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Study of Automatic Fracture Detection System Using Classification Methods: A Review

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Abstract— ***Human body consists of bones, which help in body movements. Peoples suffer for bone problems many times. In medical diagnosis, X-Ray is frequently used imaging method. A typical bone disorder is the fracture, which occurs when bone cannot resist outside force like direct blows, falls, and bend. Fractures are cracks in bones and are defined as a medical condition in which there is a break in the continuity of the bone. Detection and correct treatment of fractures are considered vital, as a wrong diagnosis often lead to ineffective patient management, increased disappointment and economical as well as legal action. This paper aims study of classification techniques that discusses their use to classify x ray images as normal or fractured.***

Keywords— ***Fracture, Classification, Combining classifier, Hough transformation***

I. INTRODUCTION

Since Wilhelm Roentgen discovered the existence of X- rays in 1895, medical imaging has advanced at a tremendous rate and has become the fundamental diagnostic tool in modern healthcare. As a combination of radiation and computer image processing technologies, digital X-ray imaging device are being widely used in many medical applications. Image classification is an area in image processing where the primary goal is to separate a set of images according to their features into one of a number of predefined categories. It is the problem of finding a mapping from images to a set of classes, not necessarily object categories. Each class is represented by a set of features (feature vector) and the algorithm that maps these feature vectors to a class uses machine learning techniques. The ability to perform binary-class image classification as an automatic task using computers is increasingly becoming important in fracture detection. This is due to the huge volume of image data available, which are proving to be difficult for manual analysis. The difficulty arises because of lack of human experts, poor quality images and time complexity. The current market need is to have techniques which can classify images as having normal or fracture, with minimum intervention from the users in an efficient and effective manner.

This paper presents a review of the various classification approaches that can be used to classify bone x-ray images as either normal or fractured. The rest of the paper considers the general classification system used and presents the concepts of combined classification.

II. GENERAL APPROACH TO CLASSIFICATION

As mentioned earlier, classification, also known as pattern recognition, discrimination, supervised learning or prediction, is a task that involves construction of a procedure that maps data into one of several predefined classes [26]. It applies a rule, a boundary or a function to the sample's attributes, in order to identify the classes. Classification can be applied to databases, text documents, web documents, web based text documents, etc. Classification is considered as a challenging field and contains more scope for research. It is considered challenging because of the following reasons:

- Information overload –The information explosion era is overloaded with information and finding the required information is prohibitively expensive.
- Size and Dimension – The information stored is very high, which in turn, increases the size of the database to be analyzed. Moreover, the databases have very high number of "dimensions" or "features", which again pose challenges during classification.

The input data for a classification task is a collection of features arranged as in row-wise fashion (records). Each record, also known as an instance or example, is characterized by a tuple (X, y) where X is the attribute set and y is a special attribute, designated as the class label (also known as category or target attribute).

A classification technique, or a classifier, is a systematic approach to building classification models from an input data set. Examples include, Decision Tree Classifiers, Rule-Based Classifiers, Neural Networks, Support Vector Machines and Naïve Bayes Classifiers. Each technique employs a learning algorithm to identify a model that best fits the relationship between the attribute set and class label of the input data. The model generated by a learning algorithm should both fit the input data well and correctly predict the class labels of records it has never seen before. Therefore, a key objective of the learning algorithm is to build models with good generalization capability, i.e., models that accurately predict the class labels of previously unknown records. First, a training set consisting of records whose class labels are known must be provided. The training set is used to build a classification model, which is subsequently applied to the test set, which consists of records with unknown class labels.

III. MACHINE LEARNING

Machine learning is the process of automating the development of some part of a system which performs some task. The algorithm, parameters to an algorithm or process can be learnt adaptively over a period of time. The overall structure of a machine learning approach to a problem involves three steps [32]:

(i) The generation of some representation of a solution to the problem.
(ii) The evaluation of the generated solution.
(iii) If the evaluated solution is not good enough, the Solution is iterated (i.e. almost always improved) and the machine learning process goes to step 2.

Given the selection of some representation of a solution to the problem, the initial generation is usually random but constrained by some parameters. For example, in a neural network the structure is fixed and the weight associated with each link is generated according to some algorithm which ensures that the initially generated solution will almost certainly not be the same from time-to-time. However, there are a wide variety of possible representations, including Feed-forward neural networks, Genetic algorithms, and Support vector machines, simulated annealing, Decision trees, Naïve Bayes Algorithm, Bayesian networks and Genetic programming.
There are, broadly, three ways in which the iteration from one solution to the next can be performed. This iteration is how the search for a good solution is carried out. Each of the three types of iteration will be summarized briefly in this section.

