3. METHODOLOGY

Increasing costs of health care in the recent past, have often made the healthcare industry investigate, adapt and apply techniques relating to automating the various processes of a hospital. In medical image processing applications, diagnosis is effective only when the concerned image has all the relevant and important information in a clear and unambiguous form. In this research work, different algorithms are carefully analyzed for detecting fractures in diaphysis and their performance are studied. This chapter presents the proposed research methodology.

3.1. PROPOSED METHODOLOGY

The present research work proposes enhancement algorithms based on the effective, synergistic integration of several image processing schemes that aim to achieve maximum accuracy during the automatic identification of fractures in 2D image of tibia diaphysis. To keep in track with the latest developments and inventions in medical field, continuous researches that focus on developing new competitive algorithms are always desirable. As these algorithms are to be used with life-sensitive medical environment, they should always aim to provide results that are highly accurate. They should have two main characteristics of being fast and doctor friendly. Performance of techniques that assist to achieve these characteristics should individually be proved before it is combined with the overall systems. The accuracy can be increased either by incorporating new optimizing techniques or by enhancing the existing algorithms to improve its performance. Most of the research work belongs to the second type.

While considering methods to improve existing works, methods that combine the advantages of various techniques have gained more attention. The solutions provided in this research work are more compatible for X-Ray images and are proposed to improve the enhancement, segmentation and classification processes of the proposed CADi-TFi systems.
In order to develop a CADi-TFi system that meets the research objectives formulated in Chapter I, the methodology is divided into four phases (Figure 3.1).

Phase I : Enhancement (to improve the quality of X-Ray Image)

Phase II : RoI-Segmentation (to extract the tibia and diaphysis portion from the X-Ray Image)

Phase III : Feature Extraction and Selection (to identify and extract optimal features that best represent the diaphysis region of the tibia bone)

Phase IV : Detection (to ascertain the presence or absence of fracture in the input X-Ray image, and if present, identify the type of fracture) and identification to establish the probable location of fracture in the segmented tibia diaphysis.

The four phases are interrelated and the output from one phase is used as input by another phase. The methods and techniques used in each of these steps are described in this section.

3.1.1. Fractures Considered by CADi-TFi System

While designing an automated system for fracture detection two points have to be carefully considered.

1. Which type of bone (for example membrandous bones, cartilaginous bones and membrcartilaginous bones)

2. Which portion of the bone (for example diaphysis, epiphysis, metaphysis)

In the current study, the methods proposed to solve the problem of fracture detection are applied to long leg bone (tibia) and focuses on the diaphysis portion of tibia (Figure 3.2).
X-Ray Image Database

PHASE I
- Enhancement
- Improved Wavelet based Denoising

PHASE II
- Segmentation
- 1. Bone Image Extraction
   Enhanced Active Contour Model
- 2. Diaphysis Segmentation
   Fast Hough Transformation

PHASE III
- Feature Extraction and Selection
- Features: Texture and Shape Features
- Selection: Enhanced Principal Component Analysis

PHASE IV
- Fracture Detection and Location Identification
- Fracture Detection: Classification
  - Classifiers: BPNN, SVM, KNN
  - Methods: Single, Static, Dynamic
  - No. of Classifiers: 2, 3-Classifier
  - Partition Method: Sequential, Random, Bagging and Boosting
  - Aggregation: Hybrid Majority Voting and Weighting Scheme
- Location Identification
  - Fast Hough Transformation with Gradient Analysis

- Denoising: PSNR, FoM, MSSI, Speed
- Segmentation: Visual Comparison, Speed
- Feature Selection: Number of Features, Classification Accuracy
- Classification: Accuracy, Precision, Recall, F-Measure, Speed

Figure 3.1: Research Methodology
Unlike fractures of the epiphysis, fractures of the diaphysis are not easily hidden by the trabecular texture. Although proximal and distal fractures account for a large proportion of all limb fractures, automating their detection was not considered in this study. Some fractures of the diaphyseal segment are easier to detect than fractures in other parts of the body, however their accurate detection is still a very difficult, important, and unsolved problem. For these reasons, diaphysis fractures in tibia were considered. Out of the various types of fractures, the research work concentrates on identifying the following types of fractures (Figure 3.3). With all the fracture types, both single and multiple fractures are considered.

