USING PATTERN RECOGNITION TECHNIQUES TO DETERMINE CHANGES IN THE GAIT OF CRANIAL CRUCIATE DEFICIENT DOGS WITH OSTEOARTHRITIS

by

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(Under the direction of Hamid R. Arabnia)

ABSTRACT

Automatically recognizing and identifying the characteristics of a cranial cruciate deficient dog‘s gait with the presence of Osteoarthritis is very helpful to the veterinarians. A cruciate deficient dog‘s gait has several features which can indicate dysfunction. These features are represented by raw data obtained from the College of Veterinary Medicine, UGA. This data was trained and tested with existing learning tools such as NeuroShell and See- 5.0 to find patterns of regularity and classification. Based on this one of the features was chosen “Internal /External rotation” angle.

In this thesis, we have discussed several pattern recognition methods to determine the dysfunction in cruciate deficient dogs with osteoarthritis. We have also discussed the building of a recognition system based on Fourier domain representation of “Internal /External rotation” angle, which has proved to be the most discerning feature between dogs with and without stifle instability and secondary osteoarthritis.

Having found this feature, to recognize the presence of osteoarthritis automatically, 3 algorithms have been implemented - Neural Network Learner, Decision Tree Learner and K-Nearest Neighbors (KNN). The recognition system performed well in the classification.

INDEX WORDS: Osteoarthritis, Gait Analysis, Flexion, Extension, Internal Rotation, External Rotation, Abduction, Adduction

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DEDICATION

To my husband, Vasanth Pathuri.

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CHAPTER 1

INTRODUCTION

Early and accurate disease detection is very important in the cure of any disease. In recent times, the immense computing power of modern machines is being used to solve these problems. As computers are becoming inexpensive and their processing speeds quadrupling every 3 years, more complex algorithms are being developed for better accuracy in detecting diseases. Problems in medicine are posing challenges not only to the experts in that field, but also to the researchers from interdisciplinary areas to come up with accurate and quick solutions. In many cases, there is a need for systems which can recognize or identify disease symptoms automatically. At the same time, one would expect that the recognition system to be reliable in producing the results. These systems are the combination of computer science research and domain specific data.

Algorithms from specialized fields such as Image Processing, Pattern Recognition, Machine Learning, Neural Networks and Genetic Algorithms are widely used in the detection of most prevailing diseases such as Breast Cancer, Lung Cancer, Osteoarthritis, Osteoporosis and Diabetes [1]. Databases are used to store information obtained from clinical trials on existing patients. These databases can be queried for finding the most discerning features of diseases. Pattern recognition techniques such as neural networks and other statistical techniques use these features to recognize and classify diseases. With the advent of advanced technologies such as X-Rays and MRIs, Images have become extremely important in identifying diseases. Image processing techniques are being used extensively to find abnormalities which characterize them. Use of image processing algorithms for Digital Mammography to detect breast cancer in women is an example of such an application [2]. In this thesis we are discussing the unstable knee and subsequent Osteoarthritis in the Canine population and building a recognition system for its detection. This disease occurs

in dogs, and impairs their movement. We have implemented pattern recognition techniques which help in recognizing this condition by analyzing the gait or movement of dogs.

Domain specific data for the recognition system consist of gait data of both normal dogs, and dogs having the disease, Osteoarthritis, secondary to cranial cruciate instability. This disease is not easy to identify, by just looking at the dog. But in-depth analysis of its gait can give conclusive evidence of the presence of the disease. This sort of in depth analysis can only be done computationally. This is because the difference between measurements of dog gaits for normal and Osteoarthritis may be very subtle, and it is extremely difficult to identify manually.

This work has looked at various measurable parameters in a dog‘s gait, and applied various mathematical and statistical methods on them. We also looked at Fourier domain representation of these parameters. The result was, Fourier representation showed a better distinction between normal and diseased dogs, than its time domain representation.

Feeding Fourier representation of data as input to various learning tools helped in distinguishing which parameter of dog gait is most useful as an input to the recognition system. These parameters are described further in the coming chapters.

Data mining tools such as See 5.0, WEKA and Fourier domain representation of data were guiding factors for the research. They helped decide which form of data would be the input to the recognition system.

A recognition system was then built based on Fourier transforms. Three algorithms, k-nearest neighbors, k-mean distances and pre-computed threshold were used in the system. The system yields 97% accuracy in recognition.

Rest of the thesis is organized as follows. Chapter 2 gives the overview of canine Osteoarthritis. Chapter 3 describes the methodologies used in the detection of Osteoarthritis in recent years, Chapter 4 describes experiments conducted on time domain and Fourier domain data to learn the patterns that lead to Osteoarthritis disease and the results of those experiments. Next, Chapter 5 describes the implementation of an Osteoarthritis recognition system based on the analysis of characteristics of dog‘s gait. Finally, Chapter 6 summarizes the work.

CHAPTER 2

OVERVIEW OF OSTEOARTHRITIS IN DOGS

Canine knee osteoarthritis is a disease that affects dog‘s knee joints, causing pain and restricting dog’s motion. The term joint refers to the place where the ends of two or more bones meet. Stability and flexibility are essential for healthy functioning of joints. In a healthy joint, ends of bones are encased in a smooth, thin layer of cartilage. The cartilage covers and cushions bones, allowing joint to move smoothly and easily.

Osteoarthritis (OA) is also known as Degenerative Joint Disease. OA is a chronic degenerative disease. It is caused due to the break down of the cartilage that cushions and protects the ends of the bones at the joints. Cartilage break down causes bones to rub against each other, causing pain and loss of movement. Over a period of time, cartilage may erode completely resulting bone to bone grinding and further disability. It affects hands and weight-bearing joints such as knees, hips, feet and the back. As cartilage breaks down, the body attempts to ”patch-up” the damage by replacing it with new bone (bone is produced at a much faster rate than cartilage, due to its abundant blood supply). The ends of the bones in the joint thicken and the new bone can result in obvious growths, most often on the limb extremities and feet, which rub together. Each step in the cycle of cartilage breakdown and inadequate repair produces pain. In addition, when cartilage is weakened or damaged, the surrounding bones place extra force on it, which may lead to excessive blood flow that can cause pain, especially at night. This disease affects soft tissues and the bones of the affected joints. This results in pain and inflammation in the joints which leads to the decreased flexibility in joints. Any joint in the body is prone to this disease. Hip, stifle, shoulder, elbow, carpus, hock and inter-vertebral joints are the most commonly affected joints. Figure 2.1 shows

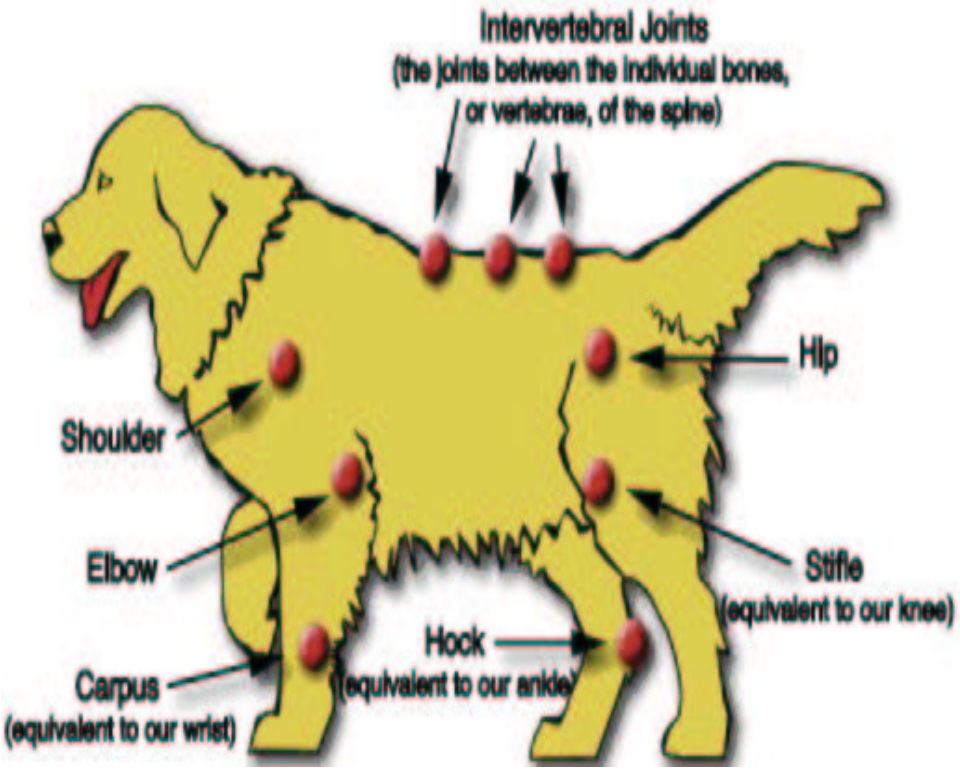

Figure 2.1: Typical dogs joints vulnerable to Osteoarthritis.

the location of a particular joint which is vulnerable to the disease with a red spot. Early symptoms of this disease are the reduction in the activity level of a dog [3].

By nature, dogs are very active. When they are affected by Osteoarthritis, they show reluctance to walk, jump, climb stairs and play. They start limping and show resistance to rising from a resting position. Figure 2.2 describes the sequence of events that occur during Osteoarthritis. Cartilage starts deteriorating when there is an increased load on joints. This leads to inflammation in the synovial membrane which causes joint pain. Due to this pain, dogs reduce their activities this in turn reduces muscle strength and support for the joints [4].

It has been estimated that as much as 20 percent of the canine population over one year of age has degenerative arthritis. Symptoms of arthritis usually come on slowly and involve the area around the joints. Damage due to arthritis progresses slowly over time and may result in several

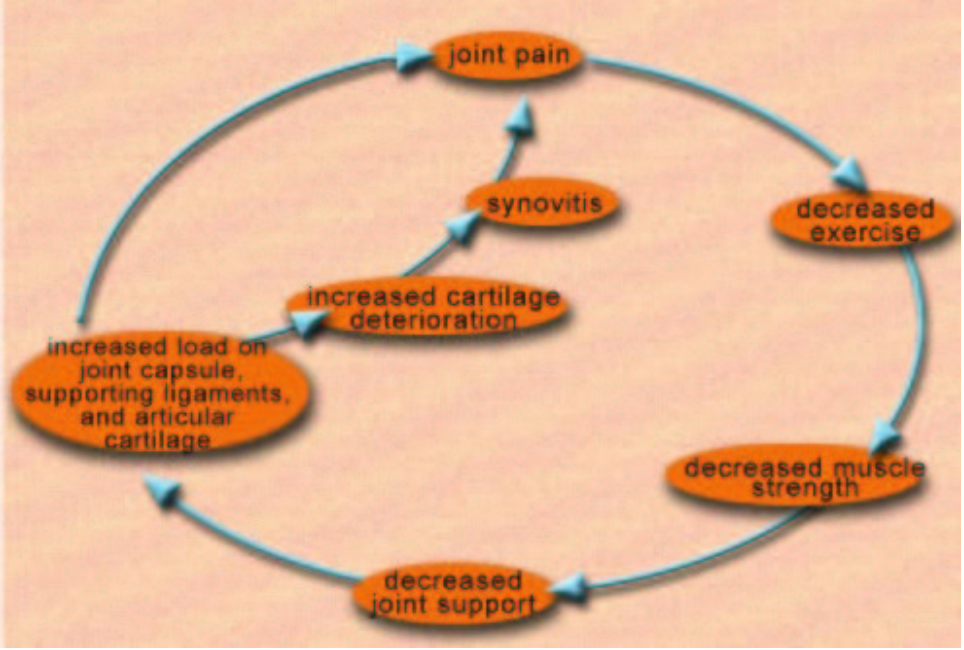

Figure 2.2: Sequence of events that result in the Osteoarthritis.

problems. The dog may have pain, especially when moving a joint. When it moves we may hear a grating sound when the roughened cartilage on the surface of the bones grinds together. Bumps or swelling may appear, especially on the limb extremities. A joint may appear sore, stiff and less flexible. All these changes can make it difficult to move around and the dog may appear to have difficulty moving [5].

The next chapter describes overview of the latest techniques that are being used in the detection of dysfunction in dogs with cruciate deficient knees and subsequent arthritis.

CHAPTER 3

RELATED WORK

Advancements in the areas of Computer Science, Molecular Biology and Biomedicine are being widely used by the veterinarians in the detection of Osteoarthritis of dogs. For human Osteoarthritis detection, state-of- the-art technologies from various domains are being used. Compared to that, experimenting with new technologies in disease detection for Canine population is limited. However, with some exceptions, most methodologies applicable in the detection of Osteoarthritis for humans can also be applicable for canine population. In the next few sections we look at techniques to detect the occurrence of Osteoarthritis in dogs.

New technologies are being used to collect the data from dog‘s gait. Data which is generated from the experiments can be analyzed to identify the presence of abnormalities in dog‘s gait. By systematic analysis of this data, it is possible to distinguish between normal dogs and dogs with OA.

Below section describes the data collection techniques which are being widely used in the research community.

3.1 DATA COLLECTION TECHNIQUES

3.1.1 KINEMATIC GAIT DATA

In recent years, kinematic gait data evaluation (data which refers to the patterns of movements) is being used in the detection of osteoarthritis among canine population [6]. Reflective markers are attached to external parts of the body. Reflections of these markers are caught while dog is trotted over the walkway and kinematic data is collected for analysis. Use of this method is gaining

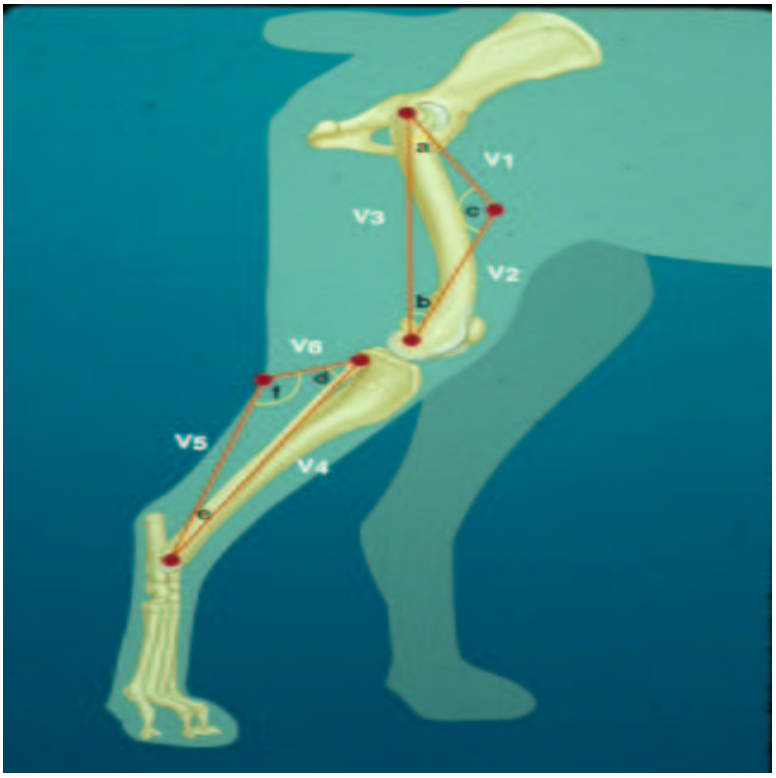

Figure 3.1: Schematic of femur, tibia and fibula showing the reference skin marker position and the triangles created to assess marker movement.

popularity in the research community [7]. Primary reason for collecting kinematic data is to analyze the motion of dogs while they are trotting. Joint angle measurements are taken using these methods while the dog is in motion and these values are used to detect abnormalities. Three dimensional kinematic measurement of the canine stifle proposed by researchers at the University of Georgia is an example of one such method. These dynamic variables collected from placing reflective markers are sent thru programs like JCA (Joint Coordinate Angles) as input for the analysis.

Figure 3.1 shows a three dimensional view of the dog‘s joints femur, tibia and fibula. It also shows positions from where dynamic gait variables are extracted by methods discussed above. In this method, retro reflective skin markers are placed on nine sites of the dog‘s femur and tibia to allow the creation of a reference axis on both the femur and tibia as shown in Figure 3.1. Kinematic

evaluations are performed as the dog is made to trot on a balanced walk way. Data collection is done with the help of high speed cameras which are connected to the dedicated computers to collect motion data from various markers [8], [9].

To reduce noise in the data, a minimum of 5 trials are conducted for each run. These dynamic data files are processed with a specialized software – JCA (Joint Coordinate Angles), which is used to calculate the three dimensional relative orientation of the tibia with respect to the femur.

