kurtosis	0.7620	0		Kurtosis	0.2341	0
	Mode/Max	0.4767	0		Mode/Max	0.0642	0
	Median/Max	0.1925	0		Median/Max	0.4992	0
	Min/Max	0.3104	0		Min/Max	0.2431	0
	Variance	0.7747	0		Variance	0.5666	0

Max- Min	0.7324	0		Max- Min	0.6789	0
(Mode - Mean) ²	0.4428	0		(Mode - Mean) ²	0.7422	0
Mode/Min	0.5960	0		Mode/Min	0.4105	0
Median/Min	0.0765	0		Median/Min	0.3982	0
Mean/Min	0.9267	0		Mean/Min	0.5629	0

The Kruskal-Wallis test was also performed on the distribution datasets of the two groups and results yield the same results as the ranksum test, thereby verifying the hypothesis test results above.

The table above (Table 4-3) highlighted in blue were the datasets where the null hypothesis was rejected at a significance level of 5% with a p-value that was lower than α . These highlighted test results were the ones that successfully discriminated between the control group and the RA group datasets. Therefore, the first objective, which was to determine the joints that could statistically discriminate between the patients and control subjects, is satisfied since:

- 1- The Median/Max, Min/Max, variance, Max-Min, Median/Min, Mean/Min of the ankle were statistically different for the control and patient group;
- 2- The standard deviation (STD), skewness, variance, Max-Min of the 1st MTP were statistically different for the control and patient groups; however, the 1st MTP is not an indicator of RA; rather, it is an indicator of osteoarthritis. It was concluded that even though the 1st MTP was able to discriminate between the two groups, it could also mean that those patients had osteoarthritis;
- 3- The skewness, Mode/Max, Mode/Min datasets of the 2nd MCP were statistically different distributions for the control and patient group;

- 4- The standard deviation (STD), Mode/max, Median/max, Min/max, variance, Max-Min, $(\text{Mode-Mean})^2$, Mean/Min datasets of the 3rd MCP showed a statistical difference between the control and patient distributions;
- 5- The control group's kurtosis datasets of the 3rd PIP was statistically different than the patient's kurtosis datasets of the 3rd PIP;
- 6- The standard deviation, Min/max, Variance, Max-Min, Mode/Min, Median/Min, Mean/Min datasets of the knee are statistically different distribution for the control and patient group.

4.3. Classification

The classifications, construction of the decision tree of the datasets were performed using the Rulequest See5 software. The classifier was generated to determine the presence of RA; to also determine the joints that effectively classified the presence of RA among the joints (2nd and 3rd MCP's, Knee and Ankle) statistically established to discriminate between the patient and control subject groups, by a process of elimination of variable (joints) and to classify the level of severity of RA (into three class groups: LOW, MEDIUM and HIGH).

4.3.1. SECOND OBJECTIVE – determining the presence of RA using the patients and control subjects dataset series

The first decision tree (DT) was generated from the dataset of the original participants in the study (Using 13 patients and 16 control subject). This was done in order to determine whether the addition of new participants into the study, had any effect on the classifier; whether the classifier showed an improvement or deteriorated. The result (Table 4-4) of the DT using this

sample size showed a level of consistent accuracy in terms of its specificity and sensitivity among the five bootstrapped DT's. Although the classifier was able to determine the presence of RA in two groups, it was not the most efficient classifier with its sensitivity ranging from 70 to 72% and its specificity ranging from 74 to 80%. The variables that varied in the DT's were the AGE and the joints (KNEE, ANKLE, MCP2, and MCP3). The root variable which was the MIN and MAX temperatures remained the same among the five bootstrapped DT's; this was used to create all five bootstrapped DT's. The AGE, KNEE and ANKLE were used to create DT 3 and 4, while the MCP2 and MCP3 were used to create DT 2 and 5.

Table 4-4: Min and Max dataset Decision Tree result (Using 13 patients and 16 control subjects)*

DT #		1	2	3	4	5
Train	Sensitivity	72.2	72.0	71.0	70.2	72.2
	Specificity	80.0	77.5	79.0	78.1	79.0
	CCR	74.7	76.3	75.2	74.3	75.8
Test	Sensitivity	72.1	72.2	70.0	72.2	72.2
	Specificity	79.2	79.2	74.0	77.0	80.0
	CCR	76.5	75.2	73.4	74.2	79.5

This same step was repeated for the remaining 11 dataset combination. These datasets were the root variables i.e., Min/Max and Median/Max (Column 1 in Table 4-5), while the AGE and joints (KNEE, ANKLE, MCP2, and MCP3). The table below (Table 4-5) illustrates the results of the DT for the different combinations and compares them with one another. From the table below, it is shown that the Min and Max dataset had the best discriminatory value of the datasets (using 13 patients and 16 control subjects) with its specificity and sensitivity at 80 and 72% respectively, while the Mode/Min and the Mean/Min had the worst with a specificity and sensitivity of 55 and 45 % respectively. However the Min/Max and Median/Min, Median/Max

and Mode/Min, and Mode/Max and Mean/Max also proved to be good discriminators, which could determine the presence of RA.

Table 4-5: Table showing the results of the DT combination of 12 different dataset series (Using 13 patients and 16 control subjects)

Dataset	Sensitivity (%)	Specificity (%)
Min and Max	72	80
Min/Max and Median/Max	65	52
Mode/Min and Median/Min	53	70
Mode/Min and Mean/Min	45	55
Mode/Max and Median/Max	48	59
Min/Max and Median/Min	69	79
Min/Max and Mean/Min	66	63
Median/Max and Mode/Min	70	77
Mean/Max and Min/Max	50	71
Min/Max and Mode/Min	61	45
Mode/Min and Median/Max	69	54
Mode/Max and Mean/Max	72	79

After using the dataset of the original participants (13 patients and 16 participants), the dataset from the newly recruited participants (13 patients and 10 participants) were inputted into the decision tree. The result (Table 4-6) of the DT reflects the increased sample size and the effect this increase had on the classifier. Using the same methodology as that used in the previous DT's (see Table 4-4), the DT was bootstrapped five times and the variables that varied in the DT's were AGE and joints (KNEE, ANKLE, MCP2, and MCP3); DT 3 and 4 were created using AGE, KNEE and ANKLE while DT 3 and 4 were created using MCP2 and MCP3. As

was in the previous DT, the Min and Max dataset had the highest specificity and sensitivity at 92 and 96% respectively. Comparing the results of the Min and Max dataset, the conclusion can be reached that the larger sample size generated a classifier that could excellently discriminate between the patients with RA and the control subjects without RA.

Table 4-6: Min and Max dataset Decision Tree result (Using 26 patients and 26 control subjects)*

DT #		1	2	3	4	5
Train	Sensitivity	100	95.3	91.0	94.4	90.0
	Specificity	93.2	92.7	88.7	86.0	87.5
	CCR	94.6	92.0	88.6	90.2	87.7
Test	Sensitivity	90.2	90.6	91.5	92.0	96.1
	Specificity	88.9	86.5	92.3	94.4	92.5
	CCR	89.4	87.6	90.7	92.2	94.5

As was done with the original sample size, the same steps were repeated for the modified sample size; five bootstrapped DT's were generated for the remaining combination of 11 other dataset series. The results for the DT's are shown in the table below (Table 4-7). This table illustrates the efficiency/accuracy of the classifiers and then compares them against one another. As was expected, the Min and Max dataset showed the highest accuracy amongst the classifiers with a sensitivity and specificity of 96 and 92% respectively. Also the Min/Max and Median/Max; Mode/Min and Median/Min; Min/Max and Median/Min; and Mode/Max and Mean/Max also proved to be excellent discriminators with a sensitivity that ranged from 89 – 96% and a specificity that ranged from 87 – 92%. Another interesting observation was from the Min/Max and Median/Max and Mode/Min and Median/Min series; these two dataset combinations proved to be excellent discriminators with the increased sample size (26 patients and 26 participants) but did not show much of a discriminatory value with the original sample size (13 patients and 16 control subjects) . Even though some of the other dataset series proved to

be fairly efficient discriminators with a specificity and sensitivity at or above 80%, they were excluded from the highlighted dataset series that proved to be the best indicators because compared to the other datasets with a sensitivity at or above 89% and a specificity at or above 87%; they were weaker. For the purpose of this thesis, a range from 85% and above was chosen using AUC index (section 2.6.10) which shows the effectiveness of a classifier according to the level of the AUC index. It appears that results of 85% or higher are excellent. As was seen with the Min/Max and Median/Max and Mode/Min and Median/Min series, it can be concluded that with a larger sample size there could be an improvement to the classifier generated for the Mode/Min and Median/Min, and Median/Max and Mode/Min dataset. Comparing the results from the classifier using the original dataset (13 patients and 16 control subjects) and the modified dataset (26 patients and 26 control subjects), the observation was made that the increase in sample size helped improve the discriminatory value of the classifier, for instance, in the Min and Max dataset, there was an increase in sensitivity from 72 to 96% and the specificity increased from 80 to 92%. The same observation was made in all the other dataset series also. Increasing the number of points in the datasets seems to have helped in a better training of the classifier and in reducing the error rate in the classification model. It is not known at this point if additional participants would lead again to better results or whether the number used in this research was sufficient and optimal.

Table 4-7: Table showing the results of the DT combination of 12 different dataset series (Using 26 patients and 26 control subjects)

Dataset	Sensitivity (%)	Specificity (%)
Min and Max	96	92
Min/Max and Median/Max	90	87
Mode/Min and Median/Min	94	92
Mode/Min and Mean/Min	80	76

Mode/Max and Median/Max	75	70
Min/Max and Median/Min	95	92
Min/Max and Mean/Min	65	60
Median/Max and Mode/Min	80	81
Mean/Max and Min/Max	79	77
Min/Max and Mode/Min	50	50
Mode/Min and Median/Max	60	62
Mode/Max and Mean/Max	89	87

From these results, the following conclusions were made; satisfying the second objective:

- 1- The Median/Max, Min/Max, Median/Min, Mode/Min, Mode/Max of the various joints (ankle and 2nd and 3rd MCP's that discriminated statistically between the patient and control subjects, also proved to be important in classifier when using the combination of Mode/Min and Median/Min, Min/Max and Median/Max, Min/Max and Median/Min, and Mode/Min and Median/Min.
- 2- The best dataset combination that effectively determined the presence or absence of RA from the sample were the Min and Max, Mode/Max and Mean/Max, Min/Max and Median/Min, Mode/Min and Median/Min, and Min/Max and Median/Max.
- 3- Increasing the sample size of the datasets helped improve the classifier generated, showing an increase of 24% in sensitivity and an increase of 12% in the sensitivity of the classifier. This improvement could be attributed on more

available datasets to be used to train the classifier, which in also improved the test set of the classifier.

4.3.2. THIRD OBJECTIVE – determining the joints that best indicates the presence of RA in patients

After successfully discriminating between the patient and control subjects, the next step was to determine from the patient datasets which joints best indicated the presence of RA by a process of elimination of variables (joints); this was done in order to determine which combination of joints generated the best classifier and then subsequently determine the specific joints that indicated the presence of RA best. The result (Table 4-8) of the DT showed a level of consistent accuracy in terms of its specificity and sensitivity among the five bootstrapped DT's. The variables that varied in the DT's were the AGE and the joints (KNEE, MCP2, and MCP3). The root variable which was the MIN and MAX temperatures remained the same among the five bootstrapped DT's; this was used to create all five bootstrapped DT's. The AGE, KNEE and MCP2 were used to create DT 1 and 4, while the AGE, KNEE and MCP3 were used to create DT 2, MCP2 and MCP3 were used to create DT 3, and the AGE, KNEE, MCP2 and MCP3 were used to create DT 5 along with the root variable. The Min and Max dataset proved to be the most efficient at determining which joints were the best indicators of RA with a sensitivity of 95% and specificity of 91%. These same steps were repeated for all the dataset series.

Table 4-8: Min and Max dataset Decision Tree result for Knee, 2nd MCP and 3rd MCP (Using 26 patients and 26 control subjects)*

DT #		1	2	3	4	5
Train	Sensitivity	100	100	96.3	94.0	99.6
	Specificity	92.5	88.6	90.2	88.6	94.0
	CCR	94.3	91.4	87.5	87.2	95.8
Test	Sensitivity	95.5	94.8	89.6	95.5	95.5
	Specificity	89.9	90.5	86.5	90.3	91.2
	CCR	92.1	91.7	87.3	92.6	94.4

Table 4-9: Table showing the results of the DT combination of 12 different dataset series for the Knees, 2nd MCP and 3rd MCP (Using 26 patients and 26 control subjects)

Dataset	Sensitivity (%)	Specificity (%)
Min and Max	95	91
Min/Max and Median/Max	79	74
Mode/Min and Median/Min	89	85
Mode/Min and Mean/Min	78	69
Mode/Max and Median/Max	72	70
Min/Max and Median/Min	65	69
Min/Max and Mean/Min	71	72
Median/Max and Mode/Min	66	57
Mean/Max and Min/Max	82	78
Min/Max and Mode/Min	80	69
Mode/Min and Median/Max	90	88
Mode/Max and Mean/Max	92	85

The Knees, 2nd MCP and 3rd MCP proved to be the best joints that indicated the presence of RA. The combination of the ankle, 2nd MCP and 3rd MCP also proved to be a good indicator of RA. The DT for the ankle, 2nd MCP and 3rd MCP was created using the same methodology as

the one used in the first DT. The variables that varied in the DT's were the AGE and the joints (ANKLE, MCP2, and MCP3). The root variable which was the MIN and MAX temperatures remained the same among the five bootstrapped DT's; this was used to create all five bootstrapped DT's. The AGE, ANKLE, MCP2 and MCP3 were used to create DT 1, while the AGE, MCP2 and MCP3 were used to create DT 2, ANKLE and MCP3 were used to create DT 3, and the AGE, ANKLE and MCP3 were used to create DT 4 and 5 along with the root variable.

Table 4-10: Min and Max dataset Decision Tree result for four different joint combinations (Using 26 patients and 26 control subjects)*

Joints	Specificity (%)	Sensitivity (%)
Knees, MCP 2 & 3	95	91
MCP 2,Knees & Ankle	65	58
MCP 3,Knees & Ankle	77	74
Ankle, MCP 2 & 3	80	76

To further establish/confirm which joints were good indicators of RA, the joints were separated and investigated individually. From this further separation it was established that the 2nd and 3rd MCP's were the joints generated the best classifier, using the Min and Max dataset. The 3rd MCP had the highest sensitivity and specificity at 90 and 88% respectively; while the joint that showed the worst discriminatory value was the ankle with a sensitivity and specificity of 56 and 61% respectively (as shown in Table 4-12). The result (Table 4-11) of the DT for the 3rd MCP showed consistent accuracy with a specificity range from 80 to 88% and a sensitivity range from 88 to 90% among the five bootstrapped DT's.