- Simple Fractures
- Simple Transverse Fractures - at right-angles or almost right-angles to the long axis of the bone.
- Simple Oblique Fractures - are those in which the break is at an angle of 30 degrees (30°) or more to the long axis of the bone.
- Simple Spiral Fractures - the line of the fracture spirals around the bone
3.1.2. Phase 1: Enhancement

X-Ray images are often degraded by the presence of Poisson noise and have to be removed to avoid incorrect diagnosis. They also suffer from low / high contrast. In applications such as fracture detection, a preprocessing step is included to adjust contrast and reduce Poisson noise (Sakata and Ogawa, 2009). In recent years, noise elimination methods using a wavelet transform have gained wide attention (Niijima, 2000). Wavelets while successful with Gaussian noise, is not very effective with Poisson noise. To solve this issue, a fast interscale decimated Bi-orthogonal Haar (Bi-Haar) transform (Zhang et al., 2008) and Independent Component Analysis (ICA) (Marusic et al., 2005) denoising method for Poisson-corrupted images is proposed.

The Bi-Haar transform and ICA are used to remove dependencies between the data streams associated with each wavelet decomposition. The thresholding function used is PURESHRINK (Luisier et al., 2010) with soft thresholding. To further improve the quality, the contrast is also adjusted.

3.1.3. Phase 2: Segmentation

The second phase of the study focuses on Segmentation that consists of procedures and techniques to extract the Region of Interest (RoI), diaphysis, from the bone X-Ray image. The procedure proposed extracts diaphysis using a
three-step process. Initially, after enhancing the input image, a multi-resolution wavelet transform is used to obtain multi-resolution representation of the input image. The motivation behind using multi-resolution wavelets is that, wavelets have the ability to represent an image at different resolutions; each resolution characterizes different structures of the image. As the resolution gets coarser, it is possible to obtain general context image details of larger structures without complex details. The segmentation process can be simplified by starting the analysis with coarse resolution and then gradually increase the resolution (Mallat, 1989). Additionally, this method has the advantage that it is very close to the method used by Human Visual System (HVS) (Mallat, 1996).

The result of wavelet transformation is a set of images at different resolutions, which are segmented using an active contour segmentation in the second step. The main challenge while using active contour models for bone segmentation is the initial seed selection. Different initial seed values leads to different segmentation result and often incorrect selection produces inaccurate segmentation. To solve this problem, this study proposes a model that uses region growing algorithm to estimate the initial seeds that can be used by the active contour. The result after applying the enhanced active contour is the separated bone structure from the X-Ray image.

The final step identifies the diaphysis region in the extracted bone image. For this purpose, a fast Hough Transformation (Donnelley et al., 2008; Hari et al., 2009) is used. This algorithm modifies the standard Hough algorithm by considering a pair of pixels simultaneously and mapping them to the parameter space. The fast Hough algorithm is used to estimate the peak spread from the bone structure image. This estimation along with two thresholds is used to detect the diaphysis. Threshold one (T1) is used to retain only those regions where the Hough line matches the bone edge and the threshold two (T2) is used to select only those lines with minimum length. The end points or beginning of diaphysis region is located by identifying edges that
deviate from the line. A bone center-line is detected by analyzing the Hough peak lines.

3.1.4. Phase 3 : Feature Extraction and Selection

The third phase of the study applies techniques to extract and select various features that best exhibit the characteristics of the segmented image. It is the process that converts the segmented image into a format that best suits the fracture and location identification tasks. The study extracts 12 types of features that are grouped into two categories - texture and shape. The texture features collected are GLCM (Gray Level Co-Occurrence Matrix) features, namely, Contrast, Homogeneity, Energy, Entropy, Mean, Variance, Standard Deviation, Correlation, Gabor Orientation (GO), Markov Random Field (MRF), and Intensity Gradient Direction (IGD). The shape features are extracted using a Fast Hough Transformation proposed by Hari et al. (2009).

The features collected are arranged in a two-dimensional matrix where each column represents a feature extracted and the row represents various features that represent the segmented X-Ray image. The final column is treated as a target label column, having a value of 0 to indicate the absence of fracture and 1 to indicate the presence of fracture. Using these 12 features, three feature vectors are created. The first one consists of only texture features, second set has only shape features and the third set with shape and texture features. The three feature vectors are respectively referred to as FS1, FS2 and FS12 respectively.