[10] The vectors measured using this method, v1, v2, v3, v4, v5 and v6 and the corresponding angles between these vectors, *a, b, c, d, e, f* , shown in Figure 3.1, are inputs to JCA.

The description of vectors and the corresponding angles is showed in Figure 3.1.

V1 = Vector magnitude: greater trochanter marker to lateral epicondyle marker.

V2 = Vector magnitude: Quadriceps marker to lateral epicondyle marker.

V3 = Vector magnitude: Quadriceps marker to greater trochanter marker.

V4 = Vector magnitude: Fibular head marker to lateral malleolus marker.

V5 = Vector magnitude: Gastrocnemius marker to lateral malleolus marker.

V6 = Vector magnitude: Gastrocnemius marker to fibular head marker.

Angle a = Angle between Quads, Lat epi and Grt troc

Angle b = Angle between Lat epi, Grt troc and Quads

Angle c = Angle between Grt troc, Quads and Lat epi

Angle d = Angle between Fib head, Lat mal, and gastroc

Angle e = Angle between Lat mal, Fib head and Gastroc

Angle f = Angle between Fib head, Gastroc and Lat mal

Outputs of JCA program are angles which are measured around the joint. The angles measured are flexion/extension angle, internal/external rotation angle, and abduction/adduction angle of the tibia. This data is trained and tested using pattern recognition algorithms such as K-Nearest Neighbors.

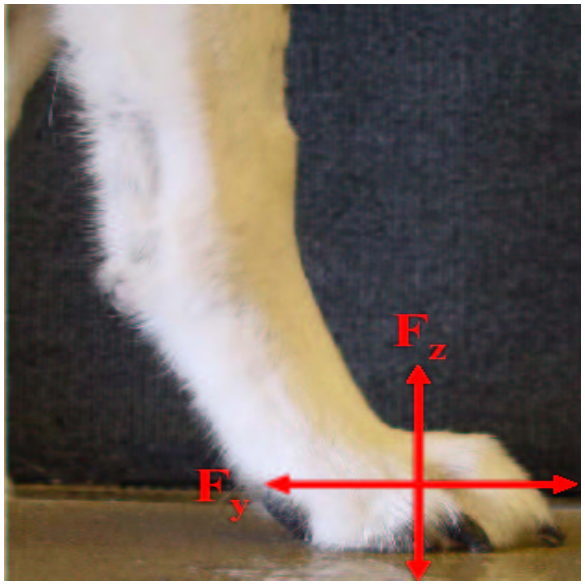

Figure 3.2: Pictorial description of the vertical ground reaction forces while the dog trots on the Force Platform. Fy represents the Craniocaudal force.

3.1.2 Kinetic Gait Data

Many veterinary teaching hospitals are using force platforms to diagnose limb abnormalities and evaluate treatment methods [11], [12]. Force platform is a platform which is used to measure the ground reaction force that is equal in magnitude and opposite in the direction of the resultant force, when an object moves on it. This method is very useful in collecting kinetic data of joint movements of a dog while it is moving on the ground. Main objective of collecting kinetic information is to estimate the actual ground reaction forces that are transmitted through the limbs of the dog.

The College of Veterinary Medicine at the University of Georgia uses this technique to detect the abnormalities in dogs. At the University of Georgia, the force platform (AMTI, model OR6-6) [1] is mounted at a level with a 40 ft. walkway. To collect gait data, the dog is led down the walkway by a handler so that as the dog trots (either right or left limb) makes contact with the force platform.

[1] Advanced Medial Technologies Inc., Newton, MA

The platform is hooked up to a dedicated computer that has specialized software (Acquire 7.0) [2] to analyze the dog‘s gait data.

At the same time, a series of photocells mounted in sequence, records the dog‘s velocity and whether or not the dog is accelerating or decelerating as he moves through the testing space. This test is repeated until sufficient data is collected for both the right and left limbs, so differences can be measured between the affected and unaffected joints. Specifically, the forces measured are vertical (downward force) peak force and its associated impulse, and craniocaudal force (Fig 3.2). This is further subdivided into braking and propulsion components, each of which measures peak force and impulse. The program gives a graphical output as well as a numeric value for each component of the forces measured. By analyzing how the numeric output changes over time, a veterinarian can assess how well an animal is healing from a procedure or how effectively the animal is responding to the treatment. The data obtained from these experiments is analyzed using decision trees for the classification of diseased and healthy dogs. This technique is also used in the gait analysis of equine population.

3.1.3 Marker- Free Method in Video Image Processing

Kinematics uses markers to collect data of dogs. Since the usage of markers to take dynamic gait attributes is associated with the procedure of mounting markers on the body, a marker-free method has been proposed. This method estimates joint center of the body, by video image processing. This marker-free method also provides a numerical estimation of 2 D center of rotation of the rigid segment and it has been extended to estimate the center of rotation of the hip joint [26]. Video images obtained are digitized off-line and are processed using Matlab. In each image, a global and a local coordinate system is defined using binary region features method. A simple threshold is used to obtain binary images of the limb. A very high accuracy in identifying center of motion of the joint can be obtained using this method.

[2] Bob Wells, Sharon Software Inc., DeWitt, MI

3.1.4 BIOMARKERS

Biomarker is a molecular indicator of specific biological property. It is a molecular marker which is associated with a particular biological function. Using biomarkers in detection of Osteoarthritis is in its premature stage. Experiments are being conducted at Cornell University to exploit biomarker disease detection techniques for Osteoarthritis in canine population [13].

Now, with increased knowledge of cartilage biology, many molecular markers have been identified by scientists. These molecular markers are released into body fluids during the process of cartilage breakdown or synthesis. Range of products associated with this process is really vast. So, testing these markers to determine the presence of Osteoarthritis is challenging. Proposed solution for this problem is to use the combination of various molecular markers to determine the presence of the disease. In this method it is possible to diagnose the disease at very early stages [14] .

Biomarker technology becomes more useful with proper data analysis. Linear relationships and normal distributions are used to compare the patterns from responses to various disease causing agents. Factor analytical [42] techniques are available to reduce the number of variables and detect the structure in relationships between the variables for classification. But the problem faced by the researchers is organizing the observed data from Biomarkers into meaningful structures. Neural Networks can effectively handle this problem by providing sophisticated modeling techniques. Neural Networks are capable of modeling extremely complex functions. Because of the non-linear structure of neural networks, they are capable of encompassing all the biomarkers without factoring. Neural Networks also keep in check the “curse” of dimensionality when dealing with large number of variables.

Data collected using the methodologies described in this section need to be analyzed in a systematic way to predict the abnormality of dog‘s gait. Below section gives an overview of the data analysis techniques that are being used in the recent years.

3.2 Data Analysis Techniques

3.2.1 Data Mining

Data mining methods are being used to search large databases to find patterns that lead to the diagnosis of diseases. Usually these databases are defined over various attributes. As the number of attributes increase, search becomes more complex. Some pattern matching algorithms which identify genome patterns have a complexity of (n^6) or more.

Sometimes, millions of attribute subsets are candidates for finding patterns. In such cases, running time of search algorithms in databases becomes very difficult to manage. Hemanth et al.[35], developed a genetic algorithm for attribute search in which attribute subsets are combined using genetic operators to select subsets that lead to interesting patterns. This algorithm partitions the search problem, which reduces the total complexity of the attribute pattern search.

3.2.2 Neural Networks

Neural networks, Machine Learning Techniques and Statistical techniques are widely used methods for analyzing data to diagnose diseases. On a coronary artery disease database, Rosenberg et al. (1993) [16], proved that the performance of a Radial Basis Functional neural network showed comparable performance with human experts. ARTMAP [32] neural network was used in learning, recognition and prediction of many diseases. Artificial Neural Networks are being used in training to predict the presence of Osteoarthritis.

As computers have become cost-effective tools, many scientists are investigating potential technologies for computer-assisted disease diagnosis. When clinical images are fully computerized, computer-assisted diagnosis becomes more meaningful and it involves very sophisticated decision–making process. Systems such as PACS (Picture Archiving and Communication System) integrate patient information and diagnose the problem. While making decisions, PACS may ignore minute details of patient data and the decision made may not be as accurate as anticipated. Convolution Neural Networks (CNN) proposed by S.C.B.Lo et.al [17] showed a better performance than the

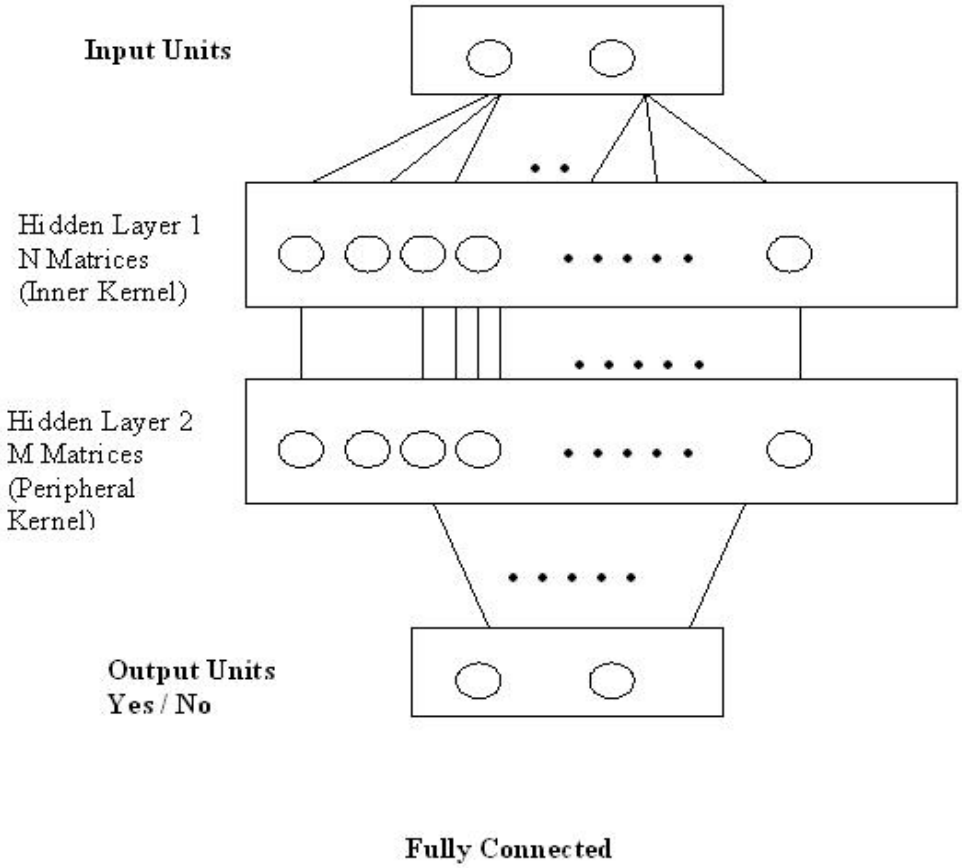

Figure 3.3: An artificial Convolution Neural Network with dual-kernel structure.

existing computer-assisted diagnosis systems. This system reduces the number of false positives and maintains high true positive detection. This neural network is based on the network structure of neocognitron [15] which simulates vision of vertebrate animals. CNN provides a background reduction method, which is useful in adjusting the overall brightness of medical images.

CNN shown in Figure 3.3 uses back propagation training method. In this network, kernels are programmed in such a way that the suspected region of the image is separated from surrounding regions. Kernels operating in the surrounding regions are named as peripheral kernels and kernels in the internal region are called inner kernels. Purpose of using this dual kernel mechanism is to

instruct kernels to learn different image patterns. Kernels‘ weights are limited by groupings. Output of this neural network is distinguishable as diseased pattern and non–diseased pattern [17].

Another new area that is drawing researchers‘ attention in the detection of Osteoarthritis is study of bone structure. Most recent research in Osteoarthritis is focusing on the proliferation of bone structure using Fourier Transforms and Neural Networks by assessing bone mineral density. This technique generates a unique “fingerprint” of an image using Fourier Transforms. Principal components analysis is then applied on these fingerprints and the resultant information is passed to a neural network for classification. By using this method, Gregory et al. [34] achieved optimistic results in the classification of Osteoarthritis.

3.2.3 Image Analysis

A canine model of the hip development is used in Cornell University. Evaluation of the hip joint using Computed Tomography (CT) is done periodically [13].

Many image analysis techniques are being used on CT images to obtain temporal changes in the size, shape and density of femur. These results help clinicians to identify and treat the disease at an early stage. Image analysis techniques may include spatial filtering (Convolution Filters, Non Convolution Filters), Image Combining, Frequency Domain Filtering, Edge Enhancement, Noise Reduction and Image Visualization.

The next chapter describes various techniques we have applied on kinematical gait data obtained from the College of Veterinary Medicine and Biological & Agricultural Engineering Department laboratories of the University of Georgia in the determination and classification of Osteoarthritis in dogs.

CHAPTER 4

EXPERIMENTAL METHODOLOGY

This project focuses on application of pattern recognition and data analysis techniques on kinematic gait data (Section 3.1.1) to determine the presence of instability in the osteoarthritic knee. Data for this project has been collected using a BTS [1] motion analysis system. This system consists of 4 infrared cameras situated around the testing space which consists of a force platform. Infrared cameras are able to collect data from reflective markers that are placed on dogs in a pre–determined coordinate system for the stifle (knee) joint. After the collection of data, each marker is classified according to the specified model. Data is edited and run through a series of programs to give final numeric outputs known as joint coordinate angles. Three of these angles are considered - Flexion/Extension, Internal/External rotation and Abduction/Adduction. These angles characterize the dog‘s gait. These tests are performed on dogs prior to and after development of Osteoarthritis secondary to cranial cruciate instability, thus we have two instances of data for each dog. One instance is with Osteoarthritis secondary to cranial cruciate instability and the other with out the disease.

4.1 DATA FILES

Each data file consists of above three angles for one complete gait cycle. Data obtained with this method is in Time Domain. The complete (100%) gait cycle is divided into 64 time frames. Each time frame is a unit of time (measured in Micro Seconds) and for each of it, we have all the three angular measurements. Figure 4.1 is an example of a sample data file. In the original data file, there

[1] Bioengineering Technology Systems, Milan, Italy

are 64 rows, each row representing all the three angles at each time frame. Entire file represents the angular values for one complete gait cycle.

In Figure 4.1, “Time” represents the time frame during which the data is measured; “F/E” represents Flexion/Extension angle; “In/Ext” represents Internal/External angle; “Ab/Ad” represents Abduction/Adduction angle. Data has been collected on 12 different dogs before and after the treatment. Total number of data files collected from the experiments on these 12 dogs were 108. 57 files represent the dogs having Osteoarthritis and the rest, 51 files belong to dogs with out the disease. To describe the ratio, 52.78% of the total data files belong to dogs with stifle instability and Osteoarthritis, and 47.2% to normal dogs. Figure 4.2 gives values for minimum, maximum, mean and standard deviation for the various angle values for above mentioned 12 dogs.

Each data file can be viewed as an instance in the problem domain. We have the data instances in the form of “attribute – value” pairs i.e. Each data instance (data file) has a value, either “normal” or “OA”, for each attribute in the data set. That means, each data file either belongs to a normal dog or a dog with Osteoarthritis. Since we know the condition of the dog on which we are conducting experiments to collecting the data, we classify the data file as either Normal (normal dog) or OA (dog with Osteoarthritis). This is the target function for the classification problem. In this case, target function has discrete output values.

Decision tree learning method is extremely useful in solving problems where data instances are represented as “attribute – value” pairs and target function has discrete outputs. Decision tree learning methods are robust to errors in training data. This method can also be used when training data contains missing attribute values or unknown values. Since the problem we are trying to solve also falls into this category, Decision Tree methods have been applied on the data set to solve the classification problem.

Some algorithms are pretty good at performing precise tasks but, when there is a need to deal with noisy data or data from the environment by adapting to circumstances with fault tolerance, algorithmic solution may not be the best fit. The clarification problem we are describing in this chapter provides many examples of this behavior. There is room to pick out structures from existing

data based on given examples (instances). To solve problems of this nature, neural networks are very useful. Neural networks have been used on the classification problem we are discussing in this thesis.

Decision tree and neural network methodologies have been applied on the data files of normal dogs and the dogs with stifle instability and secondary Osteoarthritis. This data is in time Domain. Later, data files have been analyzed to discover a specific attribute that gives most information about the classification i.e. the attribute that is the decision maker in classifying whether it belongs to a normal dog or a dog with OA.