Table 4-11: Min and Max dataset Decision Tree result for the 3rd MCP (Using 26 patients and 26 control subjects)*

DT #		1	2	3	4	5
Train	Sensitivity	100	89.5	89.5	86.7	92.4
	Specificity	82.4	83.1	77.2	80.0	96.5
	CCR	90.2	84.3	79.9	81.4	93.5
Test	Sensitivity	88.0	88.0	90.0	90.0	90.0
	Specificity	85.3	86.7	88.0	82.5	80.0
	CCR	84.7	85.2	88.9	84.8	83.0

Table 4-12: Using the min and max dataset, table showing the specificity and sensitivity of the DT (Using 26 patients and 26 control subjects)*

Joints	Specificity (%)	Sensitivity (%)
Knees	72	68
Ankles	61	56
MCP 3	90	88
MCP 2	86	80

From these results, the following conclusions were made; hence satisfying the stated objective:

- 1- The combination of the Knee, 2nd MCP and 3rd MCP or the Ankle, 2nd MCP and 3rd MCP were the best joints that indicated RA and could successfully discriminate between the patient and control groups.
- 2- The Min and Max, Mode/Min and Median/Max, Mode/Min and Median/Min, Mode/Max and Mean/Max of the combination of the Knee, 2nd MCP and 3rd MCP were the best datasets that generated excellent classifiers.
- 3- The best joints that best indicated RA in patients were the 2nd and 3rd MCP's; these results confirmed those from previous work (Adea 2009); where it was

statistically shown that these joints were able to discriminate between the patient and control group dataset. This observation is important because the 2nd and 3rd MCP's are joints in the hands where RA presents itself in the early stages in these joints.

4.3.3. ***FOURTH OBJECTIVE – determining the level of severity in the patient group; classifying them into LOW, MEDIUM and HIGH***

The DT was generated to determine the level of activity in the patient group and separate them into three classes: LOW for those patients who were either in the beginning stages of the disease or for those patients whose disease was in remission, MEDIUM for those patients who were at an intermediate level, who could not be classified as LOW, but could not be classified as HIGH either, and HIGH for those patients whose disease level has progressed to an advanced stage. The results from this classification were compared against the rheumatologists' evaluation. It is important to note that the rheumatologists evaluation of the patients used here was as at the time of the imaging session and might not necessarily reflect those patients disease activity at this present time.

Table 4-13: Min and Max dataset Decision Tree result for level of severity (Using 26 patients and 26 control subjects)*

DT #		1	2	3	4	5
Train	Sensitivity	100	100	88.2	94.4	94.4
	Specificity	90.1	90.1	83.7	80.2	80.2
	CCR	90.3	90.3	81.1	82.5	82.5
Test	Sensitivity	94.1	86.9	94.1	92.2	92.2
	Specificity	82.1	76.5	73.3	88.1	78.7
	CCR	80.0	77.7	73.3	89.2	78.5

The result (Table 4-13) of the DT using the Min and Max dataset showed the highest level of consistent accuracy in terms of its specificity and sensitivity among the five bootstrapped DT's of the dataset combinations used. The variables that varied in the DT's were the AGE, YEARS, the joints (KNEE, ANKLE, MCP2, and MCP3), and MOB (as described in Table 3-6). The root variable which was the Min and Max temperatures remained the same among the five bootstrapped DT's; this was used to create all five bootstrapped DT's. The AGE, KNEE and ANKLE, YEARS were used to create DT 2 and 3, while the MCP2, MCP3, MOB were used to create DT 4 and 5. DT #4 had the highest CCR at 89.2% with a sensitivity of 92% and a specificity of 88%. This same step was repeated for the rest of the dataset combinations and it was established that the Min and Max dataset had the highest sensitivity and specificity of the datasets. The results for the DT's are shown in the table below (Table 4-14). This table illustrates the efficiency/accuracy of the classifiers and then compares them against one another. The Min/Max and Median/Max; Median/Max and Mode/Min; Min/Max and Median/Min; and Min/Max and Mode/Min also proved to be good discriminators with a sensitivity that ranged from 85 – 92% and a specificity that ranged from 80 – 88%.

Table 4-14: Table showing the results of the DT combination of 12 different dataset series for the level of severity (Using 26 patients and 26 control subjects)

Dataset	Sensitivity (%)	Specificity (%)
Min and Max	92	88
Min/Max and Median/Max	85	80
Mode/Min and Median/Min	77	70
Mode/Min and Mean/Min	68	58
Mode/Max and Median/Max	79	74
Min/Max and Median/Min	90	85
Min/Max and Mean/Min	65	60

Median/Max and Mode/Min	88	82
Mean/Max and Min/Max	76	73
Min/Max and Mode/Min	86	80
Mode/Min and Median/Max	55	45
Mode/Max and Mean/Max	56	60

The results from the classifier were compared to the evaluations of the rheumatologist to determine the accuracy of the classifier in separating the patients into these three classes. The table below (Table 4- 15) illustrates this. The rheumatologist's evaluation of patients 1 through 13 was adapted from previous work (Adéa 2009) from his evaluation of those patients at the time of the imaging session. So it is important to note that though the disease status of those patients might currently not be the same as those evaluations made, as of the time of imaging, these were their level of RA activity. Patients 14 through 26 were the evaluations for the newly recruited patients that he did as of the time of their imaging status (Appendix F for a copy of his official evaluation).

Table 4-15: Table showing the results of the classifier and the rheumatologists' evaluation

Patient #	Sex	Rheumatologist's Evaluation	See5 Classification
1	M	Low	Low
2	F	Low	Low
3	M	High	Medium
4	F	Low	Low
5	F	Low	Low
6	M	Low	Medium
7	F	High	High
8	F	Low	Low
9	M	Low	Low
10	F	Medium	Low
11	F	Medium	Medium

12	F	Low	Low
13	F	Medium	Medium
14	F	Medium	High
15	F	Low to Medium	Low
16	M	Low to Medium	Medium
17	F	Low	Low
18	M	Low to Zero	Low
19	F	Low to Zero	Low
20	M	Low to Medium	Medium
21	F	Low to Zero	Low
22	F	Low	Low
23	F	Medium to High	High
24	F	Low to Zero	Low
25	F	Medium	Medium
26	F	Low to Zero	Low

Table 4-15 displays the assessment by the physician and the classification by DT, at this stage it is difficult to conclude that one is more accurate than the other, as physical assessment by physicians can still be problematic. However, since many of the patient cases were rated similarly by both methods (physician and DTs), it is encouraging and with more accurate development of our infrared approach and analyses, we may be able in the near future to create a useful tool to measure a patient's current status, and more particularly, the progress or regress that a patient goes through with this disease.

Table 4-16 shows the contingency table for the classifier when using the Min and Max dataset as inputs into the classifier with a combination of the knee, ankle, 2nd MCP and 3rd MCP as the joints of interest. From this table, the number of true positives were 90, where the classifier correctly classified, the number of variances from the physician for what would be called "false negatives" were 8, where the classifier classified a patient at MEDIUM as LOW or at HIGH as MEDIUM; the number of "false positives" were 2, where the classifier classified a

patient at LOW as MEDIUM or at MEDIUM as HIGH, and the number of “true negatives” were 13, where the classifier classified a patient as MEDIUM, where the patient could either be classified as LOW or MEDIUM, or HIGH, where the patient could be classified as MEDIUM or HIGH.

Table 4-16: Contingency table for Min and Max dataset using the knee, ankle, 2nd MCP and 3rd MCP

162	16
4	26

Table 4-17 shows the confusion matrix for the dataset of the three classes: LOW, MEDIUM and HIGH classification of the level of RA severity in the patient group, using the Min and Max temperature measurements of the knee, ankle, 2nd MCP and 3rd MCP. This illustrates the accuracy of the classifier in these three levels.

Table 4-17: Confusion matrix for the Min and Max dataset

	PREDICTED				
ACTUAL		LOW	MEDIUM	HIGH	SUM
LOW		128	16	0	144
MEDIUM		14	38	6	58
HIGH		0	2	4	6
SUM		142	56	10	208

From these results, the following conclusions were made; hence satisfying the stated objective:

- 1- The classifier was able to determine the level of RA activity in the patient group and was able to separate them into LOW, MEDIUM and HIGH.
- 2- The best dataset combination that effectively determined in presence or absence of RA from the sample were the Min and Max; Min/Max and Median/Max; Min/Max and Median/Min; Median/Max and Mode/Min; and Min/Max and Mode/Min.

4.4. Discussion

All the objectives stated were successfully accomplished. The first objective which was to analyze the joints to show which joint could statistically discriminate between the patient and control groups was successfully accomplished. From previous work done in 2009, Adea found that the Knee, 2nd MCP and 3rd MCP statistically discriminated between the control and patient groups; however the scope of her analysis was limited to the joints in the hands and Knees. In this thesis, the rest of the joints (Elbows, Ankles and Feet) were analyzed, and from this analysis, it was established that the ankles were also able to statistically discriminate between the patients and control subjects. These statistical analyses were carried out using MATLAB's Lilliefors test, Kruskal-Wallis test and Ranksum test. The results for the lilliefor and ranksum tests only were included in this thesis so as to avoid redundancy, because the kruskal-Wallis test was run as a confirmatory test.

The second objective which was using machine learning (Decision Trees) to generate a classifier that could show the presence or absence of RA, and to also show whether an increase in the sample size improved or deteriorated the effectiveness of the classifier were also successfully accomplished. From the results, it was deduced that not only was the classifier able to discriminate between the patients and control subjects with specificity and sensitivity of 94 and 96% respectively, but it also showed that the recruitment of additional participants (13 patients and 16 control subjects) into the study also helped to increase the performance of the classifier (9% in the sensitivity and 3% increase in the specificity).

The third objective which was to determine which joints were the best indicators of RA was successfully accomplished. The classifier was able to show that the combination of either the Knee, 2nd MCP and 3rd MCP or the ankle, 2nd MCP and 3rd MCP were the best indicators of RA. The Min and Max dataset also proved to be the best discriminators with a sensitivity and specificity of 95 and 91% respectively. However to further establish which joints were the best indicators of RA, from the four joints that were statistically proven to discriminate between the patients and the control subjects, these joints were separated and then individually inputted into the DT. The 3rd MCP and 2nd MCP proved to be the joints that best indicated the presence of RA in the patients.

The fourth and last objective, which was to determine the level of RA activity in the patient group and separate them into three classes, LOW, MEDIUM and HIGH was successfully accomplished. The Min and Max dataset proved to be the best dataset in properly classifying the group into these three classes. The results of the DT, establishing the accuracy and efficiency of the classifier were confirmed by the rheumatologist's evaluations of the patients. These results were encouraging because they showed some consistency with the rheumatologist's evaluations.

CHAPTER FIVE

5. CONCLUSIONS

This chapter provides the conclusion of this work and contributes new knowledge, to the previous work done. It also proposes some new research questions for future works to be done in the advancement of this study.

5.1. Conclusions

The four objectives that were stated at the beginning of this thesis were all accomplished. Hence the following conclusions were made from the body of the work.

1. It was observed that the 1st MTP was able to differentiate between the patients and the control subjects, however after further literature review, it was concluded that this difference could possibly be attributed to osteoarthritis and not RA, because the former is the common aging of the bones which affects the general population at one point or another as they age. This statistical analysis was done by using the non-parametric ranksum and kruskal-Wallis tests. These joints statistically showed at a significance level of 5% that they were able to differentiate between the control's datasets measurements and the patient's dataset measurements.
2. After successfully separating patients and control subjects, it was determined that, even though a couple of dataset series: Min and Max, Min/Max and Median/Max, Mode/Min and Median/Min, Min/Max and Median/Min, and Mode/Max and Mean/Max, gave high specificity and sensitivity, and acceptable discrimination parameters, the Min and Max temperature series gave the highest specificity at 92% and sensitivity at 96%.

3. The Min and Max dataset consistently proved to be the best dataset among all the datasets; it showed the highest sensitivity and specificity throughout this thesis.
4. The third objective which was to determine which specific joints were best indicators of RA in terms of classification. This was accomplished in two ways, by the process of elimination of variable (joints), where a combination of joints were inputted into the decision tree to establish which joints were good indicators. From this the observation was made that, where the 2nd and 3rd MCP's were present, there was an improvement to the accuracy of the classifier generated; the conclusion was then made that the 2nd and 3rd MCP's were the best joints for the classification. This was further confirmed a second way, where the joint were separated and generated individual classifiers, the results confirmed the previously made assertion. The 2nd MCP had a specificity of 86% and a sensitivity of 80%, while the 3rd MCP had a specificity of 90% and a sensitivity of 88%.

From this work and previous work, TIR imaging has been used to determine the presence of RA in the smaller joints of the hands, the 2nd and 3rd MCP's, where RA is known to develop in its early onset. This can also help clinicians assess the presence of RA early on by focusing on those joints that have been shown to be good indicators of the presence of RA. It can also help them better manage those patients that are already diagnosed with RA effectively and efficiently.

5.2. Contribution to knowledge

The first contribution to knowledge was the completion of the first objective of the thesis, completing the statistical analysis of the joints that were not analysed in the previous work (by Adéa) to determine if there were other joints other than the 2nd MCP, 3rd MCP and Knees that would be indicators of RA and could also differentiate between the patients and control subjects.

From the statistical analysis done on the elbows, feet and ankles (in this thesis), it was observed that the ankles are also indicators of RA.

The second contribution which was the main purpose of this thesis in the advancement of this study was the successful classification of the patients and control subjects. Using various combinations of the datasets, it was observed that the decision tree could successfully discriminate between the patients and control subjects. This new knowledge is particularly significant because it sheds new light on an area of analysis of TIR images that had not been explored in previous works. This helps to further solidify the status of TIR imaging of joints of RA patients as a potential tool that could help assess (1) the joints that need focused therapy in individual patients and (2) could help rheumatologists in early diagnosis or management therapy of already diagnosed patients in cases where physical examinations have limited usefulness.

The new knowledge gathered from this study has further buttressed the findings from the previous work (Adéa 2009) done, where from the statistical tests, it was determined that the Knee, 2nd MCP and 3rd MCP were the best joints that could discriminate between the patients and control groups. From the results of the classifier, while satisfying second objective, it was concluded that the same joints that were proven to be the best in determining the presence of RA statistically, were also proven to be good indicators of RA (the combination of the Knee, 2nd MCP and 3rd MCP) and then it was shown that individually in a classifier, the 3rd MCP had the highest sensitivity and specificity at indicating the presence of RA and also the 2nd MCP. This new knowledge helps to reinforce TIR imaging as a promising early detection tool, as with the characteristic of RA, where during the early stages, it affects smaller joints commonly in the hands and feet and then progresses to larger joints in the knees and elbows.