To solve the problem of ‘curse of dimensionality’, a feature selection algorithm that uses an enhanced version of Principal Component Analysis (PCA) is proposed. First, the feature vector generated is normalized using Z-Score method. In Z-score normalization, the value for a feature is normalized based on the mean and standard deviation of it. This method of normalization is useful because the actual minimum and maximum of a feature is unknown. In the next step, PCA is combined with Singular Value Decomposition (SVD) to
select optimal features from the normalized set. SVD is used to eliminate the weaker Principal Components (PC). The algorithm starts by calculating the SVD of the feature vector. The variance of the diagonal elements is then calculated. Next, the PCs with largest variances are selected and the transformation matrix is created only for these selected PCs. Finally, the reduced feature set is found by applying the transformed matrix to original matrix.

3.1.5. Phase IV: Fracture Detection

After selecting the important features, an ensemble classifier is built to identify the presence or absence of fracture(s). Ensembling classification allows solutions that would be difficult to reach with single classification system. Most of the existing solutions are based on building ensemble model that creates a Pool of Classifiers (PoC) belonging to the same classifier and then use an aggregation method to choose a classifier that produces best results. Care has to be taken to make sure that the created PoC satisfies the two requirements of ensembling, namely, high diversity and high accuracy (low error rate). Disagreement within the classifiers may make the ensembling task a failure. To solve this issue, the present research work considers heterogeneous ensembling where three classifiers that exhibit high diversity and high accuracy are only considered for fusion.

For this purpose, three classifiers namely, Back Propagation Neural Network (BPNN), K Nearest Neighbour (k-NN) and Support Vector Machine (SVM) are considered. The accuracy of the three selected single classifiers is evaluated using 10-fold cross validation technique and the diversity was determined using Yule’s Q method (Kuncheva and Whitaker, 2001), where Q between two classifiers is calculated using the confusion matrix. Careful analysis of Q value indicated that even though all algorithms are moderately correlated, they also exhibit high pair-wise diversities to each other. Moreover, all the three algorithms produced high accuracy. Thus, from the high accuracy
and Q values obtained, it was clear that the three selected algorithms were right candidates for ensembling.

During the creation of ensemble models, four ensemble creation methods were used. They are Sequential Selection, Random Subspaces, Bagging and Boosting (Schapire et al., 1998). Thus, for each of the three feature vectors (FS1, FS2 and FS12), and for the three classifiers (BPNN, SVM and k-NN), 21 classifiers are created to generate a pool of classifiers. A dynamic selection algorithm is then used to select the ensembles from the 21 classifier pool, which are then combined using a Hybrid Majority voting and Weighting Scheme.

One problem faced during the building of such a dynamic model, is the elevated cost of space and time complexity. Several classifiers have to be allocated in memory and be queried in order to output a final prediction. To solve this problem, a dynamic ensemble pruning technique is proposed. The dynamic pruning technique estimates the number of classifiers needed to obtain the final decision for each specific instance during the classification process. The usage of dynamic pruning technique increases the speed of classification, but however, the problem of over utilization of memory still exists.

To solve this problem, a dual-pruning algorithm is proposed. The proposed algorithm first uses a static method to identify a subset of classifiers which meets the requirements of high accuracy and low time constraints. In the next part, a dynamic method is used to further accelerate the process of classification. Thus, the proposed method combines the advantages of both static and dynamic pruning methods. Using the various methods for building ensemble models, three two-classifier heterogeneous ensemble systems and one three-classifier heterogeneous ensemble system were built.

In the final step, the fractures are detected by gradient analysis. The composite gradient measure is used which is the product of the magnitude and transformed direction information. For this purpose, the results of the fast
Hough transformation, used in the previous phase are used. The detected fractures are then highlighted using a box shape, which can be used by the radiologists.

3.1.6. Performance Evaluation

Several experiments were designed to analyze the efficiency of the algorithms proposed in the various phases. A database with X-Ray images was created, which consisted of both normal and fractured tibia bones (150 images obtained from World Wide Web and from the hospitals, Balarathna Clinic, People’s hospital and The Arya Vaidya Pharmacy, Ramanathapuram, Coimbatore). The first set of experiments used Peak Signal to Noise Ratio (PSNR), Figure of Merit (FoM), Mean Structural Similarity Index (MSSI) to test the proposed image denoising algorithm. Experimental results recognized the proposed enhanced wavelet algorithm more effective than the traditional wavelet based denoising method in terms of high quality, high characteristics of edge and structure preservation and speed. The results obtained are tabulated and discussed in Chapter 6, Section 6.2.