Since the data obtained from experiments contains values of 3 different attributes namely, Flexion/Extension angle, Internal/External rotation angle and Abduction / Adduction angle, it is useful to find out whether any particular attribute is showing a relatively large deviation from a normal dog to a diseased dog. To identify the most important attribute among the others, ID3 algorithm has been applied on training data files. ID3 algorithm learns decision trees by constructing a top–down tree, beginning with the question of which attribute should be tested at the root of the decision tree. Each attribute is evaluated using a statistical test to determine how well it alone can classify the training examples. This statistical property is called *information gain*. In this method, best attribute is selected and used as the test at the root node of decision tree. A descendent of root node is then created for each possible value of this attribute and training examples are sorted to the appropriate descendant node. This entire process is repeated using training examples associated with each descendant node to select the best attribute to test at the point in the tree [22].

Entropy defines the information gain of an attribute. It characterizes the (im)purity of an arbitrary collection of training examples. Entropy is defined as follows: Given a collection S, containing positive and negative examples of a target concept, entropy of S relative to this Boolean classification is

Entropy(S) $\equiv$ -p(positive) log p(positive) – p(negative) log p(negative)

Where p(positive) is the proportion of positive examples in S and p(negative) is the proportion of examples in S. For all calculations involving entropy, value of 0log0 is 0. If the target attribute

can take on **c** different values, then the entropy of S relative to this **c-wise** classification is defined as

Entropy(S) $\equiv$ $\sum_{i=1}^{c}$-pi log pi

Where, pi is the proportion of S belonging to class i.

Now, information gain can be defined as follows:

Gain (G, A) of an attribute A, relative to a collection of examples S, is defined as

Gain(S,A) $\equiv$ Entropy(S) - $\sum_{v \epsilon values(A)}$ (|Sv| / |S|) Entropy(Sv).

Where, value (A) is the set of all possible values for attribute A, and Sv is the subset of S for which attribute A has value v (i.e. Sv = $\{$s $\epsilon S|$A(s) | =v$\}$).

These formulae produced high "Information Gain" value for Internal/External rotation angle from the data files obtained in time domain for the classification.

After identifying the decision making attribute in time domain, all the data files have been converted into frequency domain by using Fast Fourier Transforms (FFT). "Information Gain" values have been calculated on all the three attributes in frequency domain and "Internal/External Rotation" angle values showed high value of "Information Gain" in Fourier domain. Decision trees have been applied on this attribute in Frequency Domain data to learn more about the patterns of data that lead to Osteoarthritis. Based on this observation, a recognition system has been developed to classify normal dogs and dogs with cruciate instability and secondary Osteoarthritis by taking "Internal/External rotation angle" values as input to the system. Implementation of the recognition system and results are explained in detail in the next chapter.

The sections below describe experiments which have been conducted on the data set, with existing tools such as See 5.0 and NeuroShell [2]. These experiments are used to learn patterns that lead to knee instability and subsequent Osteoarthritis. Information obtained from these experiments was the key in building the recognition system.

[2]NeuroShell is a Neural Network Package.

4.2 Classification Using Neural Networks

Data files which have been collected from the research lab are in time domain. Neural networks and decision trees have been used to classify the data collected in time domain. Neural networks have also been used in training and testing of the data which had been converted into frequency domain by applying Fourier transforms on the data obtained in time domain.

Advanced neural networks have been used to solve this classification problem. Tests were conducted using several different neural network configurations on the data set. Neural classifier, NeuroShell has been used to conduct the experiments with different architectures to get optimistic results. Back propagation neural networks showed better performance for training and testing the input data compared to all other network structures. Figure 4.3 shows a typical three-layered feed forward back propagation neural network.

Since Internal / External Rotation angle has been chosen to conduct the experiments to solve the classification problem, all the data files representing Internal / External rotation angular values of one complete gait cycle have been inputted to the neural network. Each gait cycle has 64 time frames, thus providing 64 different input parameters for the neural network. These 64 input parameters can be represented by 64 different neurons in the input layer of the neural network. All the input files belong to dogs with or with out cruciate deficient knee with Osteoarthritis. This information is useful to choose the values of “Actual Output” for Neuroshell classifier. In the experimental setup, a normal dog classification has been represented by the value zero (0) and the classification of a dog with OA has been represented by the value one (1). This output value can be represented by one neuron in the output layer of neural network. If the predicted output is less than 0.5, then the prediction is for a dog with out OA and if the predicted output value is greater than 0.5, prediction is for a dog with OA. If the value equals to 0.5, then the prediction is undecided about the dog having OA or not.

Accuracy of the resultant model trained by Neuroshell 2 is measured in terms of “Average Error”, “R Squared Value” and “Correlation Coefficient”.

Average Error (either on training set or on testing set) is the average value of the error factors over all the patterns in the particular set. Total error for each set is defined as the sum of the squares of the differences between the actual outcome and the predicted outcome of neural network. Average of this value is the average error of the data set.

“R Square Value” is a statistical indicator, which compares the accuracy of the model with the accuracy of a benchmark model wherein the prediction is just the mean of all the samples. If “R Squared Value” is 1, then the model is a perfect fit. If the value is zero (0), then the model is a poor fit. Model fits very well, if it‘s “R Square Value” is close to 1.

Correlation coefficient is the statistical measure of the strength of relationships between the actual output vs predicted outputs. This value can vary from -1 to +1. Value closer to +1, indicates the stronger positive relationship. If the value is closer to -1, stronger the negative relationship between the actual output and the network‘s predicted output.

A three layer feed forward back propagation network (BPNN), which is showed in Figure 4.4, has been used to train and test the time domain data. Choosing appropriate number of hidden neurons is an important aspect about BPNN. Using too many neurons increases the training time and may also cause overfitting problem (memorizing training patterns rather than generalizing the prediction). On the other hand, usage of fewer hidden neurons often increases the likelihood of learning algorithm being tapped in local minima. However, NeuroShell classifier provides the default number of hidden neurons to start with. To compute the default number of hidden neurons for a 3 layer network, the following formula is used.

Number of hidden neurons = 1/2 (Total number of Inputs + Total number of Outputs) + Square Root of the number of patterns present in the training file.

All the data files have been trained and tested using NeuroShell both in time domain as well as in Fourier domain. Data set has been trained and tested by using 70% of training set, 20% of testing set and 10% validation set for one set of experiments. Series of experiments have also been conducted on the data set with a mix of 60% of data as training set, 20% of data as testing set and 20% data as validation set.

For the first set of experiments, total number of hidden neurons selected by default were, 1/2 * (64+1) + $\sqrt{(70\%of108)} = 41$.

For the second set of experiments, total number of hidden neurons selected by default were, 1/2 * (64+1) + $\sqrt{(60\%of108)} = 41$.

4.2.1 Classification in Time Domain

Figure 4.5 shows the results of NeuroShell classifier on time domain data with two different training and testing sets. Note that the "Average Error" given in the Figure 4.5 is not an indication of error percentage either in the training set or in the production set. This is just the average value of all error factors in the specific data set.

Correlation Coefficient value of the resultant neural network models of the NeuroShell and the scattered plots for actual outcome vs predicted outcome corresponding to their correlation coefficient values in time domain showed in the figures 4.8 and 4.10 give the error percentage of the trained neural network which has been validated on the production set over the entire data set.

In time domain, with a 20% training data and 10% production data set, trained neural network showed good performance by yielding a correlation coefficient of positive 0.9018. This value indicates the strong positive relationship of the data set with the model. "R Squared Value" of the model for this setup is 0.8122, which is an indication of the data set that fits in the model well. This is represented as a graph in figure 4.7. In this graph, the actual outputs for all the pattern are represented with black connecting lines. In this case, actual outputs are either zeroes or ones. These patterns are straight lines parallel to X-axis corresponding to the Y-values of zero or one. Predicted patterns of the model are represented by blue connecting lines. The predicted output is following the actual output in many cases with the assumption we made in the above section (If the predicted output is greater than 0.5, it is OA. Prediction is NORMAL if the output is less than 0.5, otherwise it is undecided). Some of the patterns have violated this rule and thus treated as errors in prediction. Scattered graph plotted for the model's correlation coefficient showed in figure 4.8

shows 7 misclassifications in the overall data set. This model yields an error rate of 6.481% and accuracy of 93.519%.

Other set of experiments conducted on time domain data with 20% data as testing set, 20% data as production set and the rest of the data as training set showed poor performance on NeuroShell on its trained neural network. This data set yielded the “R Squared Value” of zero (0), which is the indication of the very poor fit of data set in its model. This model generated positive 0.2150 as correlation coefficient. This shows the poor positive relationship of data set with the trained model. Figure 4.9 shows the actual outcome vs predicted outcome of NeuroShell classifier for each and every data pattern in the data set. In this case, very few predicted patterns follow the actual pattern. Same can be viewed from the figure 4.10, which represents the actual vs predicted outcomes at its corresponding correlation coefficient. The neural network generated for this data set after training classifies 45 instances incorrectly. Error rate of this model is 41.66% and the accuracy of prediction is 58.34%.

4.2.2 Classification in Fourier Domain

Figure 4.6 shows the results of NeuroShell classifier on Fourier domain data with two different training and testing sets.

Correlation Coefficient value of the resultant neural network models of the NeuroShell and the scattered plots for actual outcome vs predicted outcome corresponding to their correlation coefficient values in Fourier domain showed in the figures 4.13 and 4.14 give the error percentage of the trained neural network which has been validated on the production set over the entire data set.

In Fourier domain, neural networks showed very good performance in terms of the accuracy of prediction, strength of positive relation between the data set and the trained model and the fitness of data set in the model. With a 20% training data and 10% production data set, trained neural network showed very good performance by yielding a correlation coefficient of positive 0.9406. This value indicates the strong positive relationship of the data set with the model. This value is

higher than the correlation coefficient values yielded in time domain, which shows the stronger relationship of the data set with the model compared to time domain. “R Squared Value” of the model for this setup is 0.8832, which is an indication of the data set that fits in the model well. Again, this value is higher than “R Squared Values” generated by models in time domain. This is represented as a graph in figure 4.11. In this graph, the actual outputs for all the pattern are represented with black connecting lines. Actual output patterns are straight lines parallel to X-axis corresponding to the Y-values of zero or one. Predicted patterns of the model are represented by blue connecting lines. The predicted output is following the actual output in many cases. Some of the patterns have violated this rule and thus treated as errors in prediction. Scattered graph plotted for the model’s correlation coefficient showed in figure 4.13 shows 4 misclassifications in the overall data set. This model yields an error rate of 3.703% and accuracy of 96.297%. This result is better than the result from time domain for the same experimental setup.

Other set of experiments conducted on Fourier domain data with 20% data as testing set, 20% data as production set and the rest of the data as training set. This data set also showed good performance on NeuroShell on its trained neural network. This data set yielded the “R Squared Value” of 0.836, which is the indication of the good fit of data set in its model. This model generated positive 0.9165 as correlation coefficient. This shows the good positive relationship of data set with the trained model. Figure 4.12 shows the actual outcome vs predicted outcome of NeuroShell classifier for each and every data pattern in the data set. In this case, many predicted patterns follow the actual pattern. Same can be viewed from the figure 4.14, which represents the actual vs predicted outcomes at its corresponding correlation coefficient. The neural network generated for this data set after training classifies 6 instances incorrectly. Error rate of this model is 5.55% and the accuracy of prediction is 94.45%. These results are better than the results obtained from time domain data for the similar training and testing set extraction.

Figure 4.15 shows the table which compares NeuroShell results in time domain data with Fourier domain data.

In-order to reduce the effect of randomness on training, testing and production data sets, NeuroShell has been trained and tested for 10 times on time domain data as well as on Fourier domain data with 70% of the data selected as training set, 20% of the data as testing set and 10% of the data as production set chosen randomly at each run. Figure 4.16 shows the result of average values of 10 runs on the data belong to each domain.

4.3 Classification Using Decision Trees

4.3.1 Classification in Time Domain

See5.0 has been used for training and testing of the data files. Height of the resultant decision tree in domain data, which is showed in 4.18, is 5 and the error rate in the classification was 13.0%. Data set has been crossvalidated with 12 folds. In *n* folds cross validation, all the data is divided *n* mutually exclusive subsets. Every time, one subset is kept aside as test data and the rest of the data, *(n-1)* subsets are merged into one set, is used for training the decision tree. This process continues for *n* times with a different subset each time for testing. Mean error observed for 12 folds crossvalidation was 27.8%. Cross validation result file is attached as appendix A of this document.

4.3.2 Classification in Fourier Domain

Since the data in Fourier domain showed huge deviation between normal dogs and stifle deficient dogs with Osteoarthritis, Decision trees perform really well in classification. Height of the resultant decision tree is 9 and it is showed in figure 4.17. In Fourier domain, error rate in the classification of testing data was 3.7%. Error rate in Fourier domain is very less, compared to the error rate time domain. Decision trees have also been applied on the data set with cross validations of 12 folds. Average error on the testing data for 12 folds was 18.4%. Experimental results using Decision tree with 12 folds are attached as appendix B of this document.

All these experiments are useful in identifying the most discerning features in the data for classification. A recognition system was developed based on the observations in Fourier domain data. The recognition system takes input as the time domain representation of data, it converts it into its

Fourier domain representation and automatically detects whether the dog has knee instability and Osteoarthritis or not. Implementation of the recognition system is explained in more detail in the next chapter.

Time	Flexion / Extension	Internal / External	Abduction / Adduction
1.09	58.279	28.585	25.736
1.10	57.351	28.921	24.977
1.11	56.490	28.867	24.233
1.12	55.266	28.533	23.251

Figure 4.1: Sample data file in time domain.

Variable Name	Flexion / Extension	Internal / External	Abduction / Adduction
Minimum Value	10.48	-23.002	-18.166
Maximum Value	92.463	78.046	66.15
Mean	49.53722	34.8065	12.80221

Figure 4.2: Distribution of the data set.

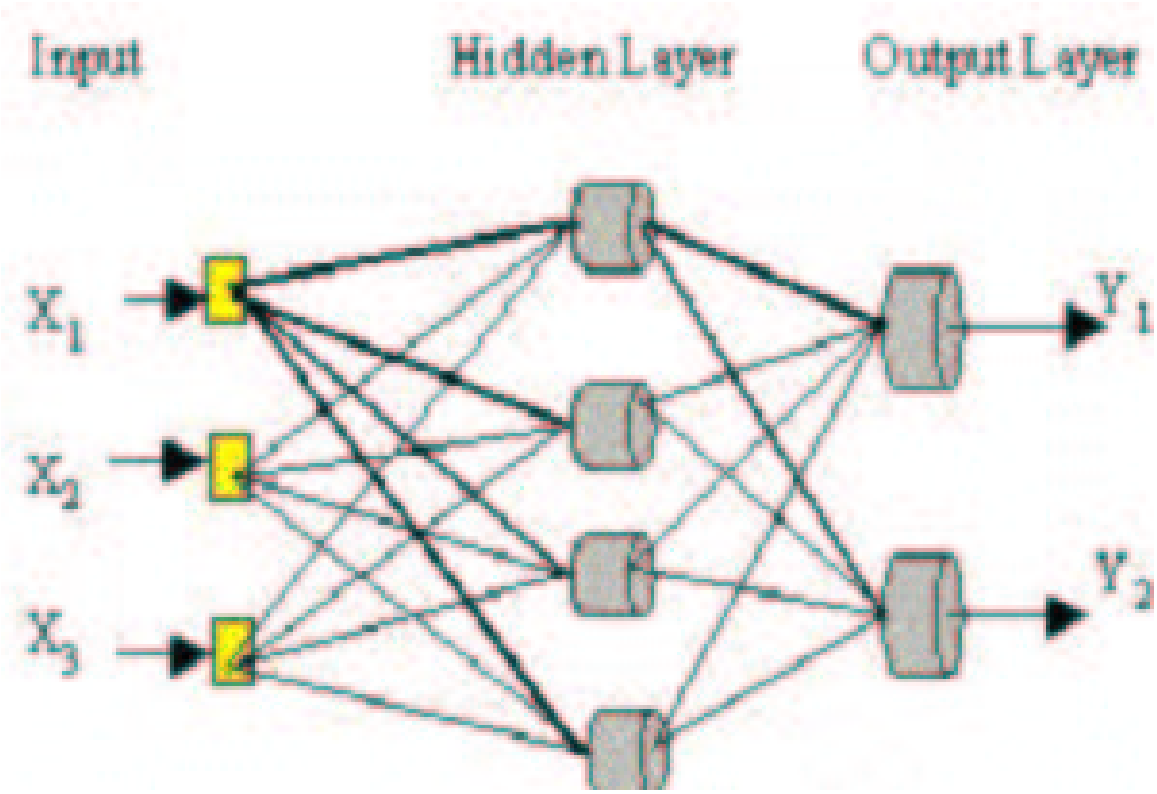

Figure 4.3: Typical Feed Forward Back Propagation Neural Network.