5.3. Future work

In order to further the thermal infrared imaging work of the MIRG's research team, it would be necessary to collect data on more patients to increase the sample size of the database to look at the impact it has on the classifier, whether it improves it or shows no impact. It would also be important to have a more diverse population during recruitment; all the patients diagnosed with RA were of Caucasian background, while about 40% of the control subjects were of Black ethnicity. From the measurements taken from the TIR images, it is important that note that, those control subjects of black ethnicity had slightly higher temperatures than those of Caucasian and Asian descent. From this observation, in future recruitment of patients, it would be important to also include patients of black ethnicity in the study to observe the effects race plays on the disease activity. As was also shown in this thesis, the recruitment of more patients in the study helped improve the classification; it showed a 9% improvement in the sensitivity and 3% improvement in the specificity. This would be an essential component in the furthering of this study.

The next step would be to explore more image processing techniques, to allow better processing and analysis of the images. The incorporation of automated segmentation and automated extraction of ROI would allow this to be possible. Currently the ROI's are being selected manually; this limits the analysis due to subjectivity from the interpreter.

The next step would be to further investigate the statistical tests performed on the datasets of these joints to further validate their accuracy. Due to the size of the datasets and the various variables being tested, these datasets are susceptible to type-1 errors. This type of error occurs when the null hypothesis is rejected when it is in fact true.

The next step would be to further analyze the joints to establish if the rest of the joints of the feet and elbow, which were unable to discriminate between the patient and control subjects, could discriminate between the two groups using supervised learning and to further investigate other methods of improving the assessment and analysis of the TIR images. Another classification method that would be worth exploring would be fuzzy classifiers, and compare the results to the current method of classification used in this thesis. Other classifiers to be considered would be artificial neural network (ANN) models.

The next step then would be the correlation of IR imaging results, statistical and classification, to be compared to RA diagnosis gold standards such as MRI and HRUS, which are the tools currently used to correctly diagnose RA. These tools can correctly classify the normal and RA patients. This would further solidify the conclusions stated in this thesis, that IR imaging is a promising tool that can be used to replace or used in support of MRI's and HRU's. This comparison would also assess if IR technology can detect inflammation as early on in the disease as MRI and HRUS. As discussed in the introductory chapter, detecting inflammation early would assist in diagnosing RA before the manifestation of clinical symptoms and improve the prognosis of the patient.

CHAPTER SIX

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APPENDICES

7. APPENDIX A – Research Participant Questionnaire

University of Ottawa

Severity of illness measures in rheumatoid arthritis from multi-spectral imaging

Research Participant Questionnaire

Name:

Email:

Telephone:

Sex:

Age:

Race:

Physical Medical disabilities/ Joint issues (If any):

Level of severity (of Pain) on a scale of 1 – 10 (Personal Assessment)

- 1 – 4 – LOW:
- 4 – 7 – MEDIUM:
- 7 – 10 – HIGH:

8. APPENDIX B – Research Participation Package

Research Participant Information and Consent Form

You are being asked to participate in a research study using an infrared (IR) camera (heat images) to determine temperature measurements of limbs. In addition, a series of color pictures using a digital camera will be taken to assess the level of mobility of extremities and joints. The research will be conducted at the University of Ottawa and will be scheduled at a convenient time.

The information collected will not contain pictures of the face and will be kept anonymous.

Purpose and Design

Rheumatoid arthritis affects 300,000 Canadians each year; it involves inflammation and symptoms like redness, swelling, heat, and pain. In this study, we plan to measure the temperature of the joints of patients diagnosed with rheumatoid arthritis and of participants without rheumatoid arthritis using an infrared camera. The assumption is that the infrared pictures of the rheumatoid arthritis patients will show inflammation of tissue or joints. A second test to be conducted at the same time is the taking of video pictures with digital cameras to assess the extent of movement of extremities and joints of both groups: patients with rheumatoid arthritis and healthy participants. This is a pilot project to assess whether these two types of tests can be helpful as an aid to the early diagnosis of rheumatoid arthritis. These tests may also help to monitor therapy in joint debilitating diseases.

Approximately 15 patients will be involved in this pilot study and 15 normal subjects.

Because the skin surface temperature variations are extremely subtle and sensitive to environmental changes:

- Do not use talcum powder, lotion, drug or deodorant on the skin on the day of the session.
- Do not consume alcoholic beverages 12 hours prior to the session.
- Do not consume hot beverages at least 1 hour prior to the session.
- Do not use procedures such as acupuncture, transcutaneous electrical stimulation (TENS machine), hot or cold patches, or any other form of physiotherapy at least 24h prior to the session. You should not do any intense physical exercises at least 4 hours prior to the session
- Avoid prolonged sun exposure for at least one week prior to the session.
- Do not smoke at least 2 hours prior to the session.
- Do not wear any rings, necklaces, and bracelets during the session.

The session will take place in a room with the following characteristics:

- Without windows or with covered windows to avoid any reflection.
- Constant uniform temperature between 20 and 25.
- Constant humidity.
- Fluorescent lights.

You will be asked to come to the biomedical laboratory of Dr. Pierre Payeur at University of Ottawa (Colonel By, Room B407) at a mutually convenient time. Both types of cameras will be available at that location. You need to wear shorts and short sleeve shirt (or change into these in a nearby bathroom).

The skin has to cool at room temperature for 10-15 minutes; then pictures are taken of the joints, hands, feet. For each body region, you will be asked to assume a position facilitating the imaging. For instance, for images of the hands (palm and back), you will be seated on a chair and will be asked to place your hand over a table. For the under-feet view, you will be seated on a chair and raise your leg, with the ankle resting on a stool. For other views, you will be standing.

You will also be asked to move your hands, elbows, knees and feet from time to time. Sequences of images will be taken with an infrared camera and several regular intra-optical video cameras. Both types of cameras will record the sequences simultaneously.

The imaging session is expected to last approximately 30 minutes.

You may be asked to participate for a maximum of three sessions in order to study the stability of the temperature distribution over time. But this is not mandatory to participate in the study. It is totally voluntary.

Are there any risks?

There are no foreseen risks to participants.

If you are a patient diagnosed with rheumatoid arthritis, the research team will capture images of your body parts affected by rheumatoid arthritis.

If you are a healthy volunteer, the research team will capture images of several healthy joints and limbs.

There is no direct contact or risk associated with gathering these images.

Are there any benefits to me if I choose to participate? While there are no immediate benefits for you, this study is expected to provide a useful tool for early diagnosis of rheumatoid arthritis.

How will my confidentiality be protected?

Your name will not be used in any publications that may arise from this study. Only group information will be published. No images of the participant's faces will be taken. The consent forms and images will be stored at Carleton and Ottawa Universities research laboratories of Dr Frize and Dr Payeur containing only numbers as reference. The images will be stored in a protected file with user id and password protection. The data will be destroyed five years after the tests are completed.

Withdrawal from the Study

If you are a patient with rheumatoid arthritis, you may withdraw from the study at any time without any impact to the care you are receiving. You can also choose to have your images withdrawn from the study completely.

If you are a healthy participant, you may withdraw from the study at any time. You can also choose to have your images withdrawn from the study completely.

Study Expenses

If you are a patient, you will be reimbursed for parking or bus expenses to attend the session at University of Ottawa. If you are a student, no compensation will be needed, as you will be on either campus and there is a free bus service between the two universities.

Questions about the Study

You may ask any questions about the research at any time. If you have questions about the research after you leave today you should contact the student co-investigator Abiola Ogungbemile at (613) 858-5712 or (613) 520-2600 ext 2068 or email: abiola.ogungbemile@gmail.com.

If you have any questions about your rights as a research subject, you may contact Leslie MacDonald-Hicks, Carleton University Research Ethics Board Coordinator at (613) 520-2517, email ethics@carleton.ca.

Consent

I have read this Research Participant Information and Consent Form and have had an opportunity to ask my study doctor and the researchers any questions I had about the study.

My questions and/or concerns have been answered to my satisfaction and I agree to participate in this study. If I decide at a later stage in the study that I would like to withdraw my consent, I may do so at any time.

A copy of the Research Participant Information and Consent Form will be provided to me.

Signatures

Name of Participant (please print):

Signature

Date

Student co-investigator: Abiola Ogungbemile

Signature

Date

9. APPENDIX C – FLIR Technical Specification

FLIR A320 Camera

IMAGING PERFORMANCE

Field of view/min focus distance 25° x 18.8°
/ 0.4 m

Spatial resolution (IFOV) 1.36 mrad

Thermal sensitivity/NETD @ 50mk @ +30 °C

Focusing Automatic or manual (built in motor)

Detector type Focal Plane Array (FPA),
uncooled microbolometer

Spectral range 7.5 to 13 μ m

POWER SOURCE

External power operation 12/24 VDC, 24W
absolute max

External power, connector type 2 pole
jackable screw terminal

Voltage allowed range 10 – 30 VDC

IMAGE PRESENTATION

Ethernet output IEEE-1394 8/16-bit
monochrome and 8-bit color

Video output composite video output, PAL
and NSTC compatible

PHYSICAL CHARACTERISTICS

Weight 0.7 kg (1.5 lbs)

Size 170mm x 70mm x 70mm

Tripod mounting UNC 1/4"– 20 (on three
sides)

MEASUREMENT

Temperature ranges

Range 1: -40°C to +120°C (-40 to
+248°F)

Range 2: 0°C to +500°C (+32 to
+932°F)

Optional: Up to +1500°C (+2732°F)

Optional: Up to +2000°C (+3632°F)

Accuracy (% of reading) $\pm 2^\circ\text{C}$ or $\pm 2\%$

Measurement modes Spot, Area, Isotherm,
Difference

Automatic emissivity correction
Variable from 0.1 to 1.0

Individual emissivity settings Individually
settable

Measurement corrections Reflected ambient,
distance, relative humidity, external
optics. Automatic, based on user input

ENVIRONMENTAL

Operating temperature range -15°C to +50°C
(5°F to 122°F)

Storage temperature range -40°C to +70°C (-
40°F to 158°F)

Humidity Operating and storage 95% relative
humidity +25°C to +40°C

Encapsulation IP 40
(IEC 60529)

Shock Operational: 25G, IEC 60068-2-29

Vibration Operational: 2G, IEC 60068-2-6

10. APPENDIX D – Raw Measurements of the Joints

10.1. 2nd MCP Raw Data Measurements

Table 10-1: Raw Data Measurements Extracted from the Control Group's 2nd MCP Joint

Control Group's 2nd MCP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT HAND	1	26.1105	24.6853	25.4597	25.5042	25.4580	0.3534	-0.2794	1.9844
	2	28.3482	25.7030	27.1593	27.1930	27.2386	0.6124	-0.1033	2.1580
	3	27.8476	26.9645	27.3119	27.3050	27.2370	0.1473	0.1713	2.7103
	4	30.0950	28.8796	29.2699	29.1995	29.1624	0.2359	1.1101	3.6497
	5	31.9448	30.4923	31.0995	31.0931	30.8663	0.3064	0.1588	2.2105
	6	34.4558	33.0637	33.6921	33.6296	33.2861	0.3598	0.2760	1.9135
	7	31.9741	30.4487	30.9595	30.8778	30.7716	0.3280	0.5527	2.2921
	8	32.8184	30.8655	31.4970	31.4279	31.2164	0.3612	0.6998	2.8610
	9	x	x	x	x	x	x	x	x
	10	35.9767	32.8570	34.3339	34.3496	34.4796	0.2265	0.0531	2.6858
	11	27.5611	25.9822	26.4582	26.3486	26.2190	0.2976	0.9900	3.1782
	12	27.3503	25.4305	26.5945	26.6153	26.9872	0.4126	-0.3342	2.5027
	13	24.4499	22.1455	23.2691	23.2255	23.0450	0.4804	0.2267	2.3356
	14	26.7441	24.3879	25.5904	25.6069	25.6069	0.4945	-0.0251	2.4962
	15	33.3864	32.3649	32.8731	32.8552	32.6824	0.2387	0.0836	1.9904
	16	29.2447	27.5989	28.1753	28.1477	28.0727	0.3244	0.4250	2.5414
	17	32.5950	30.6676	31.3209	31.2675	31.2602	0.3478	0.7991	3.6520
	18	33.0994	32.1115	32.6186	32.6317	32.6606	0.2271	-0.0597	2.0101
	19	21.8259	21.0275	21.3548	21.3236	21.3236	0.1536	0.5861	2.8897
	20	23.0784	21.8034	22.4380	22.4388	22.3755	0.3161	0.0045	2.1106
	21	24.4938	22.5959	23.5438	23.5842	24.2535	0.5098	-0.0925	1.8708
	22	28.9380	27.4029	28.1534	28.1244	27.7417	0.3823	0.0910	2.0186
	23	25.2490	23.8793	24.5167	24.5005	24.2835	0.3402	0.1298	2.0347
	24	31.7443	30.5849	31.0281	30.9800	30.9800	0.2527	0.4696	2.4755
	25	26.0381	24.3766	25.1952	25.2259	24.8870	0.3720	-0.0650	2.2085
	26	29.1376	27.2054	28.1223	28.1307	27.8982	0.3769	0.1081	2.6204
	27	33.3646	31.2415	32.2328	32.1996	31.6780	0.5563	0.1355	1.9320
	28	30.8546	28.7360	29.5722	29.5009	29.5527	0.4940	0.5274	2.5753
LEFT HAND	1	26.2329	24.2346	25.1966	25.1496	24.9796	0.3884	0.3312	2.7780
	2	27.7155	25.5182	26.6314	26.6605	26.6605	0.5214	-0.0739	2.1749
	3	26.6837	24.7830	25.6857	25.6685	25.4382	0.3921	0.2635	2.5750

4	29 2590	27 3793	28 2671	28 2519	27 9894	0 3828	0 1800	2 1998
5	32 2273	30 9688	31 6088	31 6689	31 7851	0 2859	-0 4344	2 1899
6	34 8808	33 1283	33 9226	33 9366	33 2933	0 4055	0 0045	2 0417
7	32 8696	31 5455	31 8960	31 8363	31 7854	0 2206	1 3763	5 4255
8	32 9048	30 4474	31 2677	31 2748	31 1215	0 4350	0 7281	4 1835
9	x	x	x	x	x	x	x	x
10	35 5432	31 7408	34 2995	34 2556	34 1687	0 2675	1 2854	5 7058
11	26 7669	24 6901	25 6044	25 5494	25 5993	0 4262	0 4738	2 7667
12	26 7445	25 0764	25 8706	25 8524	25 8524	0 3327	0 2228	2 4346
13	24 2248	21 6849	22 9110	22 8877	22 7302	0 5093	0 0442	2 6394
14	26 5998	23 6092	25 1774	25 2419	24 7829	0 6574	-0 1606	2 0324
15	33 5796	32 3577	32 8979	32 9056	32 8696	0 2155	0 3059	3 2486
16	29 2818	27 7119	28 3897	28 3575	28 2377	0 3109	0 2165	2 4786
17	31 5299	29 9982	30 7524	30 7996	30 4327	0 3546	-0 1281	2 0290
18	32 9413	31 8214	32 4148	32 4477	32 4586	0 2620	-0 2772	2 1671
19	21 7065	21 0435	21 3662	21 3715	21 3715	0 1438	0 0752	2 2830
20	23 1099	21 5960	22 3352	22 3239	22 5180	0 3475	0 0141	2 1621
21	24 1914	22 2091	23 2039	23 1774	22 9185	0 5571	-0 0055	1 7900
22	29 0718	27 5536	28 2733	28 2891	28 3863	0 3775	0 0732	2 1079
23	27 5987	25 3632	26 4444	26 4486	26 1058	0 5696	0 0614	1 9750
24	31 6427	30 4969	31 2203	31 2572	31 1989	0 2091	-0 9245	3 7414
25	25 9923	24 2602	25 0696	25 0257	24 8407	0 4173	0 1944	1 9646
26	29 8851	27 9283	28 7760	28 7732	28 8700	0 4366	0 1637	2 2459
27	33 2214	32 0983	32 5079	32 4450	32 3007	0 2532	0 8021	2 7932
28	30 0472	28 0333	28 9720	28 9965	29 3157	0 4338	-0 0685	2 2494
AVERAGE	28.9165	27.2343	28.0033	27.9910	27.8959	0.3678	0.1932	2.4981