The segmentation algorithm was analyzed using speed and visual analysis. The results showed that the segmentation of diaphysis using proposed enhanced active contour model combined with fast Hough Transformation is accurate and fast when compared to wavelet and traditional Hough Transformation algorithms. The results obtained are tabulated and discussed in Chapter 6, Section 6.3.

The effectiveness of the feature selection algorithm was analyzed using the number of features selected before and after applying the feature selection algorithm along with the accuracy of the classification process. Both the results indicated that the proposed PCA with SVD enhance the operation of classification and solve the problem of dimensionality. The results obtained are tabulated and discussed in Chapter 6, Section 6.4.
The last set of experiments was conducted to evaluate the performance of the proposed ensembling and fracture location identification systems. Experiments were conducted with the three feature vectors, FS1, FS2 and FS12. The experiments were conducted with the motivation of finding the best combination of heterogeneous classifiers, best feature that enhances the identification of fracture and effect of proposed dynamic ensembling on fracture identification. The performance metrics used are accuracy, precision, recall and F-Measure. The results showed that while all the proposed models produced maximum advantage in identifying fracture and increased the accuracy of classification process, the three classification system with FS12 feature set incorporated with dynamic ensemble and pruning algorithm produced the best result. The results obtained are tabulated and discussed in Chapter 6, Section 6.5.

3.2. RESEARCH CONTRIBUTIONS

The main aim of the research work is to design and develop an automatic fracture detection system that can assist radiologists during diagnosis. The bone considered is a type of long bone, named Tibia and the segment considered is the diaphyseal region of tibia. The types of fractures that affect diaphysis are analyzed. They are, simple fractures, simple transverse fractures, simple oblique fractures and simple spiral fractures. The methodology combines and enhances various image processing and classification algorithms and the contributions made in each step are presented in this section.

X-Ray images are degraded by low/high contrast and Poisson noise. The enhancement phase (Phase I), proposes techniques to solve both these problems. Existing methods such as median filter, Wiener filter have been proved to be successful in removing Poisson noise. However, they have the unwanted side effect of blurring the result that reduces the quality. To solve this problem, the study enhances the wavelet transformation based denoising
algorithm. This phase proposes a hybrid model that combines Bi-orthogonal Haar wavelet and Independent Component Analysis (ICA) to remove noise.

Segmentation is the process of extracting the Region of Interest (RoI), diaphysis region, from the X-Ray bone image. For this purpose, Phase II of the study focuses on building an enhanced active contour model. The traditional active contour model requires user intervention for initial seed selection. Incorrect selection may result with inaccurate RoI extraction. The proposed segmentation scheme extracts the diaphysis using a two-step procedure. The first step identifies the bone structure from the X-Ray image and is referred to as ‘Bone Structure Extractor (BSE)’. The second step using the resultant image of Step 1, extracts the diaphysis from the tibia bone structure. The BSE procedure combines the multi-resolution wavelet transform with active contour model and region growing algorithm to extract the bone structure from its background. The diaphysis region is then segmented from the extracted bone structure using a fast Hough Transformation that optimizes the speed of segmentation.

Phase III of the study is involved in feature extraction and selection. Here, 11 texture features and one shape feature are extracted from the input image. These features are fused to form a third feature vector. Then, an enhanced PCA is used to select significant features. The enhancement is brought forward by combining PCA results with Singular Value Decomposition (SVD) to eliminate weaker PCs.

Phase IV of the study uses a heterogenous dynamic ensembling algorithm that uses a hybrid majority voting and weighting scheme for combining the results of the base classifiers (BPNN, SVM and k-NN). It is further enhanced to use a dual-pruning technique, that combines the advantage of static and dynamic methods, to solve the memory problem faced during ensembling.
3.3. CHAPTER SUMMARY

This chapter presented an overall description of the research methodology along with a brief description of the techniques proposed. The contributions made in each phase were also presented. The next chapter (Chapter 4, Design of Preprocessing Methods) presents a detailed description of the preprocessing techniques used in the design of CADi-TFi system.