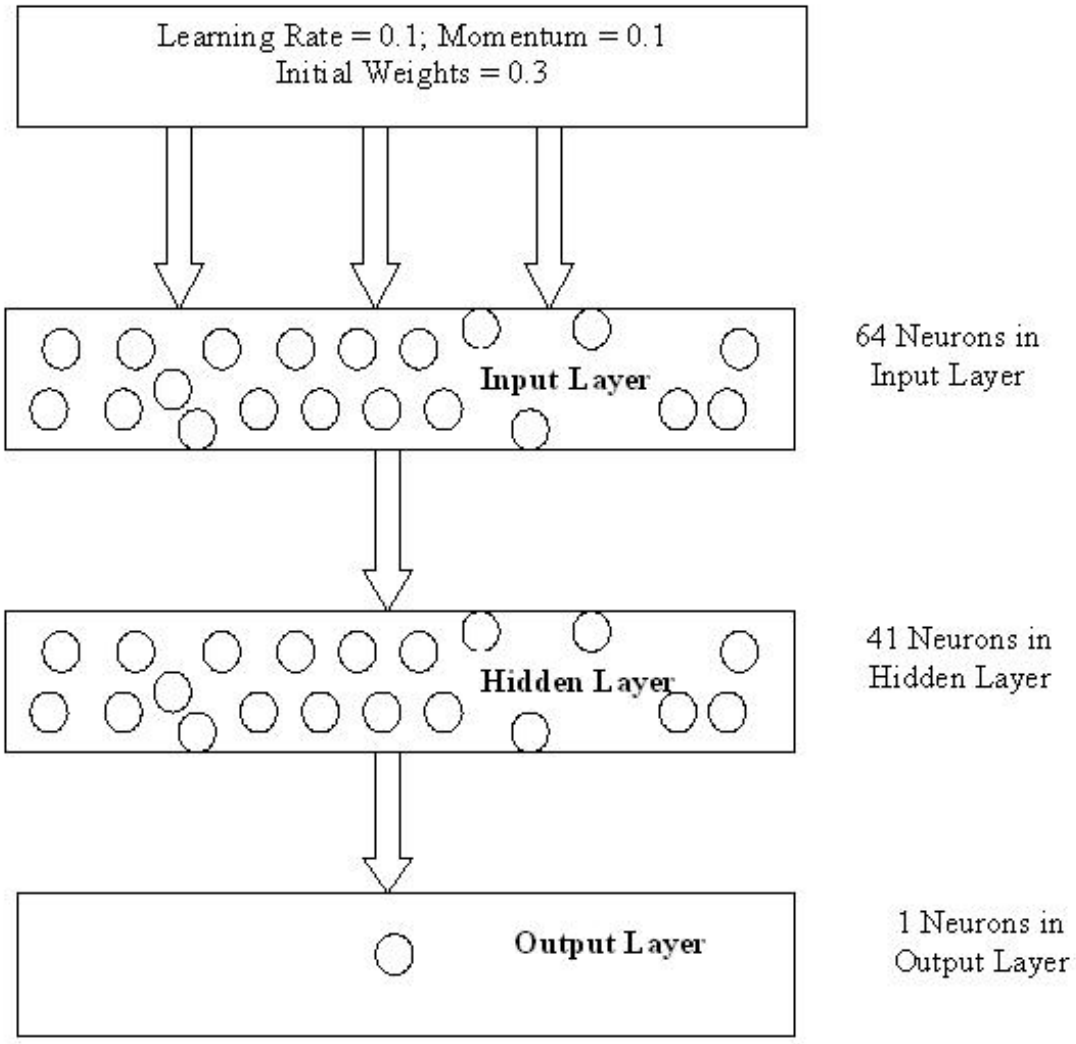

Figure 4.4: BPNN architecture used in the training and testing of time domain data.

Output	20% Testing, 10% Production	20% Testing, 20% Production
Training Patterns	77	66
Testing Patterns	21	21
Production Patterns	10	21
Minimum Average Error on Training Set	0	0
Minimum Average Error on Testing Set	0.0786729	0.0420256
R Squared Value of the model	0.8122	0
Correlation Coefficient of the model	0.9018	0.2150
Mean Squared Error of Total Data Set	0.047	0.295
Mean Absolute Error of Total Data Set	0.079	0.427
Minimum Absolute Error in Total Data Set	0	0
Maximum Absolute Error in Total Data Set	1	1

Figure 4.5: NeuroShell results in time domain data with 70% data as training set, 20% data as testing set and 10% data as production set and 60% data as training set, 20% data as testing set and 20% data as production set.

Output	20% Testing, 10% Production	20% Testing, 20% Production
Training Patterns	77	66
Testing Patterns	21	21
Production Patterns	10	21
Minimum Average Error on Training Set	0	0
Minimum Average Error on Testing Set	0.04220256	0.08
R Squared Value of the model	0.8832	0.836
Correlation Coefficient of the model	0.9406	0.9165
Mean Squared Error of Total Data Set	0.029	0.041
Mean Absolute Error of Total Data Set	0.062	0.063
Minimum Absolute Error in Total Data Set	0	0
Maximum Absolute Error in Total Data Set	0.982	0.963

Figure 4.6: NeuroShell results in Fourier domain data with 70% data as training set, 20% data as testing set and 10% data as production set and 60% data as training set, 20% data as testing set and 20% data as production set.

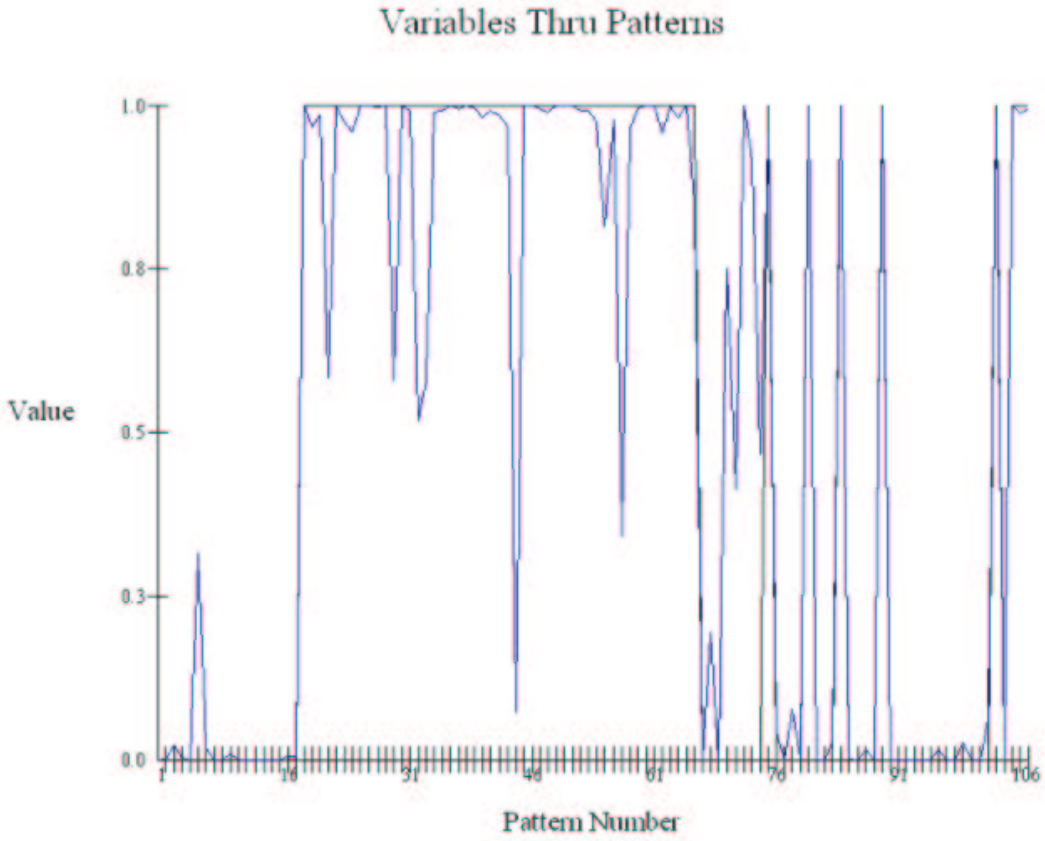

Figure 4.7: Graphical representation of actual patterns vs predicted patterns of Internal / External rotation angle corresponding to their pattern numbers, by NeuroShell in time domain, taken 20% data as testing set and 10% data as production set .

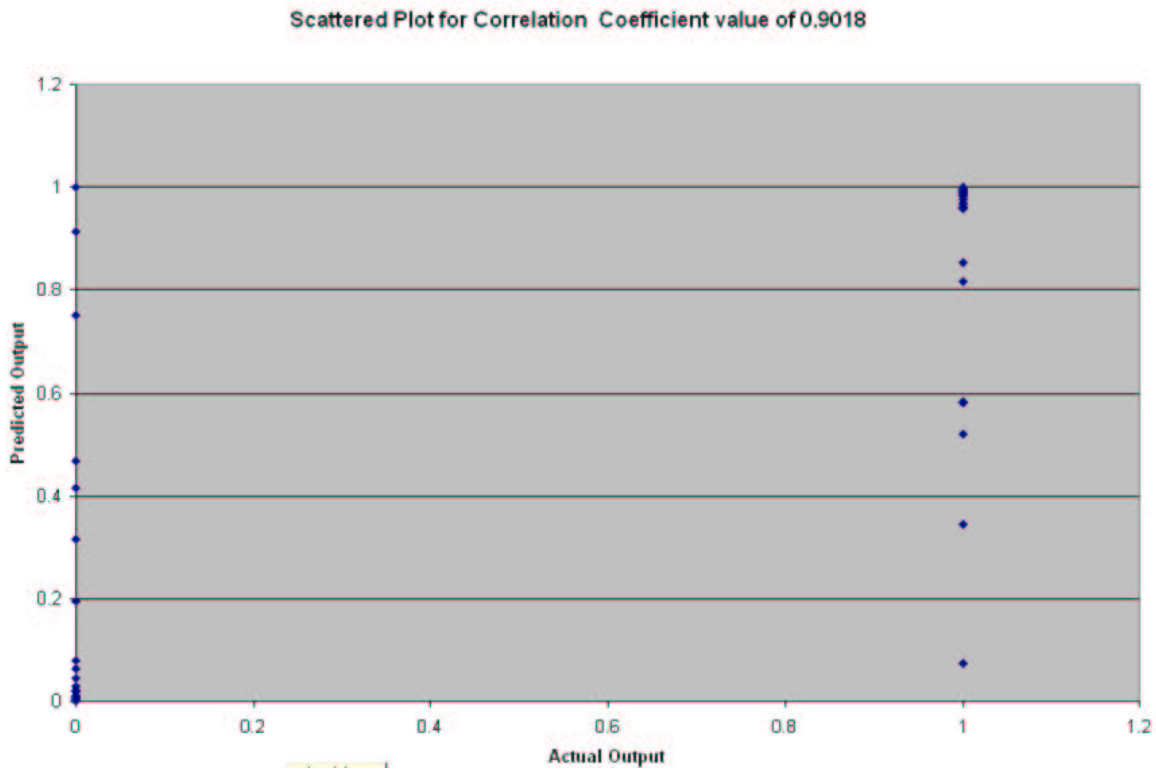

Figure 4.8: Graphical representation of Correlation Coefficient significance of Internal / External rotation angle in NeuroShell resultant model to determine the error rate in time domain data, taken 20% data as testing set and 10% data as production set .

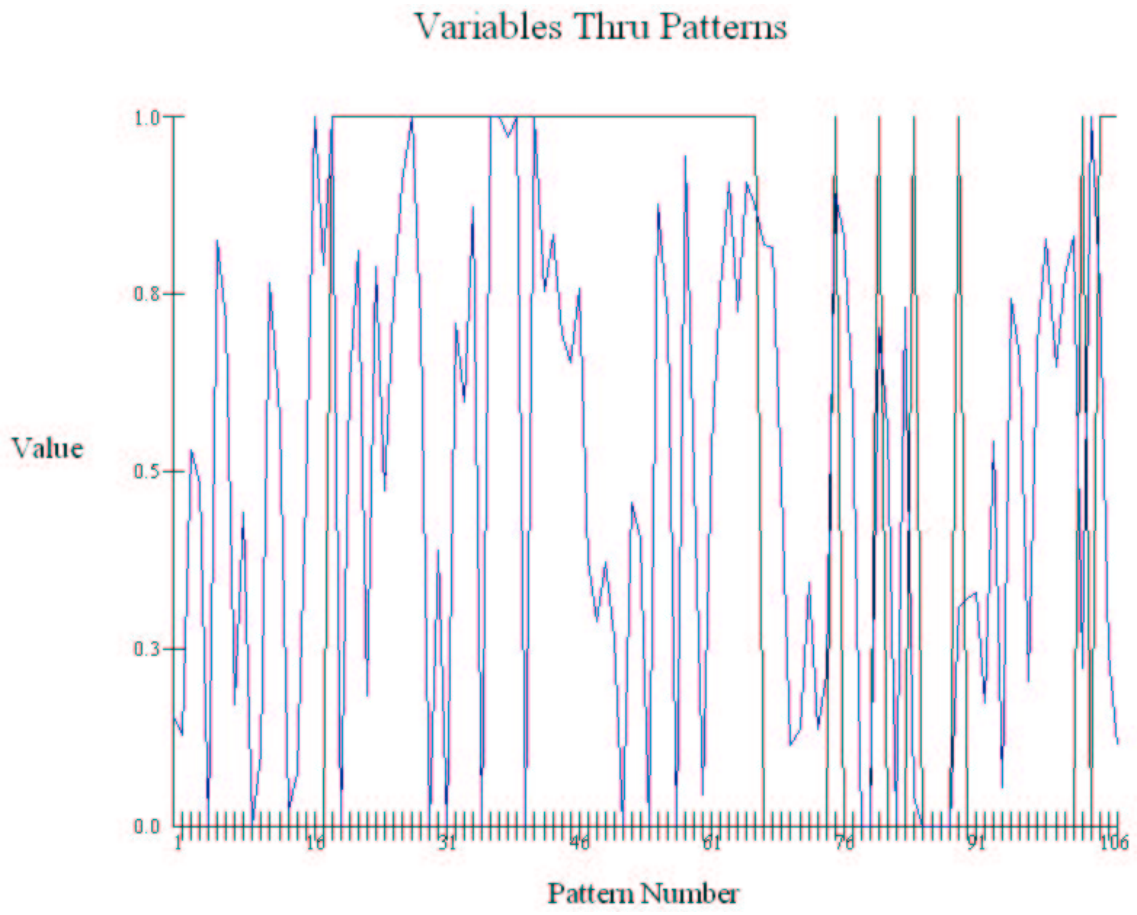

Figure 4.9: Graphical representation of actual patterns vs predicted patterns of Internal / External rotation angle corresponding to their pattern numbers, by NeuroShell in time domain, taken 20% data as testing set and 20% data as production set .

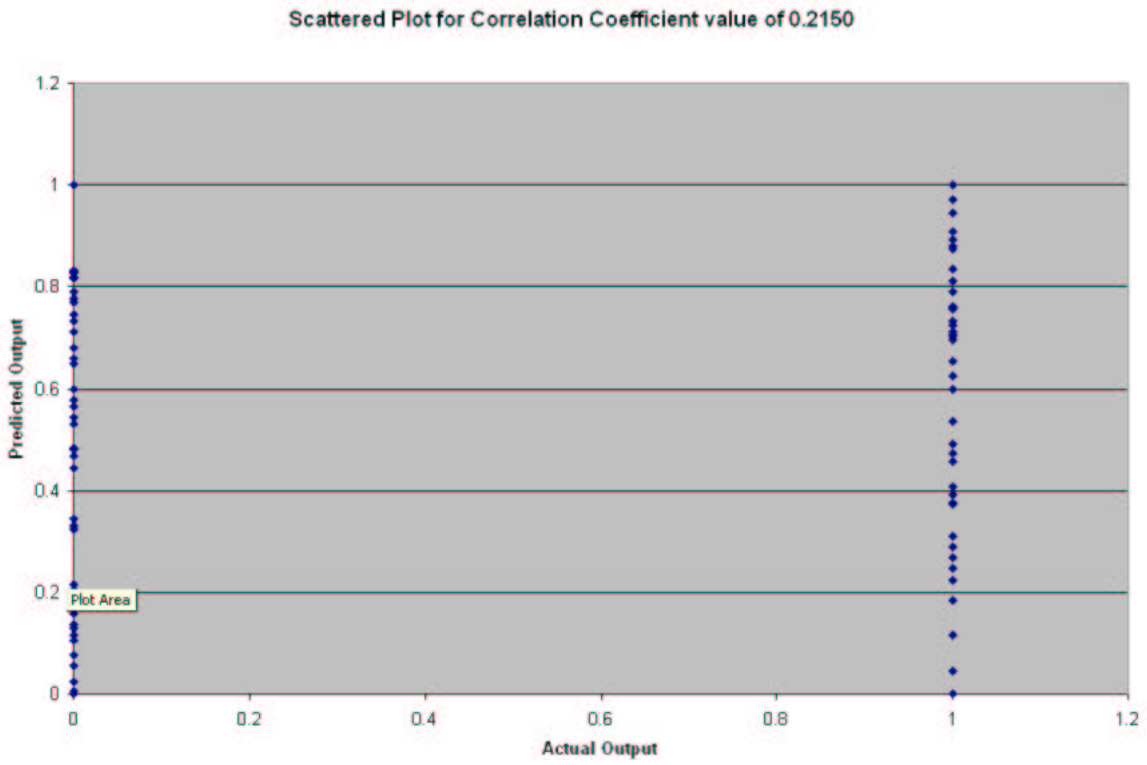

Figure 4.10: Graphical representation of Correlation Coefficient significance of Internal / External rotation angle in NeuroShell resultant model to determine the error rate in time domain data, taken 20% data as testing set and 20% data as production set .