10.2. 2nd MCP Raw Data Measurements

Table 10-2: Raw Data Measurements Extracted from the Patient Group's 2nd MCP Joint

Patient Group's 2nd MCP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT HAND	1	34.1853	32.5157	32.9144	32.8760	32.7752	0.2123	1.8015	8.9345
	2	34.3468	32.9070	33.5189	33.5539	33.7114	0.2631	-0.0834	2.7726
	3	33.6470	31.7626	32.7416	32.8710	33.0655	0.4647	-0.2646	1.6601
	4	30.0216	28.3053	29.0348	29.0589	29.3783	0.3849	-0.0057	1.8287
	5	29.8801	28.3182	29.2812	29.3025	29.2802	0.3420	-0.4080	2.4527
	6	31.6099	27.4611	29.1036	28.9679	28.8114	0.9284	0.4308	2.3475
	7	34.1497	32.4363	33.2885	33.2890	33.2639	0.2014	-0.0640	3.8788
	8	32.9120	31.7341	32.2329	32.1835	32.0749	0.2439	0.4930	2.4673
	9	31.2683	29.5413	30.2286	30.2426	30.1911	0.2889	0.0198	2.8278
	10	33.9721	31.4287	32.4823	32.4658	32.7470	0.5197	0.2233	2.3592
	11	33.7791	31.7989	32.5586	32.5878	32.8184	0.3941	-0.0181	1.9991
	12	32.6211	31.3234	31.8121	31.8036	31.8254	0.2546	0.3638	2.7489
	13	28.5139	27.5378	28.0228	28.0569	28.1170	0.1676	-0.5022	2.8177
	14	36.3383	34.7329	35.3963	35.3733	35.2655	0.3504	0.2665	2.4103
	15	33.5002	30.7022	31.0767	31.0617	30.9811	0.1701	0.4063	2.8042
	16	34.9065	31.0051	32.8640	32.8372	32.6836	0.3564	0.4078	3.2602
	17	34.4888	32.7380	33.2672	33.1863	-66.0258	0.3474	0.9733	3.7471
	18	36.0788	33.7222	34.6419	34.6090	34.2365	0.5284	0.3357	2.2699
	19	33.8627	30.8673	33.3783	33.3936	33.4484	0.2509	-0.0505	2.0165
	20	29.5843	27.3403	28.3677	28.2695	27.6421	0.6476	0.3143	1.8257
	21	32.7047	29.9366	30.4865	29.3718	30.1124	0.3896	0.9468	3.1642
	22	32.1840	29.8371	30.7553	30.7145	30.0742	0.5716	0.3297	2.1158
	23	31.9303	29.9401	30.4722	30.2607	29.9401	0.5333	1.1767	3.4005
	24	35.7879	33.8939	34.5202	34.4695	34.3530	0.3566	0.6349	3.2274
	25	26.0395	24.1037	24.9394	24.9486	24.5464	0.4471	0.1902	2.2609
	26	26.1413	24.6106	25.2165	25.1823	24.8118	0.3880	0.3001	1.9468
LEFT HAND	1	33.3571	32.3134	32.7815	32.7824	32.7176	0.1961	-0.0138	2.5599
	2	33.7114	31.8063	33.2150	33.2453	33.5610	0.2907	-0.9527	4.4021
	3	34.1972	27.4902	33.4464	33.4965	33.6399	0.4492	-5.7915	5.5579
	4	30.1469	28.3801	29.5020	29.5117	29.5117	0.2609	-0.3176	3.5379
	5	29.3841	27.5893	28.5867	28.5875	28.4455	0.3419	-0.0962	2.3800
	6	28.5128	26.3002	27.2766	27.2760	26.9391	0.4515	0.1988	2.4525
	7	33.6004	32.1542	33.0773	33.1060	33.0126	0.2997	-0.7272	3.1715
	8	33.0844	31.5378	32.3608	32.4148	32.5808	0.3553	-0.1136	1.9768

9	31 7268	30 2058	30 9235	30 9103	31 3266	0 3486	-0 0327	1 9586
10	33 8295	31 6325	32 6355	32 6101	32 4658	0 5274	0 1053	2 0062
11	33 5289	32 1325	32 9158	32 9982	33 0342	0 3331	-0 4642	2 2452
12	32 4913	31 4327	31 9641	31 9813	32 0502	0 2404	-0 0672	2 1993
13	29 1401	28 1920	28 6156	28 5737	28 4391	0 1941	0 3605	2 3810
14	36 2926	35 0806	34 6772	33 6576	33 3887	0 3109	0 0306	2 0342
15	31 4127	30 1794	30 7135	30 7022	30 4963	0 2453	0 1993	2 4978
16	33 8073	31 1820	32 9444	32 9597	32 7924	0 3679	0 0315	2 2687
17	35 2305	34 8044	33 3339	34 3220	34 5276	0 3281	0 4250	2 7150
18	35 6192	33 5971	34 5597	34 5625	33 7378	0 5134	0 0155	1 9656
19	34 2287	32 8594	33 5476	33 5424	33 4954	0 3648	-0 0041	1 9864
20	29 6879	27 7927	28 6597	28 6024	28 5501	0 4440	0 1796	2 4575
21	33 1843	31 5154	32 0534	32 9136	32 8434	0 3761	1 0095	3 2081
22	32 1735	30 1316	31 1664	31 1689	31 5508	0 5033	0 0567	1 9273
23	29 1772	28 8266	27 7900	27 8052	27 2584	0 4503	0 1723	2 8403
24	30 4983	27 8721	29 4673	28 4271	29 2039	0 3170	0 4502	2 4604
25	25 9018	23 8934	24 7957	24 7863	24 3214	0 5039	0 1405	1 8572
26	27 5711	26 0592	26 8963	25 8775	26 7035	0 4224	0 1620	2 0007
AVERAGE	32.2298	30.2973	31.1636	31.1107	29.1677	0.3738	0.0610	2.7037

10.3. 3rd MCP Raw Data Measurements

Table 10-3: Raw Data Measurements Extracted from the Control Group's 3rd MCP Joint

Control Group's 3rd MCP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT HAND	1	25.9880	24.4990	25.2549	25.2653	24.9099	0.3747	0.0264	2.0235
	2	28.8054	27.2082	28.1365	28.1678	28.4833	0.3883	-0.2086	1.9324
	3	28.1704	27.0402	27.6344	27.6595	27.7423	0.2372	-0.2217	2.2984
	4	30.3895	29.2887	29.7749	29.7406	29.6297	0.2470	0.3682	2.2880
	5	31.6907	30.3086	30.8597	30.8224	30.6758	0.3011	0.4344	2.3225
	6	34.3919	32.4155	33.1733	33.0996	33.0206	0.4710	0.5141	2.5070
	7	32.3649	30.7349	31.1827	31.1300	30.9985	0.2778	1.0317	4.2677
	8	31.9513	30.6896	31.1362	31.1361	30.8435	0.2498	0.4963	2.7302
	9	x	x	x	x	x	x	x	x
	10	35.4865	31.8650	34.2666	34.1839	34.1332	0.2519	1.7503	6.5791
	11	27.5762	26.8807	27.1890	27.1761	27.0172	0.1694	0.1757	2.0087
	12	27.8551	26.3108	27.1695	27.1765	27.1538	0.2794	-0.3697	3.2960
	13	24.4112	22.8169	23.6351	23.6326	23.4762	0.3256	-0.0919	2.3508
	14	27.3121	25.8369	26.6115	26.6378	26.7897	0.3297	-0.3488	2.3923
	15	32.9127	32.2348	32.4359	32.4372	32.4516	0.1082	0.5938	3.7834
	16	28.9249	27.2517	27.8189	27.7495	27.6140	0.3378	0.6234	2.6660
	17	32.1180	30.5869	31.0833	31.0338	30.8875	0.2834	0.6766	2.9600
	18	33.1855	32.1260	32.5662	32.5380	32.3719	0.2448	0.3700	2.2187
	19	30.1383	28.1260	28.4923	28.4509	28.3396	0.2485	0.8548	3.5078
	20	27.7442	25.1941	26.8322	25.7341	26.2961	0.1957	0.7984	3.1826
	21	26.3565	24.4733	25.2942	25.2767	25.5458	0.4046	0.4286	2.0872
	22	26.6849	25.6531	26.1656	26.1623	26.1263	0.3962	0.1233	2.3981
	23	25.0510	23.3744	24.6021	24.6514	24.7210	0.2579	0.0651	1.8849
	24	27.2220	25.0605	26.6241	26.5886	26.4800	0.6041	-0.0135	2.2091
	25	26.2791	25.0645	25.6254	25.5946	25.4050	0.2529	0.2614	2.3224
	26	29.4897	27.8875	28.4897	28.2351	28.7037	0.2613	0.2777	2.1777
	27	28.1395	26.7127	27.4735	27.4925	27.8841	0.3197	0.1078	1.9386
	28	33.6648	32.4435	32.8360	32.7968	32.5085	0.3377	-0.2523	2.2225
LEFT HAND	1	27.9548	26.5154	27.2260	27.1995	27.0858	0.3569	0.1274	2.0021
	2	28.8129	27.3523	28.1262	28.1226	27.9042	0.3491	-0.0138	2.1087
	3	27.5616	26.1888	26.8446	26.8432	26.6077	0.2789	0.0939	2.4005
	4	29.6000	28.5288	29.1702	29.1772	29.1327	0.2202	-0.3065	2.3702
	5	32.1622	30.6685	31.1935	31.1442	30.7931	0.3027	0.5650	2.6446
	6	34.4487	32.5815	33.3944	33.4007	33.6511	0.4172	0.0447	1.9892
	7	32.5310	31.3926	31.8374	31.7600	31.5965	0.2727	0.7486	2.4340
	8	31.6390	30.2856	30.7270	30.6750	30.5062	0.2576	0.8266	3.2548

9	x	x	x	x	x	x	x	x
10	35 4435	32 0100	34 5267	34 4511	34 4514	0 3063	0 6538	2 7593
11	27 4707	26 2342	26 8916	26 9186	27 0474	0 2874	-0 2636	2 1485
12	28 0504	26 6077	27 0681	27 0213	26 9417	0 2551	0 8292	3 6955
13	24 6359	23 2334	23 9262	23 9291	23 7341	0 3178	0 0527	2 1870
14	27 2970	25 9669	26 6052	26 5960	26 3715	0 3121	0 1191	2 0681
15	33 0924	32 3649	32 6331	32 6175	32 5021	0 1386	0 3769	2 5512
16	29 6376	27 8022	28 5544	28 5221	28 2227	0 3862	0 4670	2 6062
17	31 5445	30 1088	30 5492	30 4988	30 3739	0 2751	0 9564	3 6453
18	33 1066	31 7052	32 1949	32 1658	31 9955	0 2696	0 5151	2 7192
19	34 6754	30 1088	30 5494	30 6095	30 9955	0 1563	-0 0306	2 4736
20	32 9908	28 5352	31 7052	31 0126	31 6095	0 2700	0 4851	3 0246
21	24 3360	20 0772	20 9585	21 7029	21 0349	0 3525	0 0528	1 9649
22	25 9366	23 9585	21 9617	22 8371	22 6170	0 4602	0 0874	2 0442
23	31 9233	28 0772	29 1155	29 7013	29 9298	0 3681	0 3023	1 9294
24	32 1225	30 4681	30 3281	30 9514	30 0742	0 4136	-0 2103	2 0365
25	24 4335	19 7839	23 5783	23 6514	23 3685	0 4031	0 2008	1 9793
26	32 7918	30 6034	30 1348	30 0962	30 5571	0 2770	0 2027	2 0309
27	26 8177	25 4963	25 1895	25 2010	25 1129	0 3149	-0 0485	2 1638
28	29 0955	27 5378	29 1020	29 0945	29 1895	0 3190	0 5211	2 6789
AVERAGE	29.4901	27.7385	28.4166	28.4199	28.3660	0.3065	0.2581	2.4832

10.4. 3rd MCP Raw Data Measurements

Table 10-4: Raw Data Measurements Extracted from the Patient Group's 3rd MCP Joint