(i) Unsupervised – the unsupervised learning is normally used to locate patterns in the input data. No information is given to the system, which finds the patterns as to the correctness or incorrectness of the patterns.
(ii) Reinforcement - Reinforcement in terms of the quantity of information given to the system regarding the correctness of its output. Reinforcement learning is intermediary between supervised and unsupervised learning.
(iii) Supervised - When supervised learning is used the precise, correct output which should have been given for any particular training input is known to the system and used by the system to adjust the answer it will give to other training examples.

The performance of the classifiers can be determined using various performance parameters like accuracy, speed and error rate.

IV. IMAGE CLASSIFICATION

Assigning images to pre-defined categories by analyzing the contents is defined as ‘Image classification or ‘Image categorization’ [4]. Image classification normally involves the processing of two main tasks, namely, feature extraction task (extracts image features and forms a feature vectors) and classification task (uses the extracted features to discriminate the classes). Three paradigms can be identified during the classification (Figure 1).

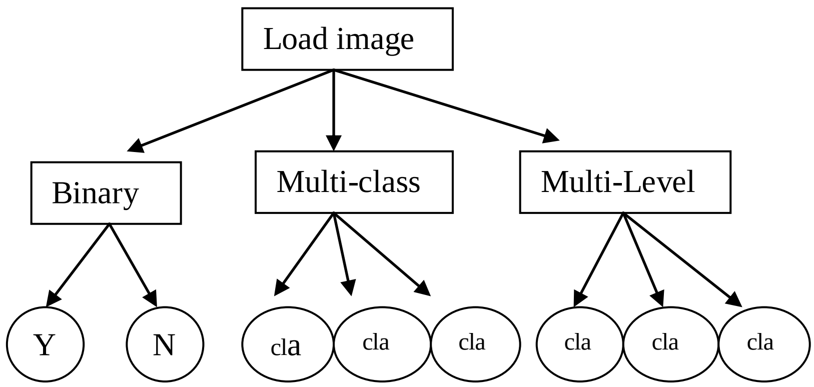

Figure 1: Image Classification & Categorization

The binary case classification classifies images into exactly two predefined classes. Here, a sample image belongs exactly to one of the two given classes. The classifier has to determine to which of the two sets the new image goes [25]. In mutli-class case, an image belongs exactly to just one class of a set of ‘m’ classes ([7], [12]). Finally, in the multi-level case, an image may belong to several classes at the same time, that is, classes may overlap [16].
In binary classification a classifier is trained, by means of supervised algorithms, to assign a sample document to one of the two possible sets. These two sets are usually referred to as belonging samples (positive) and not belonging samples (negative) respectively. This method is otherwise termed as the one-against all approach or one-against one approach. Several algorithms exist for this type of classification. They are Naïve Bayes, Linear Regression, Support Vector Machines (SVM) [11] and LVQ [22]. The binary case has been set as a base case from which the other two cases, multi-class and multi-level, are built.

In multi-class and multi-level cases, the traditional approach consists on training a binary classifier for every class and then whenever the binary base case returns a measure of confidence on the classification, assigning either the top ranked one (multi-class assignment) or a given number of the top ranked ones (multi-level assignment). More details about these three paradigms can be found in [1]. The **proposed** fusion-based image classifier defines binary-class classifiers, which is used to decide whether a given input image has fracture or not.

V. COMBINING CLASSIFIER

Broad classes of statistical classification algorithms have been developed and applied successfully to a wide range of real-world domains. In general, ensuring that the particular classification algorithm matches the properties of the data is crucial in providing results that meet the needs of the particular application domain. One way in which the impact of this algorithm/application match can be alleviated is by using group of classifier, where a variety of classifier (either different types of classifier or different instantiations of the same classifier) are pooled before a final classification decision is made.

Intuitively, fusion classification allows the different needs of a difficult problem to be handled by classifiers suited to those particular needs. Mathematically, combined classifier provide an extra degree of freedom in the classical bias/variance trade off, allowing solutions that would be difficult (if not impossible) to reach with only a single classifier. Because of these advantages, combination of classification has been applied to many difficult real-world problems.

Recently, many scholars make use of combined classifier to enhance the performance of classification. In the past several years, a lot of effort has been devoted to different combined methods to achieve better performance. In reality, how to select appropriate classification methods towards image classification is an unsolved problem [29]. According to [30] when a perfect set of features that can describe the image data is given, the accuracy of the resultant classification depends on the classifier adopted. Several solutions have been proposed for this purpose. Among which, the usage Neural Network (NN), Support Vector Machines (SVM) and Naïve Bayes based classifiers are more prominent. The reasons behind this popularity are (i) ease of implementation procedures and (ii) accurate classification. As pointed out by [27], the success rate or accuracy of a classification problem can be improved by using multiple classifiers.