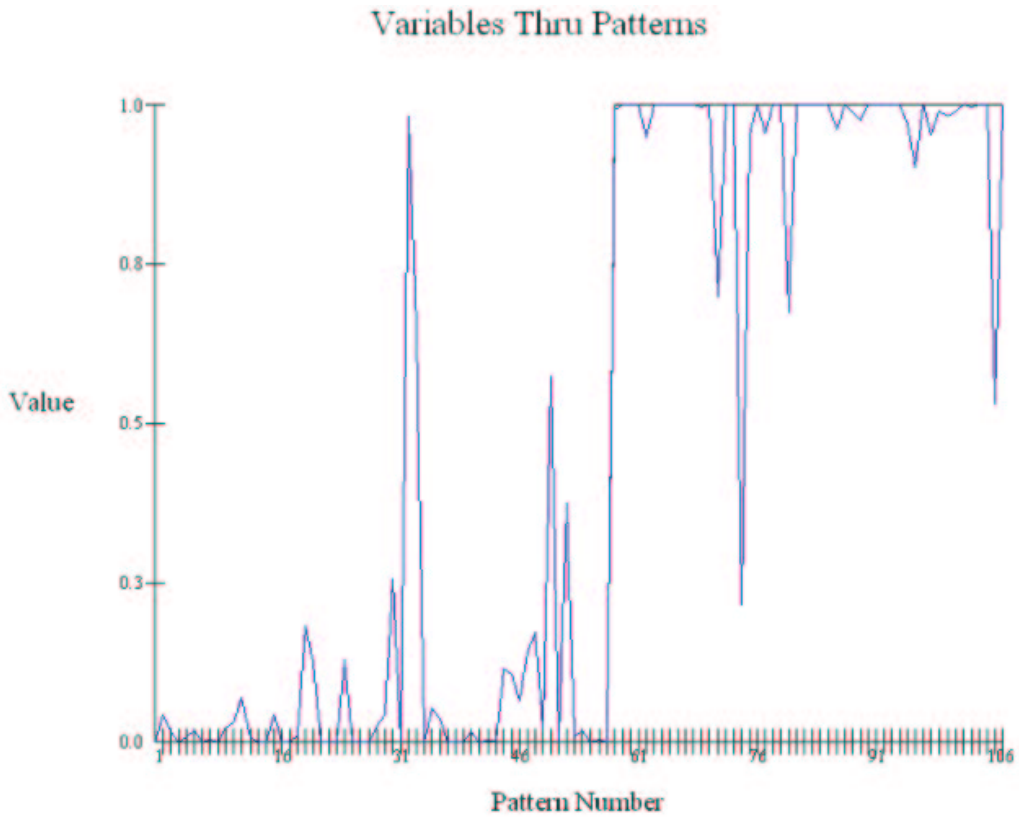

Figure 4.11: Graphical representation of actual patterns vs predicted patterns of Internal / External rotation angle corresponding to their pattern numbers, by NeuroShell in Fourier domain, taken 20% data as testing set and 10% data as production set .

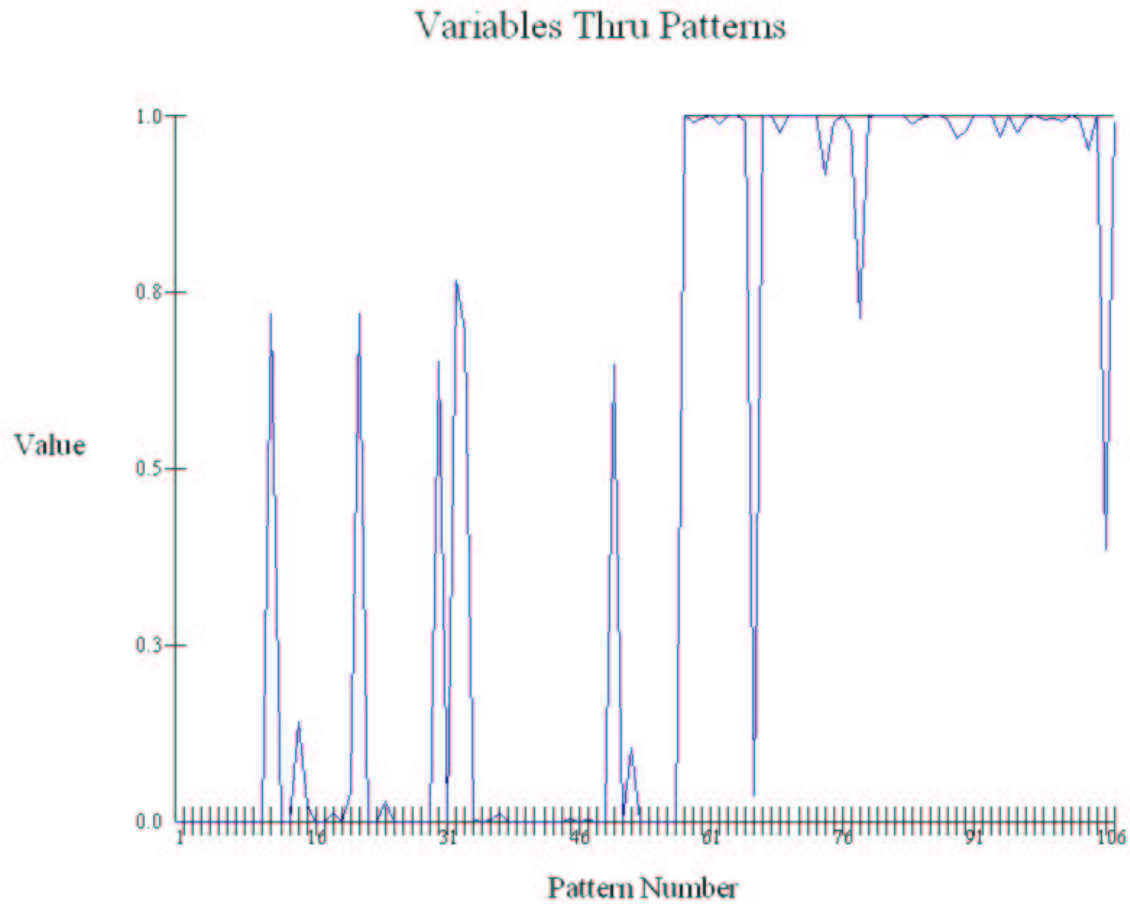

Figure 4.12: Graphical representation of actual patterns vs predicted patterns of Internal / External rotation angle corresponding to their pattern numbers, by NeuroShell in Fourier domain, taken 20% data as testing set and 20% data as production set .

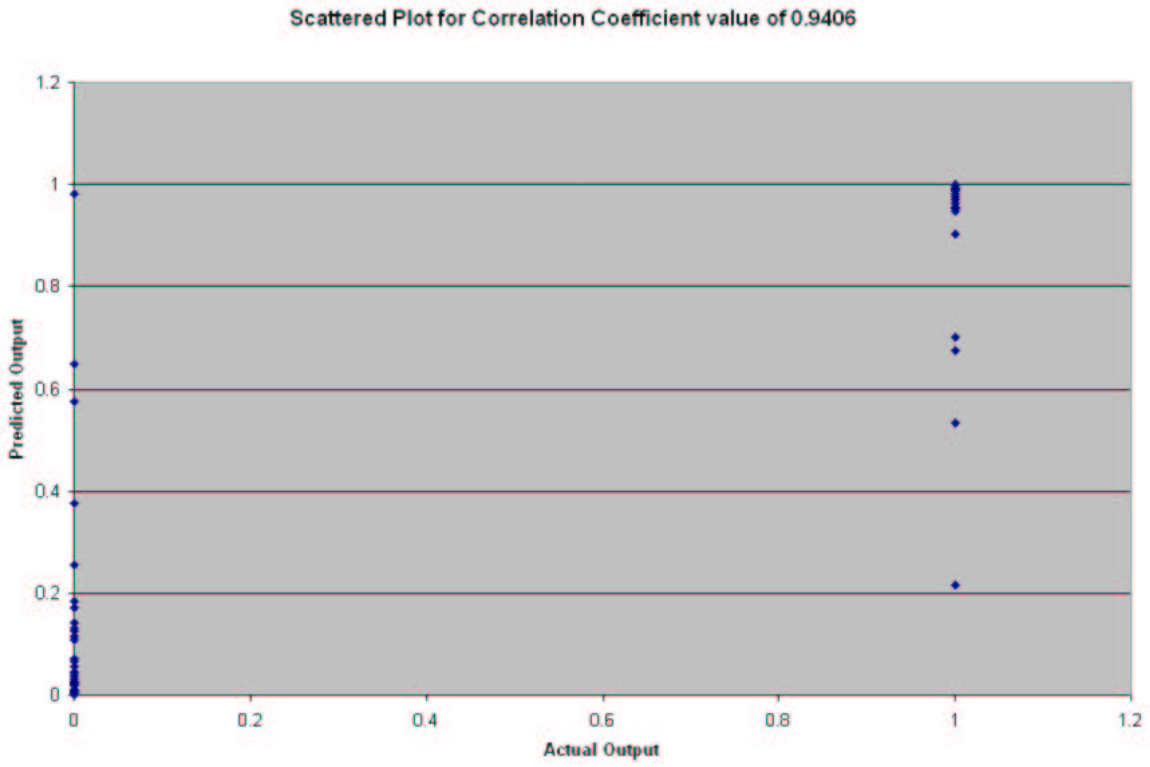

Figure 4.13: Graphical representation of Correlation Coefficient significance of Internal / External rotation angle in NeuroShell resultant model to determine the error rate in Fourier domain data, taken 20% data as testing set and 10% data as production set .

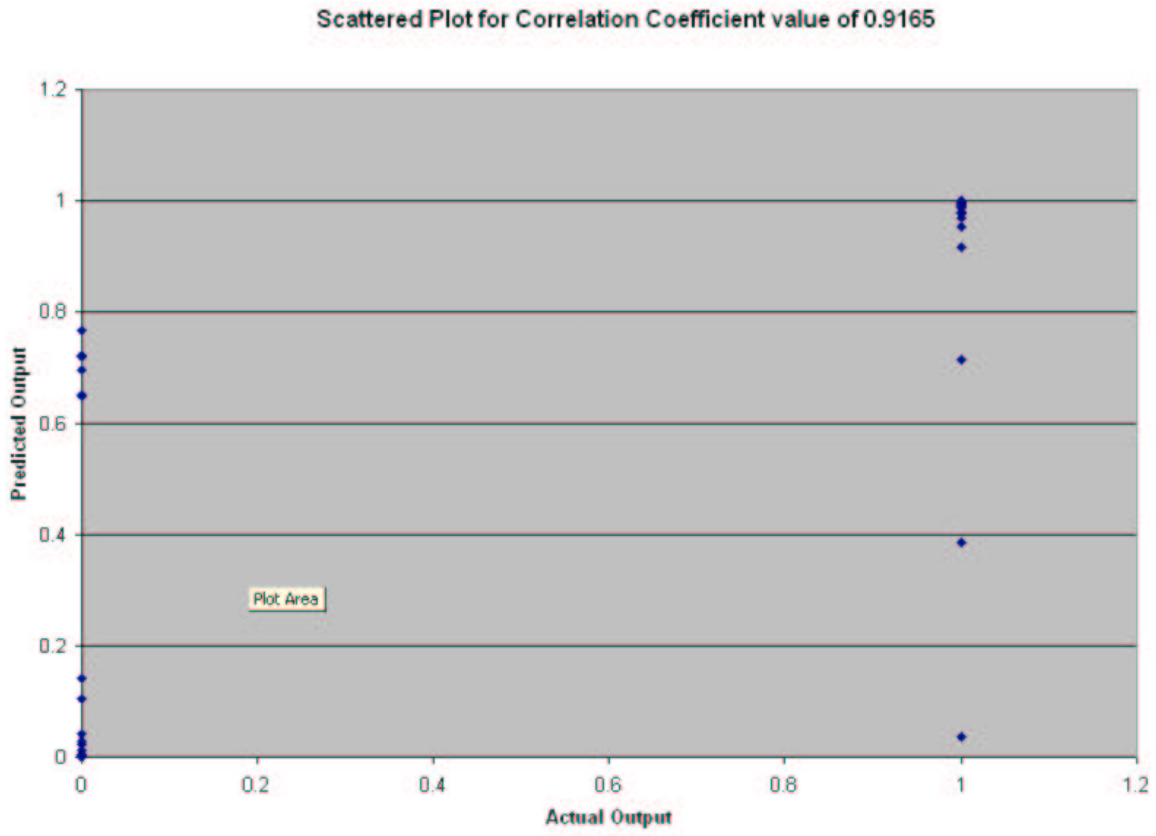

Figure 4.14: Graphical representation of Correlation Coefficient significance of Internal / External rotation angle in NeuroShell resultant model to determine the error rate in Fourier domain data, taken 20% data as testing set and 20% data as production set .

20% Testing, 10% Poduction	Value	20% Testing, 20% Production	Value
Total Errors in Time Domain Prediction	7	Total Errors in Time Domain Prediction	45
Error Rate in Time Domain	6.481%	Error Rate	41.66%
Accuracy Rate in Time Domain	93.519%	Accuracy Rate in Time Domain	58.34%
Total Errors in Frequency DomainPrediction	4	Total Errors in Frequency Domain Prediction	6
Error Rate Frequency Domain	3.703%	Error Rate Frequency Domain	5.55%
Accuracy Rate in Frequency Domain	96.297%	Accuracy Rate in Frequency Domain	94.45%

Figure 4.15: Comparision of error percentages of time domain data results with the frequency domain data from resultant neural network models in NeuroShell classifier.

Output	Value in Time Domain	Value in Fourier Domain
Number of Training Patterns	77	77
Number of Testing Patterns	21	21
Number of Production Patterns	10	10
Minimum Average Error on Training Set	0.009275	0
Minimum Average Error on Testing Set	0.25628645	0.08426752
Average R Squared Value of Data Sets	0.5858	0.8739
Average Correlation Coefficient of Data Sets	0.6744	0.935666667
Mean Squared Error of Data Sets	0.1105	0.031333333
Mean Absolute Error of Data Sets	0.202	0.056
Minimum Absolute Error within Total Data Set	0	0
Maximum Absolute Error within Total Data Set	1	0.980666667
Average Number of Errors in Prediction	8.75	4.66
Average Error Rate in Prediction	9.45%	4.83%
Average Accuracy Rate in Prediction	90.54%	95.16%

Figure 4.16: Average output values of 10 data selections on conducting experiments on time domain and Fourier domain data using NeuroShell with 70% data as training set, 20% data as testing set and 10% data as production set, to reduce the effect of randomness.