Patient Group's 3rd MCP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT HAND	1	33.7148	32.7104	33.0718	33.0629	32.9479	0.1634	0.6039	3.7875
	2	34.2114	33.1590	33.6750	33.6971	33.9117	0.2670	-0.0658	1.7664
	3	33.4965	32.6184	33.1865	33.1878	33.1662	0.1218	-0.5207	4.0262
	4	30.0953	28.8356	29.2370	29.1853	29.1036	0.2460	1.5795	5.5391
	5	29.9465	29.0944	29.5748	29.6065	29.6953	0.1492	-0.4995	2.6517
	6	30.5062	29.5176	29.8991	29.9022	29.9392	0.2060	0.4202	2.8930
	7	33.7362	32.7968	33.3208	33.3427	33.5504	0.2495	-0.2523	1.7555
	8	32.7681	31.7849	32.2695	32.2558	32.1835	0.1719	0.0768	2.7501
	9	30.8371	29.6671	30.0733	30.0216	29.9257	0.2342	0.7954	3.1084
	10	33.4865	31.8650	32.2666	32.1839	32.1332	0.2519	1.7503	6.5791
	11	33.3069	31.8498	32.4927	32.4796	32.2917	0.3363	0.2096	2.1556
	12	32.6643	31.6147	32.0417	32.0502	32.1298	0.2147	0.1873	2.3189
	13	28.5438	27.9368	28.2591	28.2519	28.1320	0.1193	0.2457	2.4683
	14	33.7569	31.2424	32.0055	32.0635	32.2086	0.3585	-0.1182	2.0425
	15	32.0316	30.6287	31.4104	31.4638	31.7480	0.3635	-0.3502	2.0057
	16	31.7239	27.4682	30.1075	30.1323	31.0596	0.3250	-0.1642	1.9944
	17	34.5043	32.6828	33.5386	33.5036	33.0606	0.4867	0.0936	1.8333
	18	35.8645	33.8081	34.8787	34.8837	34.6942	0.5340	-0.0691	2.0292
	19	25.1731	23.4249	24.1959	24.1743	24.3763	0.4166	0.1469	1.9079
	20	29.8062	27.8228	28.8122	28.8338	27.8980	0.5143	-0.0740	2.0605
	21	30.0327	28.6609	29.1920	29.1315	29.8830	0.3151	0.6092	2.7787
	22	28.7293	25.0533	27.8379	27.8983	27.9136	0.3936	-0.0867	2.0032
	23	30.2791	28.4391	29.3808	29.3629	29.8145	0.4283	0.0851	2.5326
	24	25.3656	23.9095	24.6842	24.6842	24.2054	0.3701	-0.1177	1.8501
	25	33.6240	31.9635	32.9044	32.9044	32.9795	0.4684	0.0996	2.3867
	26	34.5301	32.9509	33.7361	33.7361	33.7204	0.4267	0.0645	1.8996
LEFT HAND	1	33.3284	32.5229	32.9428	32.9407	32.9695	0.1485	-0.0659	2.8655
	2	33.3387	32.5822	33.0151	33.0223	32.9863	0.1379	-0.6092	3.3563
	3	34.0902	32.8566	33.6180	33.6542	33.7043	0.2345	-0.8674	3.7121
	4	30.7639	29.3486	29.7821	29.6967	29.6079	0.3071	0.9006	3.0437
	5	29.3915	28.6921	29.0793	29.0833	29.0721	0.1437	-0.2263	2.5309
	6	29.2876	27.8077	28.4814	28.4155	28.1533	0.3390	0.4014	2.1294
	7	33.6648	32.5373	33.1810	33.2208	33.5074	0.2846	-0.4192	2.1694
	8	33.0054	31.5159	32.2548	32.2342	31.8647	0.3351	0.2685	2.1979

9	31.7994	29.4376	30.1800	30.1137	30.1174	0.4380	0.8169	3.5398
10	33.4435	32.0100	32.5267	32.4658	32.4514	0.3063	0.6538	2.7593
11	33.4430	32.1325	32.7466	32.6960	32.9335	0.3346	0.2709	1.9305
12	32.7076	31.4691	31.9673	31.9560	31.9125	0.2450	0.2584	2.4530
13	29.4667	28.5811	28.9966	28.9690	28.8349	0.1869	0.3749	2.3855
14	34.7949	32.1885	33.8769	33.8454	33.8952	0.3856	0.3129	2.1624
15	31.3469	29.7801	30.6283	30.6214	30.6214	0.3862	-0.0570	2.1561
16	29.1710	27.1973	28.6770	27.6564	27.3389	0.7253	0.0752	2.0548
17	33.9058	29.5645	32.2060	32.1627	32.0056	0.2450	0.2818	2.8529
18	35.7649	33.3544	34.4607	34.5160	33.6049	0.6145	-0.0351	1.9241
19	35.0343	33.6675	34.3356	34.3142	34.3142	0.3707	0.2025	1.8702
20	29.3396	27.8453	28.7281	28.7629	28.9530	0.3426	-0.3860	2.4419
21	34.9442	31.5677	33.1223	33.1265	33.5198	0.4386	-0.1122	2.0793
22	32.5697	30.5818	31.6682	31.6954	31.5995	0.4936	-0.2367	2.0971
23	28.9913	26.1337	27.7096	27.7864	27.8466	0.7246	-0.1876	1.9907
24	26.2162	24.2209	25.1224	25.0883	24.0883	0.4907	0.1735	1.9479
25	26.8164	24.9949	25.9622	25.9477	25.9324	0.4664	-0.0413	1.8409
26	34.0127	31.0826	32.4938	32.4595	32.2848	0.1999	0.4287	2.7276
AVERAGE	31.7956	30.0996	30.9580	30.9317	30.8998	0.3357	0.1313	2.5451

10.5. Ankle Raw Data Measurement

Table 10-5: Raw Data Measurements Extracted from the Control Group's Ankle Joint

Control Group's Ankle Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT ANKLE	1	27.8534	24.3390	26.3450	26.4004	25.8871	0.7840	-0.4238	2.7291
	2	28.0622	24.9064	26.8268	26.8945	26.6560	0.6144	-0.4893	3.0242
	3	30.3196	25.4118	28.0196	28.0813	27.9681	0.9236	-0.5847	4.0474
	4	31.3140	27.5931	29.5924	29.6363	29.7629	0.7134	-0.3664	3.3930
	5	31.0081	28.2520	30.0832	30.1549	30.5202	0.5240	-1.1285	5.0854
	6	31.6303	27.5328	29.4204	29.4151	29.4411	0.7149	0.0599	2.7210
	7	31.1920	28.2710	29.4566	29.4217	29.6504	0.6205	0.5463	3.2773
	8	31.7405	29.5617	30.6521	30.7432	30.8921	0.4221	-0.3795	2.5546
	9	x	x	x	x	x	x	x	x
	10	34.9784	31.7331	33.3145	33.2851	32.4729	0.6849	0.1068	2.8023
	11	29.1283	26.6257	27.8146	27.8080	27.5780	0.5252	0.0249	2.4388
	12	30.2399	27.1838	28.6064	28.6454	28.9014	0.6628	-0.0116	2.5140
	13	27.8756	24.0867	26.0094	26.0677	26.2817	0.7391	-0.2199	2.6871
	14	30.1687	26.0867	28.3108	28.2940	28.0427	0.6616	0.1693	2.7739
	15	29.2964	26.3658	28.0168	28.0482	28.2502	0.5644	-0.4897	3.1700
	16	31.0008	25.7718	28.4693	28.5745	28.3161	1.0322	-0.4058	3.2326
	17	30.8264	27.8347	29.1061	28.9715	28.7252	0.6622	0.5427	2.6081
	18	32.1255	29.4612	30.9153	30.9352	30.8489	0.5341	-0.1654	2.5441
	19	29.8263	26.5570	29.4627	29.3073	28.7905	0.6588	-0.2462	1.9420
	20	32.5896	30.4446	31.3651	31.0491	31.1922	0.5797	-0.2351	2.7758
	21	30.9292	27.8029	29.6974	29.3199	29.3742	0.7554	-0.0365	2.6387
	22	32.9281	29.8512	31.1047	30.8525	30.7103	0.7215	-0.5239	2.9612
	23	30.1367	26.8077	28.8772	29.3320	29.1770	1.0009	-0.3596	2.5130
	24	31.9716	29.1119	30.3722	30.1045	29.9378	0.8599	0.5218	2.2432
	25	29.6305	26.9471	29.2348	28.9152	28.8713	1.0123	0.2214	2.4685
	26	30.5911	27.9682	29.3392	29.8277	29.4603	0.9171	-0.5579	2.9956
	27	29.6110	26.6012	28.6615	29.1930	28.5927	0.9748	-0.2506	2.7401
	28	32.4434	28.6924	30.6604	30.6727	30.4473	0.9166	0.1906	2.8489
LEFT ANKLE	1	27.7992	24.2147	26.3368	26.4423	26.2974	0.7979	-0.5758	2.6493
	2	28.2560	25.0064	26.9612	27.0592	27.5452	0.7023	-0.3186	2.4534
	3	30.4237	25.3852	28.1460	28.2673	28.5417	0.9699	-0.5259	3.9542
	4	31.4456	27.4331	29.8942	29.9900	30.3721	0.8396	-0.6696	3.3835
	5	31.1236	29.0419	30.3540	30.4172	30.3345	0.4163	-0.8660	3.9681
	6	31.8208	27.0867	29.8033	29.7660	29.6988	0.7353	-0.0782	3.2760

7	30.8784	27.9840	28.9066	28.0284	28.6169	0.6264	0.6696	3.1223
8	32.9931	29.8229	31.4291	31.4265	31.4022	0.5598	-0.1961	4.1395
9	x	x	x	x	x	x	x	x
10	34.5106	31.4597	33.2062	33.2128	33.1790	0.6601	-0.2811	2.4572
11	29.1097	25.4132	27.3286	27.4040	28.1753	0.7374	-0.2724	2.5908
12	30.0197	26.6720	28.3907	28.4058	28.2445	0.6768	0.0678	2.1802
13	27.7304	23.8300	25.7197	25.7671	25.6802	0.7701	-0.0661	2.7462
14	30.1914	26.6159	28.4660	28.4846	28.2729	0.6915	-0.0404	2.5012
15	29.0820	25.5391	27.5189	27.5407	27.7655	0.6283	-0.2704	3.1045
16	31.2238	25.7582	28.5277	28.5520	29.0414	1.1101	-0.2175	3.2410
17	31.2183	26.8602	28.6010	28.5094	28.3556	0.8842	0.5803	3.3786
18	31.6397	28.5397	30.2898	30.3592	30.1278	0.6608	-0.1536	2.2988
19	29.7766	27.6643	28.9703	28.8762	29.1723	0.7708	-0.1324	2.8480
20	32.6514	29.8683	31.5831	31.5936	31.7490	0.5322	0.0033	2.1769
21	30.7527	27.3452	29.3974	29.7267	29.6995	0.6709	-0.3191	3.1951
22	32.0124	29.6604	30.9160	31.0030	30.8464	0.8273	-0.5124	2.9449
23	30.3793	27.1248	29.2071	29.2403	28.8805	0.9702	-0.2171	2.5098
24	31.3834	29.7905	30.6065	30.0603	29.9678	0.8541	0.4379	1.7530
25	30.6415	26.8090	28.8688	28.7459	28.0516	0.9862	0.2520	2.3754
26	29.7657	26.6074	29.1131	29.2025	28.9445	0.8645	-0.5504	3.1270
27	29.9687	25.9119	28.2151	27.9956	28.4774	0.9935	0.0630	2.4197
28	30.7482	28.9589	30.1347	30.5131	30.3883	0.6979	-0.5525	2.8887
AVERAGE	30.5284	27.2118	29.0405	29.0393	29.0178	0.7513	-0.1742	2.8876

10.6. Ankle Raw Data Measurement

Table 10-6: Raw Data Measurements Extracted from the Patient Group's Ankle Joint

Patient Group's Ankle Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT ANKLE	1	31.9697	27.4458	30.1467	30.2664	30.7483	0.8949	-0.8846	3.4977
	2	31.8378	28.9974	30.5990	30.5732	30.5602	0.5256	-0.2762	3.0984
	3	31.5938	28.0131	29.8346	29.7937	29.2691	0.6992	0.0547	2.7760
	4	28.3446	23.7718	26.1864	26.1619	26.0533	0.9359	-0.3165	3.3294
	5	30.5566	26.2503	28.5739	28.5958	29.1154	0.9412	-0.1192	2.1611
	6	32.3034	29.5587	30.9645	30.9590	30.7794	0.5630	-0.0344	2.5859
	7	32.3837	29.9208	31.2544	31.2406	31.2797	0.4680	-0.2115	2.8418
	8	28.6185	25.1772	27.1556	28.5541	26.8384	0.7007	-0.4905	3.3060
	9	30.8412	27.8498	29.3508	29.3229	29.2597	0.5475	0.2320	3.1634
	10	32.0274	28.5977	30.5722	30.5933	30.3161	0.6921	-0.2232	2.4320
	11	30.8031	27.0346	28.9079	28.8938	28.9548	0.8914	0.2390	2.6156
	12	29.8828	26.8903	28.5981	28.6707	28.9467	0.5749	-0.3871	2.6858
	13	31.8759	27.3671	28.9793	29.2304	29.2217	0.8450	0.4335	3.5910
	14	34.2322	29.1906	31.7191	31.8295	31.9985	0.9902	-0.1936	2.8500
	15	34.2493	27.4005	31.0979	31.2287	30.0267	1.5685	-0.3747	3.0381
	16	33.9487	30.1974	31.9086	31.8290	31.2503	0.7747	0.2423	2.5045
	17	32.9091	28.9800	31.2136	31.2237	30.9407	0.8333	-0.4065	2.9554
	18	34.3314	31.8213	33.2495	33.3554	33.6241	0.6395	-0.4734	2.4174
	19	33.6172	29.0422	32.2029	32.4197	33.0771	1.0076	-1.1154	4.1844
	20	32.6834	27.1237	30.2634	30.3650	29.4188	1.2035	-0.8318	4.1599
	21	32.9021	28.8227	31.1374	31.2526	31.5830	0.8427	-0.4172	2.6412
	22	34.4999	31.8573	33.2832	33.2797	32.7242	0.6186	-0.1386	2.2624
	23	34.2893	31.2636	32.8094	32.8440	32.4451	0.6762	-0.2113	2.5723
	24	32.2422	28.2828	30.4856	30.6119	30.9718	0.8704	-0.2025	2.6323
	25	35.7159	31.6773	34.1794	34.6624	34.4871	0.9190	-0.3687	2.6403
	26	33.1502	28.4887	31.4680	31.6624	32.3195	1.0709	-0.7667	3.3049
LEFT ANKLE	1	31.7781	28.1375	30.1593	30.1379	30.1420	0.6959	-0.2428	2.7192
	2	32.0099	29.3693	30.6630	30.6490	30.3388	0.5172	0.1689	2.6764
	3	32.2655	29.0651	30.6455	30.6757	30.9232	0.6617	-0.3464	3.3788
	4	27.2027	23.3602	25.3303	25.2867	24.5376	0.7872	-0.1853	3.2700
	5	29.8181	26.3079	28.0958	28.0949	28.2348	0.6956	0.0993	2.6651
	6	32.6961	29.4706	31.0224	31.0170	31.0411	0.6052	0.1691	3.1176
	7	33.0406	30.8673	32.0951	32.1426	32.2373	0.3800	-0.3399	3.4557
	8	28.6609	25.5501	27.2704	27.2709	26.9252	0.6455	-0.2053	2.7689

9	29.6399	27.0290	28.2815	28.2502	28.2404	0.5539	-0.0599	2.4471
10	31.7973	28.5965	30.3848	30.3745	30.0864	0.6547	-0.2210	2.7432
11	30.7617	27.5518	29.1195	29.1461	28.9778	0.6823	0.1117	2.6385
12	29.3956	26.2974	27.9989	28.0587	27.9412	0.6883	-0.2582	2.3007
13	31.3847	26.7882	28.9555	29.0136	29.2294	0.9193	-0.0121	2.5727
14	34.2527	29.4882	31.9462	31.9396	32.0430	0.8612	-0.2666	2.9813
15	34.3253	28.2931	31.7337	31.8016	31.8168	1.3188	-0.3669	3.0688
16	33.7179	29.2543	32.1207	32.0708	31.8838	0.8039	-0.6706	5.5077
17	33.4469	29.7682	31.7048	31.7038	31.7122	0.7278	-0.0710	3.0021
18	34.5846	31.6118	33.4810	33.6042	34.0462	0.6452	-0.9163	3.8534
19	33.5753	28.2957	31.9050	32.2066	32.0904	1.2235	-1.0620	3.7026
20	32.7005	26.5773	30.5685	30.8051	30.8116	1.3647	-1.0661	4.0180
21	33.0291	29.9618	31.1890	31.2831	31.1346	0.7933	-0.1496	3.5631
22	35.0536	32.7623	33.7898	33.7332	33.3564	0.5010	0.5061	2.7365
23	34.0093	30.2121	32.4665	32.5318	32.5521	0.7287	-0.4790	2.9620
24	31.2956	27.6175	29.6139	29.7461	29.3862	0.8322	-0.2507	2.6001
25	35.6496	31.9042	34.0645	34.1377	34.4235	0.7432	-0.3424	2.7684
26	33.4440	29.4119	32.0393	32.2627	32.4511	0.8719	-0.6533	3.2089
AVERAGE	32.3336	28.5495	30.6305	30.7185	30.6302	0.7922	-0.2760	3.0187