VI. AUTOMATIC ABNORMALITY DIAGNOSIS IN X-RAY IMAGES

Research proposals with respect to automatic fracture detection are limited. Relevant work in osteoporosis has been proposed. Most research involving the analysis of orthopaedic X-ray images has been focused on detecting osteoporosis and determining fracture risk, using methods such as texture and fractal analysis. Some authors ([8], [20], [28]) have used first order statistics such as the standard deviation and mean to measure texture, while others ([24], [37]) computed second order texture statistics like the co-occurrence matrix. Other methods such as surface area measurement [3], semi-variance ([14]) and power spectral analysis to determine the fractal dimension [2] have also been used to detect osteoporosis. Caligiuri *et al*. [3] found that in some cases their method was capable of distinguishing fractured specimens from normal specimens. Fractal analysis was applied to the micro x-ray images of human knees by [21], while a multi-resolution wavelet technique was used by [23] to analyze the micro X-ray CT images of rat lumbar vertebrae. While this work is related, both used micro X-ray images rather than normal diagnostic x-rays.

Other groups have attempted to detect fractures using non- visual techniques. Ryder et al. [33] analyzed acoustic pulses as they travelled along a bone to determine if a fracture was present, [13] analyzed mechanical vibrations in a bone using a neural network model, and [34] measured electrical conductivity. Unfortunately none of these techniques are as accurate as x-rays for the diagnosis, localization and classification of long-bone fractures, and as a result they are not used in a clinical setting.

The fracture detection techniques proposed can be loosely categorized into classification-based and transform-based. The first published work on the detection of fractures in x- ray images is that of [36]. The method detected femur fractures by computing the angle between the neck axis and shaft axis. Subsequently, Gabor, MRSAR, and gradient intensity were used for fracture detection, and a simple voting scheme was used to combine the individual classifiers that work on single features ([17], [5]). Since the individual classifiers tend to complement each other, the combined method improves both the accuracy and sensitivity significantly. A similar approach of combining classifiers was also proposed by [18] who combined probabilistic combination methods for segmentation. Use of fuzzy index and reasoning is another area that is frequently used for defect detection in bones. A fuzzy index method was proposed by [19], while a fuzzy reasoning approach was proposed by [15].

Hough transforms have long been used as computationally efficient methods for detecting particular shapes in images. The use of Hough transformation in identifying fractures has also been proved advantages. The Hough transform [6] is a feature extraction technique in image analysis, computer vision, and digital image processing. It is concerned with the identification of straight lines, position of arbitrary shapes, most circles or ellipses. The important case of Hough transform is the linear transform for detecting straight lines. Compared with other algorithms that detect straight lines, Hough transform can be used to find and link segments in an image. A line in the image space is mapped to a point in the parameter space. Similarly, each pixel of the image space is transformed to a parameterized curve of the parameter space. Each transformed point in the parameter space is considered as a candidate for being a line and accumulated in the corresponding cell of an accumulator. Finally, a cell with a local maximum of scores is selected, and its parameter coordinates are used to represent a line segment in the image space. The main advantage of the Hough transform technique is that it is tolerant of gaps in feature boundary description and is relatively unaffected by image noise.

However, using Hough transform introduces computation complexity, which in turn slows the feature extraction and fracture detection process.

Randomized Hough Transform (RHT) [38] is an improvised version of Standard Hough Transform (SHT) for line detection. The basic idea behind the RHT is that, instead of transforming one pixel from image space to parameter space, two or more pixels are randomly selected and mapped to a point in the parameter space. Ji and Xie [10] proposed a method for line detection and circle detection using Randomized Hough Transform based on error propagation which improved detection robustness and accuracy by analytically propagating the errors with image pixels to the estimated curve parameters. Ho and Chen [9] introduced a high speed method for line detection using the geometric property of a pair of parallel lines. Stephen [35] proposed a probabilistic Hough transform based method where it was proved a strong relationship between the Hough Transform and the Maximum Likelihood method. Rodrigo *et al*. [31] considered straight line detection as an energy minimization problem and proposed an energy based line detection.

VII. CONCLUSIONS

This paper discussed about classification and the various methods that can be used to classify x-ray images. Fracture detection from X-ray images is a complex operation for which a limited algorithms have been proposed. Moreover, although many classification approaches have been developed, which approach is suitable for a given application area is not fully understood. Selection of a suitable classifier requires consideration of many factors, such as classification accuracy, algorithm performance, and computational resources. Several classification techniques are more popular with satellite or natural scene classification, where it has proved to be more efficient than the usage of single classifier. The limited publications mostly use SVM and Bayes classifier. Moreover, the presented works use a set of feature vectors on multiple classifiers to detect fractures. Fusion of feature vectors has not been considered. Thus, in future, the usage of multiple classifiers to detect fractures in X-ray images is to be probed.

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