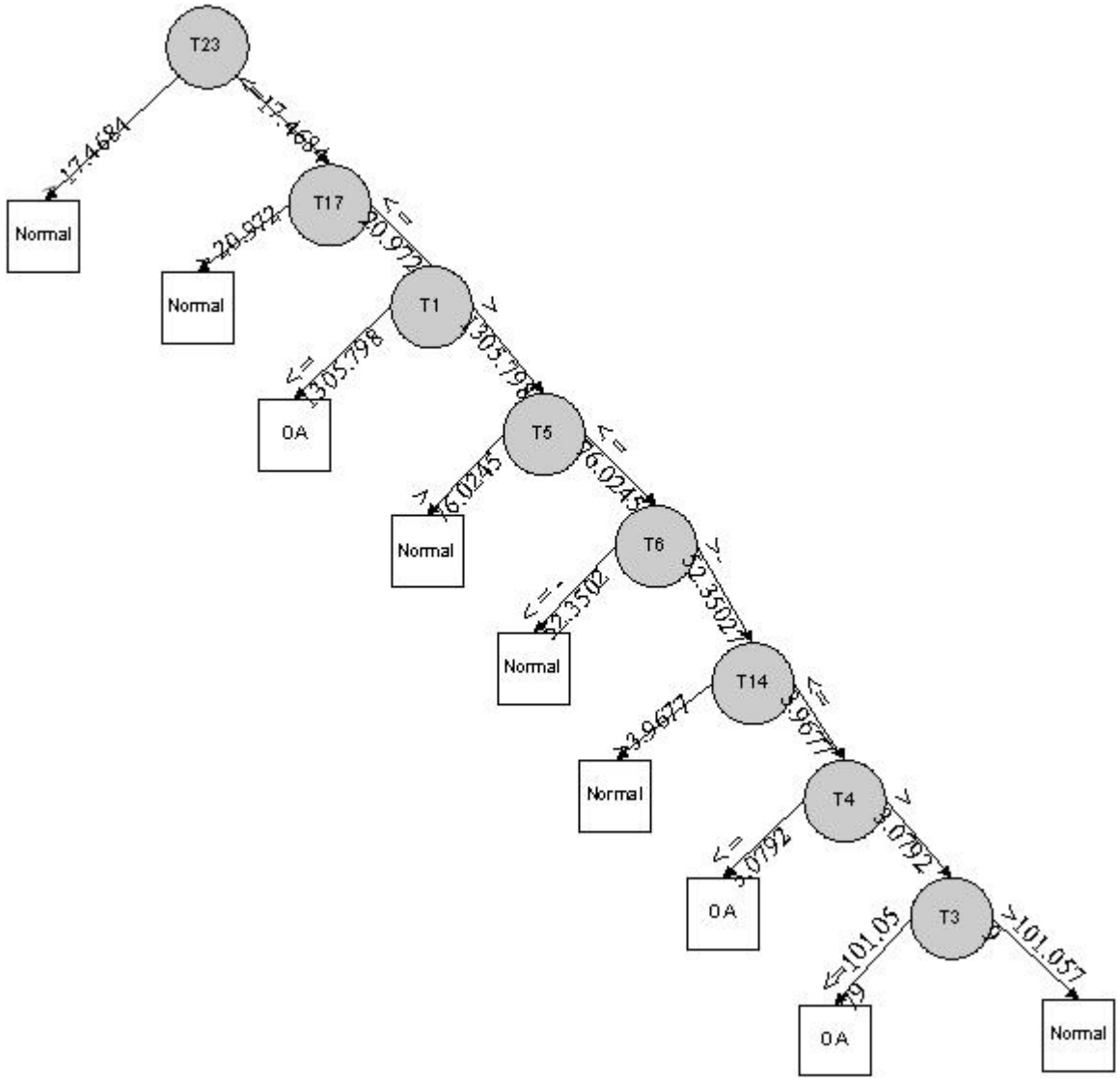

Figure 4.17: Resultant decision tree after training the data set in Fourier domain using See5.0

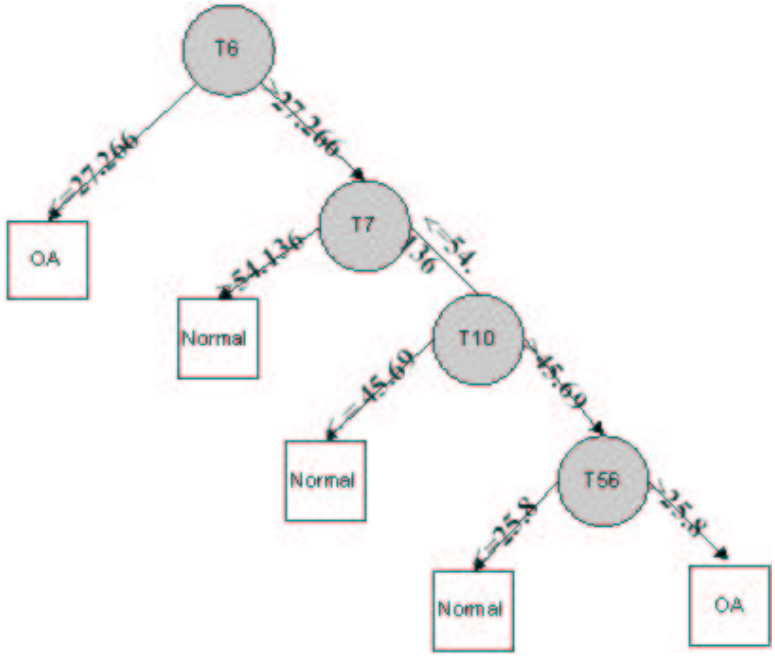

Figure 4.18: Resultant decision tree after training the data set in time domain using See5.0

CHAPTER 5

RECOGNITION SYSTEM

Data files have been trained and tested in time domain as well as in Fourier domain. Graphically, in time domain it is very hard to distinguish between normal and diseased dogs, where as in Fourier domain it is visually distinguishable. To further explain, sample graphs in both time and Fourier domains are given below. Figure 5.1 shows the time domain representation of a sample gait with and without stifle instability and subsequent Osteoarthritis. The dotted curve in the figure represents the behavior of a dog with stifle instability and Osteoarthritis and the solid curve represents the behavior of a dog without stifle instability and Osteoarthritis. Figure 5.2 shows the same data in Fourier domain. Here the curves are distinguishable. The curve belonging to the normal dog shows deviation whereas the other curve which belongs to a diseased dog is almost a straight line. Curves of In/Ext rotation in Real and Imaginary axis of Fourier domain show similar behavior. Experiments have been conducted on the data from the Real and Imaginary axes.

Based on observations from experiments conducted on “Internal/External rotation angle using Decision trees and ID3 algorithm on the data file in time domain and in Fourier domain, data in Fourier domain showed more deviation between a normal and a diseased dog than data in time domain.

The next step was to build a recognition system with input as Fourier domain representation of internal/external rotation angle, as this was the chosen attribute for classification.

The recognition system takes time domain data values of Internal/External rotation angle and recognizes if the data belongs to a normal or diseased dog. The input raw data is converted to Fourier domain representation. It is then passed as input to the learning algorithms described below.

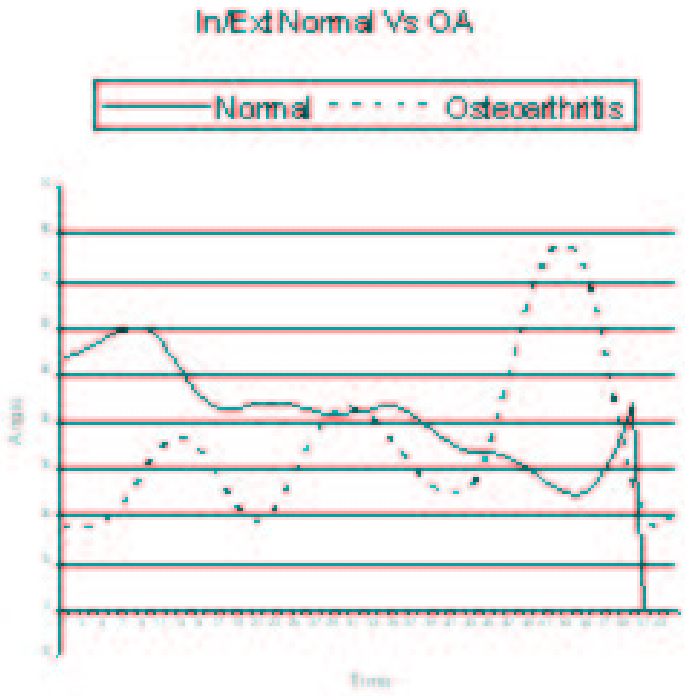

Figure 5.1: Sample curve of the time domain data.

Recognition system has been implemented with a total of three different algorithms. First one is the neural network classifier which is explained in the previous chapter, second one is the decision tree, explained in the previous chapter and the third algorithm is the lazy learning, K - Nearest Neighbor algorithm, which is explained in the below sections.

Learning algorithms require a training set. Training set consists of randomly selected files for both categories – normal and diseased. Based on the training result, the recognition system classifies the testing file and the output Raster file is displayed along with the classification result. Figure 5.3 shows a sample Raster file generated by the recognition system for a normal dog and Figure 5.4 shows a sample Raster file for a dog with stifle instability and subsequent Osteoarthritis.

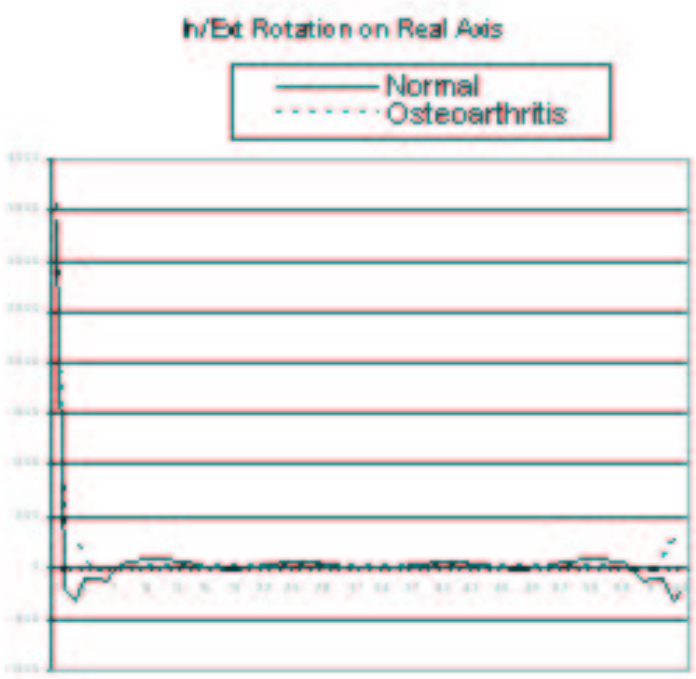

Figure 5.2: Fourier representation of normal and diseased dog.

5.1 System Architecture

Figure 5.5 shows the architecture of the recognition system. Training data is first input into the recognition system. System stores all the training data into 2 classes, normal and stifle instability and secondary Osteoarthritis.

A sample raw data file is input to the system. Fourier transform of the raw data file is computed. This Fourier transform is input to the learning algorithms described in the next section. Based on the training data and input data, the learning algorithms output the classification result as normal or stifle instability and secondary Osteoarthritis.

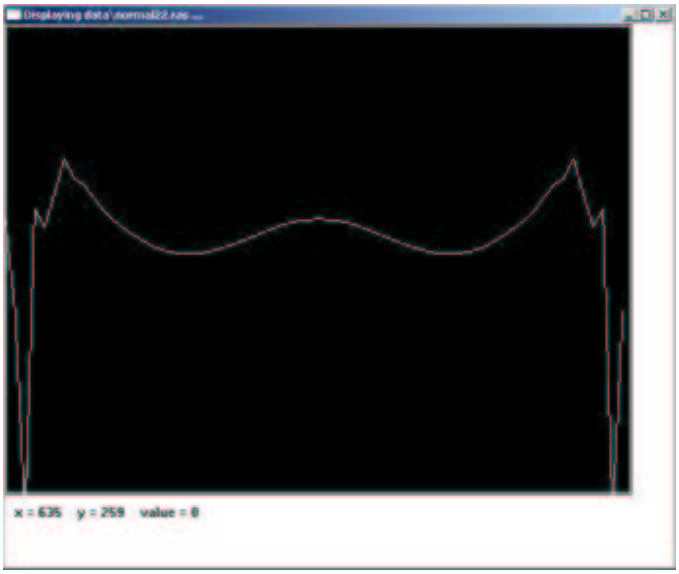

Figure 5.3: Raster Graph generated by the recognition system for a sample normal dog.

5.2 Learning Algorithms

5.2.1 Neural Networks

NeuroShell classifier has been used to train and test the data to predict the classification of the given file. Neural networks showed better performance in classification in Fourier domain data. The trained neural network with the best performance on Fourier domain testing data, described in section 4.2.2 of this document, has been implemented as one of the classification algorithms for the stifle instability and Osteoarthritis recognition system.

Recognition system takes the values of “Internal / External rotation” angle in time domain. This file will be sent to the class “FFT” of the system and Fast Fourier transforms will be applied on the input time domain data file. The resultant Fourier domain data on the real axis will be sent to the “FrequencyNeuro” class of the recognition system. All the 64 elements of the input file will be sent to an array called “inarray” and the single element “outarray” value will be computed based on the trained neural network. If the value is less than 0.5, then the input file is classified as the

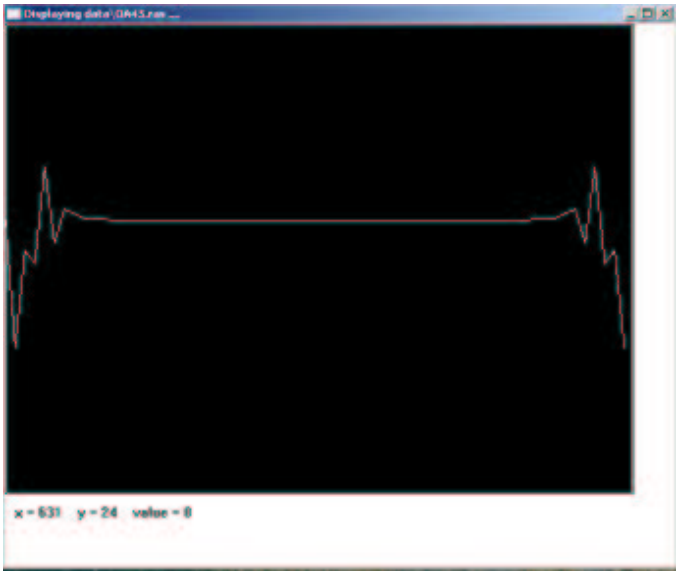

Figure 5.4: Raster Graph generated by the recognition system for a sample dog affected by stifle instability and Osteoarthritis

normal dog file. If it's value is greater than 0.5, then input file belongs to dog with stifle instability and Osteoarthritis. Otherwise, classification is undecided. Accuracy obtained on the classification of data using this algorithm is 96.297%.

Since the implemented neural network is the trained network for the data set for this application, this network works only for the classification of canine cranial cruciate deficient knee Osteoarthritis, with the input values of "Internal / External rotation" angle of knee joints.

5.2.2 Decision Trees

Experiments conducted using See5.0 tool on time domain data and Fourier domain data of "Internal / External rotation" angles of different dogs, Fourier domain data showed better performance in terms of prediction accuracy. These experiments are explained in detail in the section 4.3.2 of this document. Classification accuracy of 96.3% is achieved by using this algorithm.

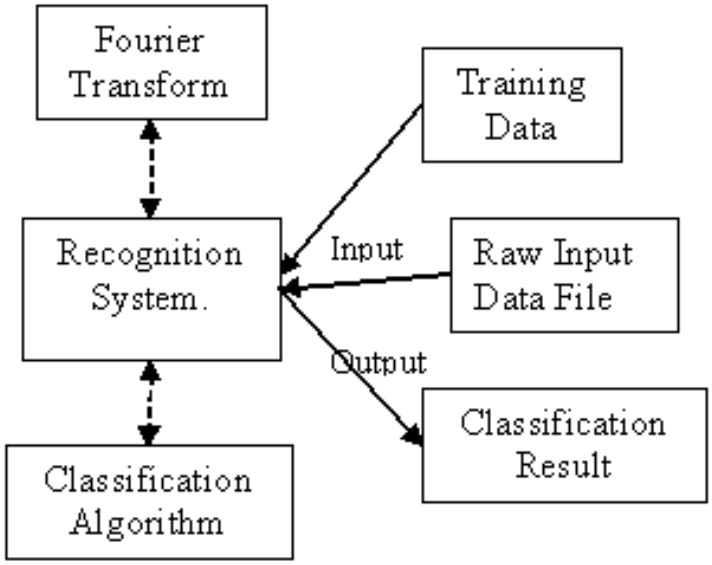

Figure 5.5: Representation of the system architecture for the recognition system.

In order to classify the input file using this decision trees, the input file has to be given to the recognition system with the time domain values of “Internal / External rotation” angle of dog‘s gait. These values will be converted into Fourier domain using “FFT” class and ”DecisionTree” class of the recognition system performs the test for classification and send the result of the classification as an output.