10.7. Knee Raw Data Measurement

Table 10-7: Raw Data Measurements Extracted from the Control Group's Knee Joint

Control Group's Knee Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT KNEE	1	30.2493	27.0934	28.7182	28.8543	29.0781	0.5696	-0.3387	2.7822
	2	29.8330	27.8514	29.1100	29.1639	29.3204	0.3243	-1.0887	4.4812
	3	30.3823	27.6369	29.6064	29.6745	29.7189	0.4351	-1.5978	6.4680
	4	33.0060	28.4765	31.0202	31.1515	31.4141	0.8399	-0.4804	2.9319
	5	31.3194	28.8498	30.3849	30.4923	30.6025	0.4187	-0.9371	3.9023
	6	31.9233	28.7535	30.9183	31.0716	31.3124	0.5506	-1.0887	3.7233
	7	31.1884	28.4174	29.9771	29.9628	29.9037	0.5265	-0.3303	2.8037
	8	32.3423	30.2193	31.3156	31.3332	31.3769	0.3390	-0.2411	2.8205
	9	x	x	x	x	x	x	x	x
	10	34.9168	31.7518	32.5376	32.4879	32.4435	0.2537	-0.2411	2.8205
	11	30.6826	26.7517	29.4577	29.6591	29.7035	0.7381	-1.1407	3.7774
	12	30.9250	26.6305	29.0497	29.1184	28.7909	0.9487	-0.2888	2.1461
	13	28.7083	25.6913	27.7761	27.9298	28.2299	0.6067	-1.0905	3.6389
	14	30.6606	26.1121	29.2306	29.3109	29.4147	0.5991	-0.7396	3.6096
	15	29.6450	28.4024	29.1597	29.1556	29.1110	0.1573	-0.2628	3.6784
	16	32.1769	28.3350	30.6243	30.7056	31.4509	0.9255	-0.3442	2.1790
	17	30.9753	28.2957	29.7534	29.8431	30.0277	0.5805	-0.2536	2.1453
	18	31.7626	28.6323	29.9560	30.0130	30.0425	0.5676	-0.0333	2.5365
	19	30.8818	28.7093	29.6176	29.5545	29.4510	0.4230	0.4212	2.9208
	20	31.1849	26.7520	28.9324	29.5060	27.9673	1.4030	-0.0829	2.1434
	21	31.9461	29.7658	30.9790	31.0026	30.9723	0.4588	-0.2453	2.4632
	22	33.1517	30.4013	31.5042	31.4710	31.5409	0.6110	0.3955	2.4687
	23	33.0313	28.9112	31.5421	31.5473	31.5908	0.7020	-0.0461	2.5535
	24	32.2327	29.8022	30.9163	30.9013	31.0103	0.4961	0.1217	2.3382
	25	32.7248	30.2190	31.5015	31.5960	31.8871	0.5328	-0.2720	2.1915
	26	30.9320	28.4579	29.6620	29.6253	29.8871	0.4949	0.2134	2.8147
	27	32.9695	29.5539	31.1985	30.4198	30.4198	0.7611	0.1838	2.5940
	28	32.0975	29.6307	30.6450	30.6584	30.6584	0.3394	0.2175	2.1083
LEFT KNEE	1	31.9546	28.1278	30.1671	30.0943	29.8948	0.5649	0.2520	2.9179
	2	31.2692	28.4383	29.6503	29.6549	29.6921	0.3858	-0.0075	3.5097
	3	30.5880	27.3428	29.5864	29.6375	29.6523	0.4350	-1.4072	6.3791
	4	32.6894	29.0360	31.0510	31.2172	31.5961	0.7624	-0.4195	2.4765
	5	31.2099	27.9969	29.7904	29.8810	30.3086	0.6447	-0.3787	2.5655
	6	32.3288	29.2670	31.0810	31.1884	31.3562	0.5707	-0.5929	2.7631

7	31.9523	28.4248	30.0810	30.0955	30.6396	0.6653	-0.0310	2.3417
8	32.5085	29.9613	31.1837	31.2383	31.3186	0.4801	-0.1617	2.4846
9	x	x	x	x	x	x	x	x
10	x	x	x	x	x	x	x	x
11	30.1904	26.1274	28.6153	28.8127	29.4147	0.8386	-0.7738	2.8185
12	31.3339	25.9748	28.9712	29.0738	29.8297	1.0518	-0.3539	2.2779
13	29.8069	26.0968	28.4322	28.5889	28.8574	0.6943	-0.8351	3.2502
14	30.6679	26.5846	29.1372	29.2738	29.5185	0.7781	-0.6062	2.7147
15	31.3489	27.9526	29.0225	28.9696	28.8430	0.3935	0.7195	4.7714
16	31.7637	28.8057	30.5102	30.5222	30.3752	0.6596	-0.2578	2.2600
17	31.4511	29.1911	30.4602	30.4841	30.7556	0.4091	-0.3273	2.7163
18	32.5668	30.1332	31.8815	31.9448	32.1332	0.3070	-0.5449	2.6813
19	31.0112	28.9556	30.0171	30.0405	29.9449	0.4350	0.0621	2.7336
20	31.2127	29.3340	30.2880	30.3099	30.6817	0.4085	0.0364	2.4442
21	32.1106	29.4588	30.8626	30.7905	30.6371	0.5970	0.0528	2.3730
22	32.6867	31.3312	31.3474	31.2515	31.1200	0.6045	0.3256	2.0612
23	32.1782	29.3177	30.9403	31.0435	31.1517	0.6302	-0.4218	2.4431
24	32.5899	29.5267	31.2324	31.3655	31.2396	0.7146	-0.3546	2.2461
25	33.1541	30.6279	31.9397	31.9428	31.7582	0.4955	-0.2256	2.9612
26	30.5725	29.0539	29.3215	29.3142	29.1580	0.5034	-0.0045	2.6146
27	33.1962	28.0539	30.3078	30.9401	27.8857	1.8433	-0.0791	1.9894
28	32.4306	30.4098	31.3831	31.3753	31.2556	0.4796	0.1419	2.2115
AVERAGE	31.5713	28.5362	30.1888	30.2456	35.5173	0.6096	-0.2989	2.9082

10.8. Knee Raw Data Measurement

Table 10-8: Raw Data Measurements Extracted from the Patient Group's Knee Joint

Patient Group's Knee Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT KNEE	1	31.8352	28.9828	30.6760	30.7776	31.0996	0.5633	-0.6414	2.8053
	2	31.6898	29.8763	30.7146	30.7316	30.8564	0.3305	-0.1307	2.4253
	3	31.8352	28.9828	30.6760	30.7776	31.0996	0.5633	-0.6414	2.8053
	4	29.0738	25.9060	28.0741	28.1629	28.2454	0.5395	-1.1527	4.6386
	5	30.7923	28.6024	30.0984	30.2120	30.5576	0.4687	-0.7398	2.6766
	6	31.2748	28.6398	30.1301	30.1751	30.5796	0.4721	-0.4066	2.3680
	7	32.0746	28.6530	31.3990	31.4206	31.5081	0.2433	-0.1090	2.6753
	8	29.8076	27.6595	28.7702	28.7760	28.8878	0.3868	0.1107	2.5216
	9	29.0441	26.7597	27.9101	27.8551	27.7574	0.4155	0.4489	2.7057
	10	31.9810	29.9032	31.1506	31.1880	31.4214	0.3226	-0.5389	3.0899
	11	30.4033	28.9828	29.9602	30.0130	30.0720	0.2136	-1.2839	4.6348
	12	31.2724	28.9586	30.2112	30.2908	30.4745	0.3652	-0.2989	2.3884
	13	30.5438	28.1095	29.3482	29.3480	29.3184	0.3617	-0.1871	3.5468
	14	33.6014	26.3101	31.4178	31.1578	30.9722	0.3467	0.9371	2.8288
	15	34.1353	25.8397	29.5971	29.3221	29.8995	0.4684	1.4689	4.3860
	16	34.1020	25.4773	29.5329	29.4123	29.6651	0.5238	0.6582	2.8727
	17	36.0924	26.0837	31.8603	31.9895	32.6804	0.0750	-0.2713	1.9801
	18	34.6762	27.4921	31.7774	31.7178	31.8732	0.4497	0.8105	3.8275
	19	33.4867	29.0936	30.7787	30.8009	29.2327	0.5825	1.1321	2.1117
	20	31.5817	28.7599	29.5814	29.4362	29.1383	0.4154	0.9974	3.4010
	21	33.7065	29.9555	31.3749	31.2701	31.1676	0.4005	0.6440	3.0244
	22	31.2330	28.0778	31.3142	30.0309	30.4576	0.3470	0.5555	2.0406
	23	33.2233	29.6511	30.5988	30.5902	29.3866	0.1998	0.2890	2.1639
	24	31.3467	28.6874	30.7960	30.8363	29.2576	0.2984	-0.0572	3.5622
	25	30.9871	27.7813	29.0544	30.2118	30.3741	0.4469	0.6921	3.6718
	26	32.4456	29.6547	30.1920	30.8419	30.7761	0.4384	0.8383	1.7672
LEFT KNEE	1	32.1325	29.2579	31.0218	31.1872	31.3988	0.6037	-0.7395	2.7100
	2	31.4200	29.5205	30.5332	30.5110	30.4669	0.3355	-0.0295	2.6400
	3	31.8645	29.4685	30.5154	30.4742	29.8097	0.5694	0.2446	1.9134
	4	28.1704	25.5611	27.3531	27.4409	27.6821	0.4235	-1.1194	4.3429
	5	31.0850	28.7592	29.8999	29.9170	29.8801	0.4175	-0.1652	2.5133
	6	31.0484	28.4754	30.0377	30.1751	30.3297	0.5569	-0.5574	2.4235
	7	31.1434	29.3693	30.4272	30.4474	30.4400	0.2915	-0.5222	3.2053
	8	31.6323	27.1840	29.2335	29.1704	27.1840	0.9486	0.0730	2.0262

9	28.8878	26.9493	28.0124	28.0279	27.9979	0.3666	-0.2073	2.7337
10	31.7561	22.8927	29.5297	30.5878	30.4703	2.5207	-1.5207	4.4411
11	31.5372	29.4583	30.2717	30.2414	30.1457	0.3803	0.3999	2.7651
12	32.7652	29.1966	30.9183	30.9437	31.0972	0.7165	-0.0808	2.4402
13	31.3485	28.1470	29.4361	29.4000	29.3555	0.4705	0.8634	4.9584
14	32.1542	26.2905	30.8363	30.7960	30.7813	0.2984	0.6921	3.5622
15	29.7629	23.4403	28.1458	28.0544	27.6874	0.4469	0.3473	3.6718
16	31.7907	24.5952	30.2118	30.1920	29.2576	0.3006	-0.0572	1.7672
17	33.9736	30.3593	32.2559	32.2654	32.1106	0.3085	-0.0345	2.6561
18	33.8877	26.6206	32.7104	32.8055	33.0266	0.4384	-0.2861	2.2536
19	31.8101	28.7699	30.0147	29.9456	29.1135	0.2736	0.2649	1.9185
20	30.0186	24.8746	302.9605	29.8419	29.1334	0.2262	0.4762	2.2989
21	33.4628	25.6989	30.9359	30.8156	30.3741	0.3157	0.8383	3.3442
22	34.0068	26.1724	31.8489	31.7761	31.7033	0.3753	0.2046	2.7792
23	32.9113	28.7300	30.6915	30.7617	31.1481	0.5758	-0.0658	3.0489
24	31.8198	27.1576	31.1135	31.1969	31.3042	0.3357	0.0935	4.6589
25	33.1034	28.6784	31.9898	31.9507	31.3481	0.4640	0.0027	5.8334
26	31.6547	302.1483	30.5615	30.7568	30.8303	0.4943	0.0270	3.5678
AVERAGE	33.0895	31.6711	31.8761	30.3275	30.2084	0.4556	0.0436	3.0268

10.9. 1st MTP Raw Data Measurement

Table 10-9: Raw Data Measurements Extracted from the Control Group's 1st MTP Joint

Control Group's 1st MTP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT FOOT	1	24.2016	22.6434	23.3888	23.3588	23.7264	0.3790	0.2001	1.9621
	2	29.9253	27.1222	28.5628	28.5139	28.4466	0.6713	0.0898	2.1108
	3	26.9480	25.2132	26.0436	26.0190	25.6590	0.4222	0.1218	2.0344
	4	33.7582	31.4655	32.9004	32.9774	33.3219	0.5018	-0.6832	2.8102
	5	26.2339	25.1218	25.6764	25.6754	25.6601	0.2142	0.0060	2.5213
	6	28.9754	27.4384	28.1223	28.1158	27.9882	0.3002	0.1470	2.2877
	7	33.2137	32.0818	32.7524	32.7752	32.7824	0.2299	-0.4045	2.6393
	8	28.8562	28.2508	28.5517	28.5501	28.5352	0.1021	0.1399	2.8317
	9	x	x	x	x	x	x	x	x
	10	34.6685	30.8989	33.7408	33.7299	33.5458	0.4012	0.0994	2.0501
	11	22.0583	21.2222	21.5729	21.5495	21.4857	0.1620	0.3376	2.4129
	12	25.8675	23.9914	24.8913	24.8988	25.2303	0.4419	0.0611	2.0405
	13	27.7345	27.1004	27.3934	27.3726	27.2819	0.1214	0.4158	2.4990
	14	24.2160	23.2320	23.7378	23.7408	23.7876	0.2074	0.0400	2.1545
	15	27.8754	27.1436	27.5567	27.5969	27.6496	0.1586	-0.6367	2.6455
	16	27.3491	26.2863	26.9402	26.9404	27.1752	0.2255	-0.1575	1.8823
	17	25.9588	24.6815	25.2809	25.2759	25.0215	0.2657	0.0986	2.3161
	18	27.8228	26.8860	27.3251	27.3100	27.2344	0.2238	0.0835	1.8930
	19	33.3786	32.0891	32.7542	32.8040	33.0414	0.3221	-0.2416	1.7394
	20	28.5651	27.7776	28.2692	28.3032	28.3482	0.1499	-0.7922	3.0216
	21	24.4965	23.2961	23.8487	23.8356	23.5857	0.2664	0.1915	2.1937
	22	25.8371	24.7908	25.3368	25.3383	25.2998	0.2556	-0.0645	1.9373
	23	21.9154	21.2782	21.5809	21.5654	21.5176	0.1126	0.6268	3.3867
	24	24.9297	23.8824	24.3769	24.3569	24.0771	0.2805	0.0798	1.5892
	25	24.6350	23.8812	24.2393	24.2316	24.3481	0.1795	0.1230	1.9920
	26	23.9046	22.7681	23.3283	23.3261	23.3496	0.2302	0.0467	2.4634
	27	26.1552	25.2039	25.5717	25.5578	25.4348	0.1739	0.6779	3.5864
	28	27.3566	26.3854	26.8314	26.8190	26.6062	0.2209	0.1953	1.9796
LEFT FOOT	1	25.4843	23.1392	24.1866	24.1861	24.2327	0.5211	-0.0249	2.0158
	2	29.6889	27.4623	28.4125	28.3792	27.9443	0.4825	0.3010	2.2026
	3	27.2206	25.8200	26.4386	26.3931	26.3473	0.3134	0.2918	2.2012
	4	33.2646	31.1884	32.4726	32.4588	33.0277	0.4459	-0.1705	2.1729
	5	26.3407	24.8671	25.6196	25.6371	25.9129	0.3230	-0.1372	2.0839
	6	28.9083	27.8679	28.3385	28.3145	28.3257	0.2062	0.3435	2.4165

7	32.8688	31.5517	32.4744	32.5229	32.5157	0.2453	-1.3251	4.7342
8	28.8114	28.1158	28.3948	28.4006	28.4006	0.0995	0.1747	3.6495
9	x	x	x	x	x	x	x	x
10	33.6992	29.5121	32.1233	32.1381	33.9761	0.2286	-0.0903	2.3287
11	22.3513	21.3900	21.8073	21.7883	21.5813	0.2138	0.2209	2.1339
12	25.8522	23.9681	25.0607	25.0994	25.4995	0.4224	-0.3534	2.1321
13	27.0776	26.6452	26.8682	26.8730	26.8882	0.0703	-0.0365	3.0517
14	24.2549	22.9728	23.6256	23.6470	23.6470	0.2918	-0.0993	2.1302
15	27.5742	26.8025	27.1143	27.1209	27.1815	0.1195	0.1021	2.9990
16	27.3189	26.4388	26.8708	26.8645	26.7810	0.1514	0.3062	2.9335
17	25.4681	24.5188	25.0134	25.0138	24.8671	0.2016	-0.0670	2.2858
18	27.6345	26.5516	27.0645	27.0414	26.9087	0.2351	0.2532	2.3102
19	33.2997	32.5229	32.9702	32.9623	32.9120	0.1156	-0.3894	4.4183
20	28.0708	27.1890	27.6577	27.6647	27.7852	0.1656	-0.2074	2.4583
21	23.3509	22.3434	22.7790	22.7696	22.6356	0.2091	0.1781	2.4261
22	25.5458	24.2871	24.8870	24.8603	24.8680	0.3004	0.2388	2.1397
23	21.8519	21.1423	21.3989	21.3820	21.3580	0.1158	0.7371	3.6522
24	24.8679	23.4919	24.0240	23.9798	23.7107	0.3234	0.4402	2.1872
25	25.0987	24.2083	24.6763	24.6621	24.5111	0.2028	0.0435	2.0416
26	23.5767	22.6420	23.0904	23.0986	23.0278	0.2076	-0.0413	2.0682
27	26.4603	25.5655	25.9236	25.9105	25.9258	0.1507	0.4833	3.3473
28	27.0768	26.0420	26.5421	26.5149	26.4464	0.2354	0.1522	2.1941
AVERAGE	26.9517	25.7686	26.3566	26.3530	26.3430	0.2536	0.0407	2.4869

10.10. 1st MTP Raw Data Measurement

Table 10-10: Raw Data Measurements Extracted from the Patient Group's 1st MTP Joint

Patient Group's 1st MTP Result									
		Max (°C)	Min (°C)	Mean (°C)	Median (°C)	Mode (°C)	STD	Skewness	Kurtosis
RIGHT FOOT	1	26.4603	25.6729	26.4603	26.1322	26.2391	0.1911	-0.3768	2.0682
	2	30.5625	29.2529	29.6008	29.5502	29.4463	0.2022	1.2153	4.9357
	3	26.8837	26.0366	26.4304	26.4419	26.5029	0.1837	0.0046	2.0453
	4	25.1227	23.3039	23.9799	23.9214	23.5075	0.4114	0.4806	2.2887
	5	25.9717	24.8412	25.3942	25.3887	25.3810	0.2169	0.0664	2.6271
	6	25.4809	23.7768	24.6428	24.7019	25.1191	0.4377	-0.2073	1.7482
	7	28.5427	27.8153	28.2277	28.2508	28.3332	0.1461	-0.4551	2.3864
	8	30.9908	29.1630	30.2475	30.2794	30.2352	0.3692	-0.3692	2.8555
	9	x	x	x	x	x	x	x	x
	10	x	x	x	x	x	x	x	x
	11	26.3459	25.2655	25.7925	25.7879	25.8492	0.2282	0.0160	2.2189
	12	26.2914	24.7709	25.3989	25.3647	25.1183	0.3377	0.2952	2.1530
	13	26.8797	24.6494	25.6749	25.6130	25.0590	0.5891	0.1972	1.7888
	14	26.3078	25.3810	25.7871	25.7496	25.9181	0.2165	0.2933	2.2051
	15	34.1045	31.7189	33.1312	33.1374	33.1374	0.5604	-0.1998	2.1249
	16	27.0660	26.4953	26.7977	26.8077	26.8609	0.1110	-0.1727	2.6423
	17	24.8217	23.3196	24.0627	24.0616	24.1549	0.3542	0.0523	1.9894
	18	26.3078	25.0574	25.7465	25.7534	25.5040	0.2773	-0.0145	2.0693
	19	26.0405	24.6865	25.2951	25.2424	24.9262	0.3167	0.3530	1.9727
	20	28.9530	27.5969	28.3274	28.3107	28.2508	0.2983	0.0235	2.0636
	21	29.0292	26.9872	28.1368	28.1704	27.4786	0.5548	-0.1194	1.7762
	22	27.1916	26.5773	26.9219	26.9266	26.9721	0.1004	-0.2345	3.1701
	23	29.9549	29.4593	30.7194	29.7258	29.7332	0.0859	-0.1598	2.6804
	24	26.6201	25.7343	26.2478	26.2620	26.2544	0.1788	-0.3940	2.5350
	25	26.4134	25.2262	25.7188	25.6949	25.7869	0.2530	0.3008	2.3521
	26	26.3702	25.2671	25.8737	25.8660	25.9425	0.2102	-0.0263	2.6502
LEFT FOOT	1	27.6345	26.7873	27.2436	27.2420	27.3478	0.1709	-0.1159	2.4140
	2	31.7189	31.0177	31.4479	31.4565	31.5732	0.1193	-0.3026	2.9753
	3	27.5431	26.7468	27.1300	27.1229	26.9521	0.1841	0.1497	2.0413
	4	24.8603	23.9292	24.3829	24.3725	24.1705	0.1971	0.1383	1.9114
	5	25.4809	24.6710	25.1092	25.1500	25.2039	0.1820	-0.3598	2.1606
	6	25.4656	24.1743	24.8504	24.8876	25.0651	0.3018	-0.2219	2.0462
	7	28.7592	28.0182	28.4228	28.4455	28.4455	0.1503	-0.4090	2.4912
	8	25.4613	23.8356	24.5908	24.5741	24.3414	0.3423	0.1448	2.2140

9	x	x	x	x	x	x	x	x
10	x	x	x	x	x	x	x	x
11	27 1588	26 2391	26 6229	26 5897	26 4983	0 1894	0 4518	2 2669
12	26 3448	24 7631	25 5463	25 5338	25 6259	0 3150	0 0642	2 5641
13	28 5139	25 4210	26 9471	27 0010	27 5076	0 7388	-0 0740	1 9913
14	27 1285	25 7419	26 5471	26 5516	26 6277	0 3050	-0 2614	2 5147
15	31 4930	29 2827	30 6247	30 7242	31 0250	0 5328	-0 4743	2 2414
16	28 3263	27 4373	27 9222	27 9354	27 9279	0 1752	-0 3062	2 6079
17	24 6670	23 0528	23 8370	23 8317	23 7888	0 3380	0 0212	2 2032
18	25 6883	24 3763	25 0937	25 1423	25 2424	0 3057	-0 2432	1 8982
19	25 4502	24 1898	24 8086	24 8335	25 0189	0 2654	-0 2260	2 2090
20	28 4604	27 4762	27 9084	27 8980	27 8905	0 2127	0 1506	2 2725
21	28 6342	25 9519	27 3330	27 3579	27 0932	0 5136	-0 0993	3 0428
22	27 2445	25 6302	26 5415	26 5469	26 7900	0 3370	-0 2349	2 3808
23	29 3555	28 2369	28 9317	28 9504	28 9392	0 2191	-0 4523	2 5086
24	26 8708	25 7189	26 4063	26 4222	26 1781	0 2586	-0 2396	2 1035
25	25 9247	25 2570	25 5729	25 5722	25 5031	0 1212	-0 0636	2 5903
26	25 9655	24 1604	25 4035	25 4671	25 6897	0 3650	-0 9090	3 4045
AVERAGE	27.3513	26.0452	26.7467	26.7239	26.7116	0.2848	-0.0688	2.3834

11. APPENDIX E _ Decision Trees

11.1 Decision Tree(classification) Results of presence or absence of RA

Table 11-1: Min/Max and Median/Max Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	76.4	71.2	75.4	77.3	77.3
	Specificity	60.2	52.5	56.8	58.3	60.7
	CCR	65.3	59.8	63.1	64.8	66.0
Test	Sensitivity	60.8	63.4	65.2	65.2	63.6
	Specificity	48.5	50.8	52.3	52.3	51.2
	CCR	51.7	54.1	56.8	56.8	54.7

Table 11-2: Mode/Min and Median/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	70.8	67.1	64.3	59.6	59.6
	Specificity	63.8	60.7	59.2	55.1	54.9
	CCR	66.3	62.5	60.8	56.5	56.1
Test	Sensitivity	53.4	50.8	52.1	48.7	49.2
	Specificity	70.0	65.4	65.4	60.8	69.3
	CCR	54.7	50.6	52.5	48.8	49.3

Table 11-3: Mode/Min and Mean/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	68.9	74.2	69.3	70.0	75.4
	Specificity	56.3	58.8	54.1	55.9	61.7
	CCR	58.6	62.5	59.7	59.9	64.6
Test	Sensitivity	45.2	44.6	44.6	42.2	45.2
	Specificity	50.6	46.5	41.9	51.6	55.0
	CCR	47.9	45.7	42.3	46.7	51.1

Table 11-4: Mode/Max and Median/Max Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	72.3	66.4	70.9	67.1	70.9
	Specificity	69.2	62.4	58.2	56.7	62.4
	CCR	69.8	63.4	63.6	60.9	65.7
Test	Sensitivity	48.1	48.1	44.3	45.9	47.1
	Specificity	45.7	59.3	58.8	54.6	55.3
	CCR	47.9	54.7	52.6	51.3	52.2

Table 11-5: Min/Max and Median/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	82.5	82.5	80.4	78.5	78.5
	Specificity	79.0	74.5	77.8	72.4	72.4
	CCR	79.8	77.2	78.1	74.5	74.5
Test	Sensitivity	69.0	69.0	67.1	65.4	60.3
	Specificity	79.4	76.1	72.5	62.8	62.8
	CCR	73.2	71.6	68.8	63.1	60.6

Table 11-6: Min/Max and Mean/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	82.6	75.4	80.3	79.8	79.8
	Specificity	77.6	65.4	78.6	70.2	70.2
	CCR	78.1	68.4	77.5	73.0	73.0
Test	Sensitivity	66.4	58.5	62.5	66.4	66.4
	Specificity	57.9	50.5	58.6	60.1	63.3
	CCR	60.2	52.5	58.6	61.3	62.9

Table 11-7: Median/Max and Mode/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	85.2	73.4	82.6	80.3	80.3
	Specificity	80.2	68.8	78.3	75.4	75.4
	CCR	80.2	72.1	79.5	76.9	76.9
Test	Sensitivity	70.2	65.4	70.2	69.4	69.4
	Specificity	75.5	58.7	77.1	68.9	65.6
	CCR	71.9	61.1	72.7	68.2	66.5

Table 11-8: Mean/Max and Min/Max Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	79.3	68.7	77.5	73.2	70.4
	Specificity	70.0	63.1	75.7	63.6	69.9
	CCR	69.7	60.9	71.6	63.4	65.2
Test	Sensitivity	50.3	50.3	45.6	43.2	49.6
	Specificity	71.1	65.4	50.3	49.7	51.7
	CCR	55.7	52.9	43.0	41.5	45.7

Table 11-9: Min/Max and Mode/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	81.5	76.4	80.3	70.0	76.9
	Specificity	70.1	65.6	73.7	69.3	72.3
	CCR	70.8	66.0	72.3	64.6	69.6
Test	Sensitivity	60.3	61.2	59.8	56.1	59.8
	Specificity	45.6	45.6	42.6	47.5	40.4
	CCR	49.9	50.4	47.2	47.8	46.1

Table 11-10: Min/Max and Mode/Min Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	86.5	75.4	85.9	85.9	84.1
	Specificity	75.2	73.1	70.0	71.4	73.6
	CCR	75.2	69.3	73.0	74.1	73.9
Test	Sensitivity	69.2	69.2	64.8	60.5	60.5
	Specificity	54.4	48.0	50.1	53.2	50.3
	CCR	56.8	53.6	52.5	51.9	50.4

Table 11-11: Mode/Max and Mean/Max Decision Tree result (Using 13 patients and 16 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	92.4	90.1	88.7	88.7	85.6
	Specificity	83.3	76.3	79.4	79.4	80.5
	CCR	83.9	79.2	79.1	79.1	80.1
Test	Sensitivity	70.6	67.4	71.6	71.6	72.2
	Specificity	63.3	60.2	65.1	62.0	79.1
	CCR	63.0	59.8	64.4	62.8	71.7

Table 11-12: Min/Max and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	96.1	88.9	88.9
	Specificity	92.7	88.7	90.2	83.5	83.5
	CCR	94.4	90.5	91.2	82.2	82.2
Test	Sensitivity	93.4	90.1	87.4	85.3	85.3
	Specificity	81.1	87.3	80.3	79.4	82.1
	CCR	82.3	83.7	78.9	77.4	78.7