Implemented decision tree is based on the training and testing of Fourier domain representation of “Internal / External rotation” angle of knee joints for canine population. This decision tree is specific to this application only.

5.2.3 K-Nearest Neighbors

K- Nearest Neighbors algorithm is one of the most basic Instance-Based Learning algorithms. Every input data file is an instance. The data file contains 64 values corresponding to the internal

/ external rotation angle. Fourier transform of these values is computed. This is the feature vector of length 64 and can be used for classification. This can also be represented as a point in 64 dimensional space. The feature vectors of each file in the training data set are pre computed. Feature vector of the input test data file is also computed. Approximately, 25% of error rate was observed in the classification of testing data with a K - value of 9.

Let the test instance *xt* be described by the feature vector *(*$xt_1, xt_2, \ldots xt_n$)where xt_r denotes the value of the r^{th} internal/external rotation angle of file *xt*.

Training algorithm:

- For each training example $x, f(x)$, add example to the list *training_examples*.

Classification Algorithm:

- Given a test instance *xt* to be classified. Let *x1, x2,. . . xk* denote the k instances from t*raining examples* that are nearest to *xq*. Nearness is computed by computing the distance d (xt, xi) where i, ranges over all training examples.

Distance between the two instances *xi* and *xj* is defined as *d(xi,xj),* where

$$d(xi,xj) \equiv \sqrt{(\sum_{r=1}^{64}(xi_r - xj_r)^2)}\ .$$

- *xt* is then classified as the majority class - normal or diseased, present in the k instances *x1,x2 ... xk* computed above.

5.3 Class Diagrams

Figure 5.6 shows the class diagram of the recognition system. The class “LoadTrainingData” loads the data file to be classified using loadFile() method and the training data is loaded into the classification system using loanTrainingData() method. Training data consists of data of normal dogs and the dogs with OA with appropriate classification. The training data and the testing data which is loaded into the system are in time domain. This data is passed to the class FFT and the

method fft() transforms all the data in time domain into frequency domain. FeatureVector class takes the data in frequency domain and computes the relative differences between each data point in 64 dimension space. This class also provides a method, computeRMS(), to compute the RMS value of each data file.

After computing the Feature Vector for each data file, the Classifier class classifies the data file. The Classifier performs three different classification algorithms on the Feature Vector of input data file. With the application of classification algorithms, the Classifier decides whether the data file being tested belongs to the normal dog or the dog with Osteoarthritis.

After the classification is done, the Image class stores and writes out Raster files of the data file in the frequency domain. Bresenham class provides the functionality of Bresenham line generation algorithm. The plot() method from the PlotRasterGraph class, plots the curve on the output file. A user-friendly graphical user interface has been provided for the easy navigation of the system.

5.4 Interface to the Classifier

For the convenience of the users, a graphical user interface and a command line interface have been provided to the recognition system. Figure 5.7 shows a sample snapshot of the GUI of the recognition system while classifying a normal dog data. Figure 5.8 shows a snapshot of same interface while classifying a dog having stifle instability and Osteoarthritis. Figure 5.9 shows the snapshot of the recognition system‘s command line interface. This snapshot shows the classification of a dog with and with out Osteoarthritis.

In GUI interface, path to data file to be tested has to be entered in the text box next to “Test File” and desired name and path to the output file generated by the recognition system has to be entered in the text box next to “Image File”. By clicking “Classify” button, recognition system classifies the file being tested on it either as “NORMAL” (data file belongs to a dog with out having Osteoarthritis) or “Osteoarthritis” (data file belongs to a dog having Osteoarthritis) in the lower right corner of the screen. Classification made by individual algorithms is displayed separately.

Output Raster file is generated for each data file which is tested on the recognition system and its path is specified at the bottom of the screen.

In the command line interface, above steps take place sequentially at the command prompt. Figure 5.9 shows these steps.

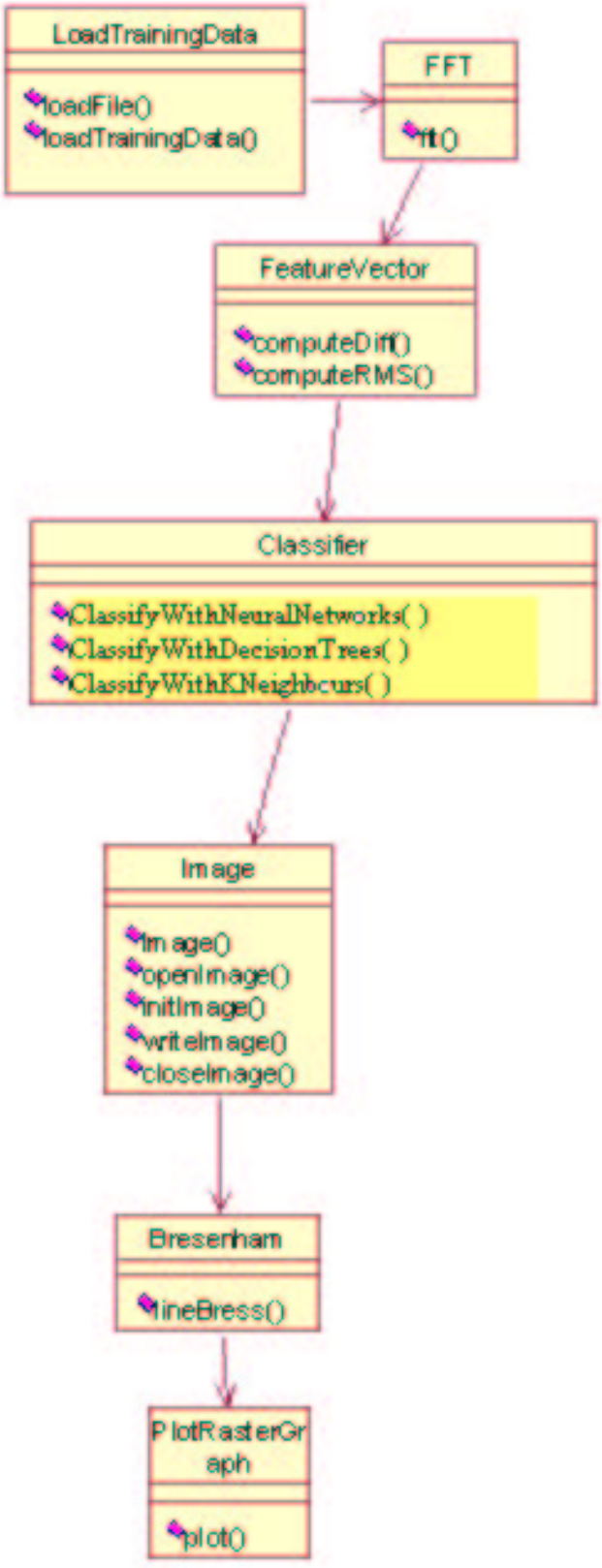

Figure 5.6: Class diagram for the recognition system.

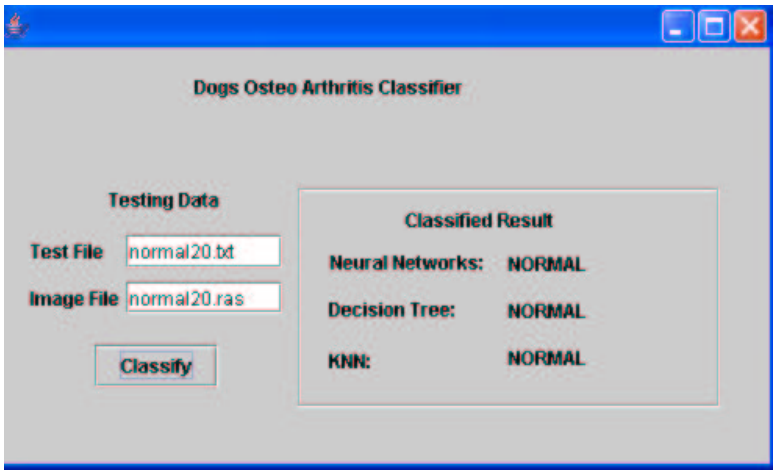

Figure 5.7: Snapshot of the recognition system in GUI mode classifying a normal dog.

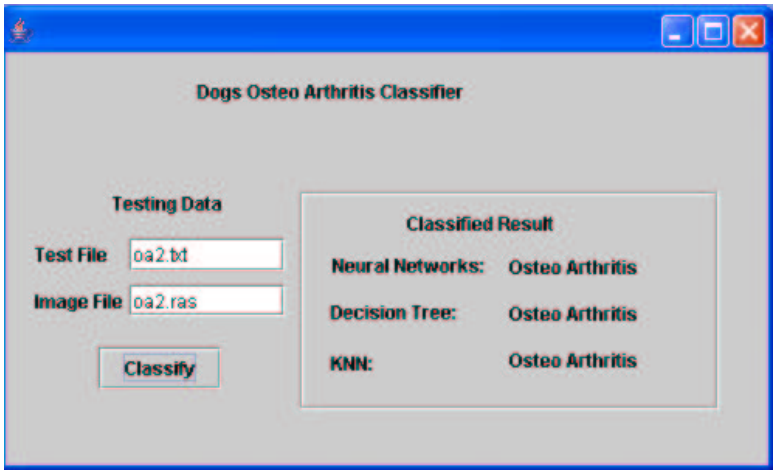

Figure 5.8: Snapshot of the recognition system in GUI mode classifying a dog with Osteoarthritis.

```
yeluri@atlas % java Driver
        ****** Welcome TO Osteo Arthritis Classifier *******


45 47

 .. Loaded training data


 Normal Dogs Training data from : data/TrainingData/normal/

 OA Dogs Training data from : data/TrainingData/normal/


************************************
        GIVE INPUT TEST FILE

>data/normal20.txt

        GIVE OUTPUT IMAGE RASTER FILE

>data/normal20.ras


        CLASSIFIED RESULT

1.K-Means Classifier:                   NORMAL
2.DecisionTree result:                  NORMAL
3.Neural Networks result:               NORMAL

        VIEW OUTPUT IMAGE IN :data/normal20.ras
************************************
        GIVE INPUT TEST FILE

>data/oa49.txt

        GIVE OUTPUT IMAGE RASTER FILE

>data/oa49.ras
        CLASSIFIED RESULT

1.K-Means Classifier:                   Osteo Arthritis
2.DecisionTree result:                  Osteo Arthritis
3.Neural Networks result:               Osteo Arthritis

        VIEW OUTPUT IMAGE IN :data/oa49.ras
```

Figure 5.9: Snapshot of the recognition system in command line mode classifying a normal and an Osteoarthritis dog.

CHAPTER 6

CONCLUSION

Our recognition system shows high accuracy in classifying dogs with stifle instability and Osteoarthritis in Fourier domain. The result based on learning algorithms described in previous chapter was 96.297% of accuracy using neural networks, 96.3% of accuracy using decision trees and about 75% of accuracy using K - Nearest Neighbours on the data set.

Often, it is very useful to work on functions and on their transforms as occupying two different domains. They are referred to as lower and upper domains. But, in most applications, they are called time and frequency domains. Operations performed in time domain have corresponding operations in the frequency domain and this relationship is vice versa. This principle allows one to move between these two domains to perform the operations where they are convenient and most advantageous. Based on this concept, experiments were conducted both in time and frequency domain values of “Internal / External rotation” angle of canine knee joints for this project. Based on these experiments, we discovered that the data shows better distinction in the Fourier domain than in the time domain for the attribute “Internal/External rotation” angle.

Applicability of Computer Science research in the field of medicine over the recent decades has had tremendous positive impact. Any research with out the applicability to the real world problems will not draw much attention. Interdisciplinary research between the fields of Computer Science and Medicine has lead to very useful solutions for previously difficult problems. The main advantage has been automating processes, which require a lot of manual effort. Some of the latest techniques developed by the researchers can be directly adapted as the solutions to the real world problems. Other techniques may provide support for those techniques in terms of improvement, accuracy and user friendliness of the solution. Techniques discussed in this thesis are the subset

of overall disease detection mechanisms that are currently applicable in various medical domains. We can also look into the applicability of these methods in the analysis and detection of other prevailing diseases.

6.1 Future Work

This work focuses on the Osteoarthritis disease that affects only the knee joints of canine population. As we discussed in chapter 2, there are several other joints such as shoulder joints, elbow joints and carpus joints of dogs that are effected by Osteoarthritis most commonly. The recognition techniques discussed in this thesis can be examined if they show similar distinction for the Osteoarthritis detection problem for these joins.

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APPENDIX A

DECISION TREE RESULTS ON CROSS VALIDATION OF 12 FOLDS IN TIME DOMAIN

See5 [Release 2.01] Wed Jul 06 19:28:35 2005

Options:

Do not use global pruning

Cross-validate using 12 folds

Class specified by attribute ‘result’

Read 108 cases (65 attributes) from 108TimeRows.data

[Fold 0]

Decision tree:

T6 <= 27.266: 1 (25/1)

T6 > 27.266:

:...T5 > 54.06: 0 (15)

T5 <= 54.06:

:...T6 > 47.94001: 1 (12)

T6 <= 47.94001:

:...T13 <= 43.606:

:...T60 > 17.078: 0 (25/2)

: T60 <= 17.078:

: :...T11 <= 33.397: 1 (4)

: T11 > 33.397: 0 (2)

T13 > 43.606:

:...T64 > 25.283: 1 (9/1)

T64 <= 25.283:

:...T55 <= 29.676: 0 (4)

T55 > 29.676: 1 (3/1)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

9 3(33.3%) <<

[Fold 1]

Decision tree:

T5 <= 27.211: 1 (24)

T5 > 27.211:

:...T49 > 47.194: 0 (11)

T49 <= 47.194:

:...T53 > 33.245:

:...T30 <= 40.488: 0 (3/1)

: T30 > 40.488: 1 (15)

T53 <= 33.245:

:...T12 > 49.942: 0 (11)

T12 <= 49.942:

:...T11 > 44.156: 1 (6)

T11 <= 44.156:

:...T58 > 22.781: 0 (17)

T58 <= 22.781:

:...T12 <= 33.116: 1 (7/1)

T12 > 33.116: 0 (5)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

9 3(33.3%) <<

[Fold 2]

Decision tree:

T5 <= 27.211: 1 (28/1)

T5 > 27.211:

:...T6 > 55.4: 0 (11)

T6 <= 55.4:

:...T6 > 47.94001:

:...T17 <= 38.347: 0 (2)

: T17 > 38.347: 1 (12)

T6 <= 47.94001:

:...T49 > 47.194: 0 (8)

T49 <= 47.194:

:...T54 > 33.375: 1 (7/1)

T54 <= 33.375:

:...T58 > 17.702: 0 (21/1)

T58 <= 17.702:

:...T57 <= 3.201: 0 (3)

T57 > 3.201: 1 (7/1)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

9 3(33.3%) <<

[Fold 3]

Decision tree:

T6 <= 27.266: 1 (27/1)

T6 > 27.266:

:...T13 <= 40.017:

:...T60 <= 17.078: 1 (4/1)

: T60 > 17.078: 0 (26/1)

T13 > 40.017:

:...T5 > 56.333: 0 (8)

T5 <= 56.333:

:...T64 <= 32.33:

:...T42 > 25.824: 0 (8)

: T42 <= 25.824:

: :...T20 <= 41.805: 1 (2)

: T20 > 41.805: 0 (2)

T64 > 32.33:

:...T64 <= 55.537: 1 (17)

T64 > 55.537:

:...T6 <= 49.556: 0 (2)

T6 > 49.556: 1 (3)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

10 3(33.3%) <<

[Fold 4]

Decision tree:

T8 <= 27.29: 1 (20)

T8 > 27.29:

:...T5 > 56.333: 0 (11)

T5 <= 56.333:

:...T44 > 48.549: 0 (7)

T44 <= 48.549:

:...T39 > 38.551: 1 (11)

T39 <= 38.551:

:...T42 <= 14.403: 1 (5)

T42 > 14.403: 0 (45/16)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

6 4(44.4%) <<

[Fold 5]

Decision tree:

T6 <= 27.266: 1 (27/1)

T6 > 27.266:

:...T26 <= 32.542:

:...T24 > 19.059: 0 (21)

: T24 <= 19.059:

: :...T46 <= 17.532: 1 (4/1)

: T46 > 17.532: 0 (2)

T26 > 32.542:

:...T24 > 48.853: 0 (10)

T24 <= 48.853:

:...T7 > 54.136: 0 (7)

T7 <= 54.136:

:...T39 > 33.341: 1 (20/1)

T39 <= 33.341:

:...T42 <= 28.438: 1 (4)

T42 > 28.438: 0 (4)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

9 2(22.2%) <<

[Fold 6]

Decision tree:

T6 <= 27.266: 1 (26/1)

T6 > 27.266:

:...T17 <= 39.882:

:...T7 <= 30.062:

: :...T4 <= 27.437: 0 (2)

: : T4 > 27.437: 1 (4)

: T7 > 30.062:

: :...T25 <= 34.307: 0 (23)

: T25 > 34.307:

: :...T32 <= 39.28: 1 (4/1)

: T32 > 39.28: 0 (6)

T17 > 39.882:

:...T25 > 45.76: 0 (8)

T25 <= 45.76:

:...T7 > 55.077: 0 (4)

T7 <= 55.077:

:...T14 <= 49.688: 1 (17)

T14 > 49.688:

:...T14 <= 54.49: 0 (2)

T14 > 54.49: 1 (3)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

11 2(22.2%) <<

[Fold 7]

Decision tree:

T5 <= 27.211: 1 (27/1)

T5 > 27.211:

:...T7 > 54.136: 0 (9)

T7 <= 54.136:

:...T14 <= 38.069:

:...T63 > 27.149: 0 (21)

: T63 <= 27.149:

: :...T60 <= 18.871: 1 (4)

: T60 > 18.871: 0 (6/1)

T14 > 38.069:

:...T63 <= 25.549: 0 (5)

T63 > 25.549:

:...T52 > 51.935: 0 (3)

T52 <= 51.935:

:...T39 > 33.341: 1 (19)

T39 <= 33.341:

:...T48 <= 27.056: 1 (2)

T48 > 27.056: 0 (3)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

10 1(11.1%) <<

[Fold 8]

Decision tree:

T6 <= 27.266: 1 (26/1)

T6 > 27.266:

:...T13 <= 39.272:

:...T63 > 27.149: 0 (22)

: T63 <= 27.149:

: :...T60 <= 18.871: 1 (4)

: T60 > 18.871: 0 (6/1)

T13 > 39.272:

:...T7 > 54.136: 0 (8)

T7 <= 54.136:

:...T51 > 56.925: 0 (5)

T51 <= 56.925:

:...T64 > 25.283: 1 (20/1)

T64 <= 25.283:

:...T41 <= 26.129: 1 (4/1)

T41 > 26.129: 0 (4)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

9 2(22.2%) <<

[Fold 9]

Decision tree:

T6 <= 27.266: 1 (28/1)

T6 > 27.266:

:...T52 > 47.916: 0 (10)

T52 <= 47.916:

:...T54 > 33.375:

:...T17 <= 38.347: 0 (3/1)

: T17 > 38.347: 1 (13)

T54 <= 33.375:

:...T60 <= 14.888: 1 (3)

T60 > 14.888:

:...T13 <= 43.111:

:...T44 > 16.612: 0 (19)

: T44 <= 16.612:

: :...T1 <= 30.64: 1 (2)

: T1 > 30.64: 0 (3)

T13 > 43.111:

:...T12 <= 48.431: 1 (5)

T12 > 48.431:

:...T38 <= 40.938: 0 (10)

T38 > 40.938: 1 (3/1)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

11 0(0.0%) <<

[Fold 10]

Decision tree:

T6 <= 27.266: 1 (27)

T6 > 27.266:

:...T7 > 54.136: 0 (11)

T7 <= 54.136:

:...T11 > 45.799:

:...T63 <= 23.829: 0 (2)

: T63 > 23.829: 1 (17/1)

T11 <= 45.799:

:...T60 <= 17.078:

:...T50 <= 55.362: 1 (5)

: T50 > 55.362: 0 (2)

T60 > 17.078:

:...T36 <= 47.844: 0 (33/3)

T36 > 47.844: 1 (2)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

8 5(55.6%) <<

[Fold 11]

Decision tree:

T6 <= 26.928: 1 (26/1)

T6 > 26.928:

:...T25 > 46.28: 0 (11)

T25 <= 46.28:

:...T37 > 43.215: 1 (9)

T37 <= 43.215:

:...T64 > 54.765: 0 (13)

T64 <= 54.765:

:...T64 <= 48.895: 0 (33/12)

T64 > 48.895: 1 (7)

Evaluation on hold-out data (9 cases):

Decision Tree

————————-

Size Errors

6 2(22.2%) <<

[Summary]

Decision Tree

—- ————————-

Fold Size Errors

0 9 33.3%

1 9 33.3%

2 9 33.3%

3 10 33.3%

4 6 44.4%

5 9 22.2%

6 11 22.2%

7 10 11.1%

8 9 22.2%

9 11 0.0%

10 8 55.6%

11 6 22.2%

Mean 8.9 27.8%

SE 0.5 4.2%

(a) (b) <-classified as

—- —-

37 14 (a): class 0

16 41 (b): class 1

Time: 0.4 secs

APPENDIX B

DECISION TREE RESULTS BY USING CROSS VALIDATIONS IN FOURIER DOMAIN

See5 [Release 2.01] Sun Jun 12 17:15:37 2005

Options:

Cross-validate using 14 folds

Class specified by attribute ‘result’

Read 108 cases (65 attributes) from 103FrequencyRealRows.data

[Fold 0]

Decision tree:

T1 <= 1271.304: 1 (20)

T1 > 1271.304:

:...T16 > 8.381947: 0 (25)

T16 <= 8.381947:

:...T22 > 13.84253: 0 (15/1)

T22 <= 13.84253:

:...T6 <= -52.35027: 0 (4)

T6 > -52.35027:

:...T5 > 76.02459: 0 (6/1)

T5 <= 76.02459:

:...T2 > 228.5803:

:...T3 <= 159.7666: 1 (2)

: T3 > 159.7666: 0 (3)

T2 <= 228.5803:

:...T1 > 1894.722: 1 (17)

T1 <= 1894.722:

:...T10 > 1.744953: 1 (4)

T10 <= 1.744953:

:...T28 <= 8.350965: 0 (3)

T28 > 8.350965: 1 (2)

Evaluation on hold-out data (7 cases):

Decision Tree

———————-

Size Errors

11 1(14.3%) <<

[Fold 1]

Decision tree:

T23 > 17.46849: 0 (34/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (23)

T1 > 1305.798:

:...T5 > 76.02459: 0 (7/1)

T5 <= 76.02459:

:...T23 <= -12.23808: 0 (2)

T23 > -12.23808:

:...T4 <= -9.497302: 1 (12)

T4 > -9.497302:

:...T3 <= -152.1301: 0 (2)

T3 > -152.1301:

:...T3 <= 99.14782: 1 (6)

T3 > 99.14782:

:...T9 > 3.144437: 0 (3)

T9 <= 3.144437:

:...T33 <= -2.207028: 0 (2)

T33 > -2.207028: 1 (4)

Evaluation on hold-out data (7 cases):

Decision Tree

————————-

Size Errors

11 1(14.3%) <<

[Fold 2]

Decision tree:

T23 > 17.46849: 0 (30/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T5 > 72.89264: 0 (7/1)

T5 <= 72.89264:

:...T4 <= 3.079278:

:...T14 <= 3.967708: 1 (18)

: T14 > 3.967708: 0 (2)

T4 > 3.079278:

:...T3 <= 101.0579: 1 (6/1)

T3 > 101.0579: 0 (5)

Evaluation on hold-out data (7 cases):

Decision Tree

————————-

Size Errors

9 1(14.3%) <<

[Fold 3]

Decision tree:

T23 > 17.46849: 0 (32/1)

T23 <= 17.46849:

:...T16 > 19.03276: 0 (7)

T16 <= 19.03276:

:...T5 > 106.8482: 0 (4)

T5 <= 106.8482:

:...T3 <= -299.2485: 0 (3)

T3 > -299.2485:

:...T1 <= 1495.122: 1 (27)

T1 > 1495.122:

:...T1 <= 2009.52: 0 (3)

T1 > 2009.52:

:...T2 <= -207.4632: 0 (2)

T2 > -207.4632:

:...T2 <= 228.5803: 1 (19/1)

T2 > 228.5803: 0 (4/1)

Evaluation on hold-out data (7 cases):

Decision Tree

————————-

Size Errors

9 1(14.3%) <<

[Fold 4]

Decision tree:

T23 > 17.46849: 0 (31/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (21)

T1 > 1305.798:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T14 > 3.967708: 0 (5/1)

T14 <= 3.967708:

:...T2 > 222.7046:

:...T7 <= -22.14393: 1 (2)

: T7 > -22.14393: 0 (5)

T2 <= 222.7046:

:...T5 <= 19.34089: 1 (13)

T5 > 19.34089:

:...T32 <= -5.012384: 0 (2)

T32 > -5.012384:

:...T6 <= 6.71286: 0 (2)

T6 > 6.71286: 1 (8)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

11 1(12.5%) <<

[Fold 5]

Decision tree:

T23 > 17.46849: 0 (33/1)

T23 <= 17.46849:

:...T16 > 19.03276: 0 (6)

T16 <= 19.03276:

:...T6 <= -60.51318: 0 (4)

T6 > -60.51318:

:...T1 <= 1402.684: 1 (22)

T1 > 1402.684:

:...T5 <= 71.73939: 1 (29/7)

T5 > 71.73939: 0 (6/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

6 2(25.0%) <<

[Fold 6]

Decision tree:

T23 > 17.46849: 0 (30)

T23 <= 17.46849:

:...T1 <= 1305.798: 1 (21)

T1 > 1305.798:

:...T16 > 12.00539: 0 (8)

T16 <= 12.00539:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T5 > 76.02459: 0 (6/1)

T5 <= 76.02459:

:...T2 > 224.2647:

:...T3 <= 159.7666: 1 (2)

: T3 > 159.7666: 0 (3)

T2 <= 224.2647:

:...T1 > 1894.722: 1 (16)

T1 <= 1894.722:

:...T10 > 1.744953: 1 (4)

T10 <= 1.744953:

:...T28 <= 7.657263: 0 (3)

T28 > 7.657263: 1 (2)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

11 2(25.0%) <<

[Fold 7]

Decision tree:

T23 > 17.46849: 0 (32/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (5)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T5 > 76.02459: 0 (7/1)

T5 <= 76.02459:

:...T4 <= -12.03159: 1 (14)

T4 > -12.03159:

:...T8 <= -11.71484: 1 (4)

T8 > -11.71484:

:...T2 <= -34.46019: 1 (5/1)

T2 > -34.46019: 0 (6)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

9 3(37.5%) <<

[Fold 8]

Decision tree:

T23 > 17.46849: 0 (31/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T5 > 76.02459: 0 (7/1)

T5 <= 76.02459:

:...T1 > 2009.52: 1 (19/2)

T1 <= 2009.52:

:...T8 > 1.28107: 0 (3)

T8 <= 1.28107:

:...T3 <= 74.087: 1 (4)

T3 > 74.087: 0 (3/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

9 3(37.5%) <<

[Fold 9]

Decision tree:

T23 > 17.46849: 0 (30/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (20)

T1 > 1305.798:

:...T6 <= -52.35027: 0 (5)

T6 > -52.35027:

:...T5 > 76.02459: 0 (7/1)

T5 <= 76.02459:

:...T8 <= -11.71484: 1 (10)

T8 > -11.71484:

:...T2 > 228.5803: 0 (3)

T2 <= 228.5803:

:...T1 > 2122.528: 1 (10)

T1 <= 2122.528:

:...T3 <= -152.1301: 0 (2)

T3 > -152.1301:

:...T7 <= -4.254474: 0 (2)

T7 > -4.254474: 1 (5/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

11 0(0.0%) <<

[Fold 10]

Decision tree:

T23 > 17.46849: 0 (34/1)

T23 <= 17.46849:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T5 > 76.02459: 0 (7)

T5 <= 76.02459:

:...T6 <= -37.81735: 0 (5)

T6 > -37.81735:

:...T16 <= 8.381947: 1 (29/6)

T16 > 8.381947: 0 (3)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

6 1(12.5%) <<

[Fold 11]

Decision tree:

T23 > 15.61584: 0 (33/1)

T23 <= 15.61584:

:...T11 > 11.63593: 0 (7)

T11 <= 11.63593:

:...T5 > 106.8482: 0 (4)

T5 <= 106.8482:

:...T2 <= -189.1317: 0 (3)

T2 > -189.1317:

:...T1 <= 1402.684: 1 (23)

T1 > 1402.684:

:...T17 <= -11.964: 0 (2)

T17 > -11.964:

:...T3 <= 101.0579: 1 (14)

T3 > 101.0579:

:...T1 <= 2326.634: 0 (4/1)

T1 > 2326.634:

:...T2 <= 228.5803: 1 (6)

T2 > 228.5803: 0 (4/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

10 3(37.5%) <<

[Fold 12]

Decision tree:

T23 > 17.46849: 0 (30/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T5 > 76.02459: 0 (9/1)

T5 <= 76.02459:

:...T14 > 3.967708: 0 (5/1)

T14 <= 3.967708:

:...T4 <= 3.079278: 1 (17)

T4 > 3.079278:

:...T3 <= 99.14782: 1 (4)

T3 > 99.14782: 0 (7/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

8 0(0.0%) <<

[Fold 13]

Decision tree:

T23 > 17.46849: 0 (31/1)

T23 <= 17.46849:

:...T17 > 20.972: 0 (6)

T17 <= 20.972:

:...T1 <= 1305.798: 1 (22)

T1 > 1305.798:

:...T5 > 76.02459: 0 (8/1)

T5 <= 76.02459:

:...T14 > 3.967708: 0 (5/1)

T14 <= 3.967708:

:...T4 <= 2.898072: 1 (16)

T4 > 2.898072:

:...T31 <= -2.129507: 0 (5)

T31 > -2.129507: 1 (7/1)

Evaluation on hold-out data (8 cases):

Decision Tree

————————-

Size Errors

8 1(12.5%) <<

[Summary]

Decision Tree

—- ————————-

Fold Size Errors

0 11 14.3%

1 11 14.3%

2 9 14.3%

3 9 14.3%

4 11 12.5%

5 6 25.0%

6 11 25.0%

7 9 37.5%

8 9 37.5%

9 11 0.0%

10 6 12.5%

11 10 37.5%

12 8 0.0%

13 8 12.5%

Mean 9.2 18.4%

SE 0.5 3.3%

(a) (b) <-classified as

—- —-

50 8 (a): class 0

12 38 (b): class 1

Time: 0.5 secs

APPENDIX C

TYPICAL OSTEOARTHRITIS DETECTION METHODOLOGIES

There are many traditional methods used to detect the presence of the disease. In recent years, there are substantial improvements in implementing the traditional techniques for better accuracy and understanding of the problem. Apart from these, researchers have come up with many new techniques to detect the presence of osteoarthritis at the early stages. Typical tests which are conducted to detect the presence of the disease are described below.

C.1 ORTHOPEDIC EXAMINATION

A thorough orthopedic examination can reveal the presence of joint pain, swelling and tenderness. A careful observation to the dogs case history also gives some suspicious hint towards the presence of the osteoarthritis. There are several different diagnoses which are very particular to dogs of different age groups and breeds.

C.2 RADIOGRAPHS

X-rays are usually an essential diagnostic tool. Since the majority of degenerative arthritis seen in small pets is secondary to some congenital or acquired event, radiographic diagnosis of this inciting cause is very important and provides very useful information.

C.3 CONTRAST STUDIES

Usually the diagnosis of degenerative arthritis is fairly straightforward, but sometimes, additional views or ”stress” views may be required. Injecting contrast (dye) into the joint and obtaining a radiograph is seldom necessary. Also, advanced imaging techniques such as CT and MRI are seldom necessary. Bone scans involve injecting a small amount of a radioactive material in the body that would normally accumulate

in the bone. By using a specialized camera it is possible to record the radioactive material in the joints, an area of increased accumulation may help the clinician to detect a subtle area of lameness.

C.4 Aspiration Joint Fluid

Degenerative arthritis is just one of many types of joint disease that can occur. The other large category of joint diseases is termed ”inflammatory.” With these diseases, a large amount of white blood cells are attracted to the joint from various disease processes. The most common of these are autoimmune diseases. Canine rheumatoid arthritis is an example of this type of arthritis. This type of arthritis is uncommon when compared to degenerative arthritis. Aspiration of joint fluid can be helpful in determining is the arthritic process is inflammatory (rheumatoid like) or non-inflammatory (degenerative arthritis).

C.5 Sampling the Joint Fluid

In order to find out the infectious arthritis, a small needle is inserted into the joint and a small amount of fluid is taken by using a syringe and the fluid be tested. This process is called arthrocentesis or Joint Tap.

C.6 Ultrasonograph

This is an imaging procedure to determine the presence of the disease in dogs. This involves the examination of the joints soft issues and accessible cartilage surfaces using an ultra sound machine. This procedure gives more details.