Table 11-13: Mode/Min and Median/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	96.8	89.6	90.1	98.6
	Specificity	92.5	90.7	82.5	84.6	87.5
	CCR	94.1	90.8	83.1	84.4	90.1
Test	Sensitivity	89.6	90.9	94.1	92.2	92.2
	Specificity	78.9	86.5	92.3	90.6	86.1
	CCR	81.3	85.7	90.2	88.4	83.2

Table 11-14: Mode/Min and Mean/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	80.0	75.9	78.6	73.1	78.6
	Specificity	77.1	72.1	69.8	68.1	73.4
	CCR	77.6	73.0	73.2	69.6	75.0
Test	Sensitivity	79.2	72.2	73.9	72.2	80.0
	Specificity	74.0	69.2	64.1	69.2	76.3
	CCR	75.6	69.7	68.0	69.7	77.2

Table 11-15: Mode/Max and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	88.3	73.9	80.7	80.7	80.7
	Specificity	75.6	67.1	77.3	70.6	75.6
	CCR	76.3	65.5	74.0	70.7	73.2
Test	Sensitivity	71.2	69.9	75.4	70.8	69.9
	Specificity	70.5	60.7	70.2	62.4	65.6
	CCR	65.9	60.3	67.8	61.6	62.8

Table 11-16: Min/Max and Median/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	100	90.6	87.7
	Specificity	85.4	82.7	78.1	86.6	77.5
	CCR	90.7	87.4	84.1	85.6	78.6
Test	Sensitivity	94.2	91.3	95.1	91.3	86.1
	Specificity	89.9	83.5	92.3	84.9	72.5
	CCR	89.1	84.4	90.7	85.1	75.3

Table 11-17: Min/Max and Mean/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	89.6	80.6	84.8	84.8	84.8
	Specificity	79.1	78.9	70.1	68.3	65.8
	CCR	79.4	74.8	72.5	71.6	70.3
Test	Sensitivity	65.4	58.7	63.3	58.7	58.7
	Specificity	60.2	54.5	58.6	55.1	55.1
	CCR	59.8	53.6	57.0	53.9	53.9

Table 11-18: Median/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	80.0	77.5	79.0	78.1	79.0
	Specificity	72.6	70.2	75.3	72.2	75.3
	CCR	72.3	69.9	71.2	71.2	73.3
Test	Sensitivity	79.2	79.2	77.7	79.2	80.0
	Specificity	72.2	66.6	71.0	80.1	81.4
	CCR	71.7	68.9	70.4	75.7	80.4

Table 11-19: Median/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	95.2	78.9	86.4	77.1	83.6
	Specificity	82.9	80.2	78.3	72.3	72.3
	CCR	83.1	73.6	76.4	67.7	71.0
Test	Sensitivity	75.4	78.4	78.4	79.4	79.4
	Specificity	68.3	66.1	74.2	70.0	77.2
	CCR	64.9	65.3	68.3	67.7	70.3

Table 11-20: Min/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	69.1	54.5	54.5	70.0	62.3
	Specificity	56.9	50.3	48.3	62.5	55.4
	CCR	60.2	49.4	47.4	62.4	54.9
Test	Sensitivity	48.2	46.5	46.5	50.0	45.2
	Specificity	44.7	33.2	38.9	50.0	39.1
	CCR	43.5	35.9	38.7	50.0	38.4

Table 11-21: Mode/Min and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	78.6	78.6	65.9	78.6	75.4
	Specificity	66.1	59.9	60.6	70.2	58.1
	CCR	66.1	64.3	60.3	70.0	61.8
Test	Sensitivity	58.3	60.1	60.1	60.1	55.7
	Specificity	48.9	62.4	52.2	52.2	50.3
	CCR	50.6	57.3	52.2	52.2	49.0

Table 11-22: Mode/Max and Mean/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	90.5	88.3	94.4	83.3
	Specificity	86.7	85.5	73.3	86.0	79.3
	CCR	86.0	81.1	77.4	83.0	79.1
Test	Sensitivity	89.1	89.1	78.3	78.3	81.4
	Specificity	74.9	87.2	63.3	67.1	67.1
	CCR	72.9	79.5	66.1	69.3	73.3

11.2. *Decision Tree results for elimination of Variables (Joints)*

11.2.1. *Results for Knee, 2nd MCP and 3rd MCP combination*

Table 11-23: Mode/Min and Median/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	96.4	87.9	88.6
	Specificity	83.9	68.7	86.5	77.1	77.1
	CCR	80.0	78.4	84.9	77.1	76.5
Test	Sensitivity	89.1	89.1	78.3	81.6	81.6
	Specificity	74.9	85.2	68.3	74.9	74.9
	CCR	80.6	84.4	63.3	72.1	72.4

Table 11-24: Mode/Min and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	87.5	94.0	94.0
	Specificity	86.5	84.9	85.5	88.6	88.6
	CCR	85.2	83.6	81.6	86.7	85.5
Test	Sensitivity	90.0	90.0	90.0	87.2	87.2
	Specificity	78.6	88.2	84.6	86.3	86.3
	CCR	76.5	80.2	76.5	78.3	77.5

Table 11-25: Mode/Max and Mean/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	100	91.1	91.1
	Specificity	89.3	82.6	75.4	82.6	74.3
	CCR	90.2	86.7	79.5	78.2	81.2
Test	Sensitivity	92.3	80.6	83.1	83.1	80.6
	Specificity	85.0	77.4	82.5	80.6	77.4
	CCR	85.0	77.4	81.7	76.3	76.4

Table 11-26: Mean/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	95.6	95.6	86.7	84.3	88.6
	Specificity	83.9	68.7	86.5	77.1	77.1
	CCR	81.6	75.2	80.4	79.3	79.3
Test	Sensitivity	78.6	78.6	80.3	80.3	78.8
	Specificity	77.3	76.8	78.0	75.2	75.2
	CCR	72.6	70.4	77.9	73.6	70.7

11.2.2. Result for 3rd MCP

Table 11-27: Min/Max and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	85.4	85.4	91.6	91.6
	Specificity	89.9	80.6	83.4	87.5	87.5
	CCR	87.4	78.9	76.5	78.9	80.2
Test	Sensitivity	88.5	85.5	85.5	75.8	88.1
	Specificity	82.2	78.6	83.4	68.6	86.4
	CCR	79.9	77.1	81.1	65.3	83.5

Table 11-28: Min/Max and Mean/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	100	97.5	94.6
	Specificity	89.4	80.6	79.9	86.7	85.2
	CCR	86.9	82.0	81.5	78.7	79.3
Test	Sensitivity	90.0	90.0	90.0	90.0	90.0
	Specificity	86.8	78.7	90.0	76.3	77.2
	CCR	84.4	78.7	88.2	79.1	78.6

11.3. *Decision Tree results of level of severity of RA*

Table 11-29: Min/Max and Median/Max Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	95.2	86.9	90.3
	Specificity	85.5	84.9	86.9	85.5	85.5
	CCR	86.3	86.0	85.1	84.2	82.5
Test	Sensitivity	92.1	92.1	87.3	78.8	85.2
	Specificity	78.6	72.9	63.3	67.6	80.1
	CCR	80.3	77.5	70.3	68.2	82.7

Table 11-30: Median/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	87.4	92.3	92.3
	Specificity	89.5	85.5	80.6	85.5	85.5
	CCR	90.8	88.8	80.0	88.9	88.9
Test	Sensitivity	90.0	88.0	90.0	90.0	90.0
	Specificity	85.3	77.9	85.3	78.4	80.6
	CCR	86.6	80.9	86.6	78.2	85.4

Table 11-31: Min/Max and Median/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	100	100.0	86.4	95.3
	Specificity	83.3	73.3	83.3	85.5	86.4
	CCR	84.4	76.9	82.1	86.2	78.9
Test	Sensitivity	88.1	88.1	88.3	88.1	88.3
	Specificity	80.2	82.4	75.6	80.1	67.3
	CCR	83.6	80.1	78.4	80.2	77.8

Table 11-32: Min/Max and Mode/Min Decision Tree result (Using 26 patients and 26 control subjects)

DT #		1	2	3	4	5
Train	Sensitivity	100	89.8	84.4	96.7	90.3
	Specificity	96.3	87.4	87.4	80.5	80.8
	CCR	96.2	88.6	80.9	88.6	86.6
Test	Sensitivity	86.2	78.6	82.1	78.8	82.1
	Specificity	80.2	76.9	67.5	64.1	80.6
	CCR	80.2	75.8	74.8	75.5	78.4

12. APPENDIX F – Official Rheumatologists' Evaluation sheet

Patient #	Imaging Date	Rheumatologist's Evaluation
Patient 1	April 29 2008	Low
Patient 2	April 25 2008	Low
Patient 3	May 8 2008	High
Patient 4	June 12 2008	Low
Patient 5	June 12 2008	Low
Patient 6	June 13 2008	Low
Patient 7	June 13 2008	High
Patient 8	June 16 2008	Low
Patient 9	June 17 2008	Low
Patient 10	June 17 2008	Medium
Patient 11	June 19 2008	Medium
Patient 12	June 21 2008	Low
Patient 13	June 24 2008	Medium
Patient 14	December 16 2010	Moderate
Patient 15	December 16 2010	Low to moderate
Patient 16	December 16 2010	Low to moderate
Patient 17	December 18 2010	Low
Patient 18	December 20 2010	Low to 0
Patient 19	December 20 2010	Low to 0
Patient 20	December 20 2010	Low to moderate
Patient 21	December 20 2010	Low to 0
Patient 22	December 22 2010	Low
Patient 23	January 5 2011	moderate to high
Patient 24	January 8 2011	Low to 0
Patient 25	January 12 2011	moderate
Patient 26	January 13 2011	Low to 0

*Note that the Evaluation of the Patients 1 through 13 was adapted from the rheumatologist's evaluation of those patients at the time of the imaging session from previous work (Adéa 2009)

_____
Rheumatologist's Signature

_____
Date

April 27/2011.

_____
Student Signature

_____
Date

April 27, 2011

13. APPENDIX G - Science behind Infrared Imaging

13.1. *Electromagnetic Spectrum*

The electromagnetic spectrum is divided arbitrarily into a number of wavelength regions, called bands, distinguished by the methods used to produce and detect the radiation. Thermography makes use of the infrared spectral band. At the short-wavelength end the boundary lies at the limit of visual perception, in the deep red. At the long-wavelength end it merges with the microwave radio wavelengths, in the millimeter range. The infrared band is often subdivided into four smaller bands. They include: the near infrared (0.75–3 μm), the middle infrared (3–6 μm), the far infrared (6–15 μm) and the extreme infrared (15–100 μm) (FLIR Systems, 2007).

Fig. 13-1: Electromagnetic Spectrum (FLIR Systems, 2007)

Thermal infrared imaging's earliest application was for military use. This technology was developed solely for the purposes of warfare: using thermal IR cameras for night vision and human detection. Due to the nature of its very first applications, most thermal IR cameras

function in the far infrared range (6–15 μm), since the signal at these wavelengths can travel through most variations in the environment such as smoke, smog, dust, humidity.

13.2. ***Blackbody Radiation***

A blackbody is defined as an object which absorbs all radiation that impinges on it at any wavelength. The apparent misnomer black relating to an object emitting radiation is explained by Kirchhoff's Law, which states that "a body capable of absorbing all radiation at any wavelength is equally capable in the emission of radiation" (FLIR Systems, 2007). The blackbody is an ideal body. It absorbs all incident radiation and is conversely a perfect radiator; this implies that a blackbody absorbs and emits the maximum theoretically possible energy at a given temperature" (Ng, 2009).

13.3. ***Planck's Law***

Planck's law is used to describe the radiation emitted by a black body. Planck was able to describe the spectral distribution of the radiation from a blackbody by means of the following formula:

$$W_{\lambda b} = \frac{2\pi hc^3}{\lambda^5 \left(e^{\frac{hc}{\lambda kT}} - 1 \right)} \times 10^{-6} [\text{Watt} / \text{m}^2 \mu\text{m}] \quad (13.1)$$

Where $W_{\lambda b}$ is the blackbody spectral radiant emittance at wavelength λ , c is the velocity of light (3×10^8 m/s), h is the Planck's constant (6.626×10^{-34} Joule sec.), k is the Boltzmann's constant (1.380×10^{-23} Joule/K), T is the absolute temperature (K) of a blackbody and λ is the wavelength (μm)

Planck's formula, when plotted graphically for various temperatures, produces a family of curves. Following any particular Planck curve, the spectral emittance is zero at $\lambda = 0$, then increases rapidly to a maximum at a wavelength $\lambda_{\max}$ and after passing it approaches zero again at very long wavelengths. In essence, the higher the temperature; the shorter the wavelength at which a maximum occurs.

Fig. 13-2: Emissive Power of a Blackbody at Different Temperatures and Wavelengths According to Planck's Radiation Law (FLIR Systems, 2007)

13.4. Wein's Displacement Law

Wein's law can be expressed by differentiating the Planck's formula with respect to λ , and then finding its maximum. This is expressed in the equation below:

$$\lambda_{\max} = \frac{2898}{T} [\mu\text{m}] \quad (13.2)$$

where $\lambda_{\max}$ is the maximum emissive power and T is the temperature (in K).

Wien's formula expresses mathematically the common observation that colors vary from red to orange or yellow as the temperature of a thermal radiator increases. The wavelength of the color is the same as the wavelength calculated for $\lambda_{\max}$. A good approximation of the value of $\lambda_{\max}$ for a given blackbody temperature is obtained by applying the rule-of-thumb $3\,000/T\ \mu\text{m}$.

At room temperature (300 K) the peak of radiant emittance lies at $9.7\ \mu\text{m}$, in the far infrared in the electromagnetic spectrum. The figure below shows the Planckian curves from 100K to 1000K. The dotted line represents the maximum radiant emittance at each temperature according to Wien's displacement law (FLIR Systems 2007).

Fig. 13-3: Planckian Curves Plotted on Semilog Scale (FLIR Systems, 2007)

13.5. *Stephan-Boltzmann Law*

Stephan-Boltzmann law is described as the total radiant emittance of a blackbody, this is expressed by integrating Planck's formula from $\lambda = 0$ to $\lambda = \infty$. In other words, Stefan-Boltzmann formula, states that the total emissive power of a blackbody is proportional to the fourth power of its absolute temperature. Graphically, $W_{\lambda b}$ represents the area below the Planck curve for a particular temperature. It can be shown that the radiant emittance in the interval $\lambda = 0$ to $\lambda_{\max}$ is only 25% of the total, which represents about the amount of the sun's radiation which lies inside the visible light spectrum.

Using the Stefan-Boltzmann formula to calculate the power radiated by the human body, at a temperature of 300 K and an external surface area of approx. 2 m^2 , we obtain 1 kW. This power loss could not be sustained if it were not for the compensating absorption of radiation from surrounding surfaces, at room temperatures which do not vary too drastically from the temperature of the body – or, of course, the addition of clothing (FLIR Systems 2007).