General Approach to Classification: Various Methods can be used to classify X-ray images

Dr. N. Subhash Chandra[#1], B.Uppalaiah[#2], Prof. G. Charles Babu[#3], K. Naresh Kumar[*4], P. Raja Shekar[*5]

[#1, #2,#3] *Computer Science Engineering Department, Holy Mary Institute of Technology & Science (HITS COE)*
Bogaram, Hyderabad, Andhra Pradesh, India
[1]subhashchandra_n@yahoo.co.in
[2]bnp.uppalaiah@gmail.com
[3]babu_gundupalli@yahoo.co.in

[*4]*Department of MCA, Anurag Engineering College (AEC)*
Anantagiri, Kodad, A.P, India
[4]nareshk03@gmail.com

[*5]*Computer Science Engineering Department, Geethanjali College of Engineering & Technology (GCET)*
Cheeryala, Hyderabad, A. P, India
[5]*rajashekar.parupati@gmail.com*

Abstract— **X-Ray is one the oldest and frequently used devices, that makes images of any bone in the body, including the hand, wrist, arm, elbow, shoulder, foot, ankle, leg (shin), knee, thigh, hip, pelvis or spine. A typical bone ailment is the fracture, which occurs when bone cannot withstand outside force like direct blows, twisting injuries and falls. 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 important, as a wrong diagnosis often lead to ineffective patient management, increased dissatisfaction and expensive litigation. The main focus of this paper is a review study that discusses about various classification algorithms that can be used to classify x-ray images as normal or fractured.**

Keywords—— **X-ray, Classification, Machine Learning, Fusion classifier.**

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 is organized as follows. The working of a general classification system is presented in Section 2. Section 3 reviews the various machine learning classification methods, while Section 4 presents the concepts of fusion classification. Section 5 concludes the work.

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, 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 - 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 3.3).
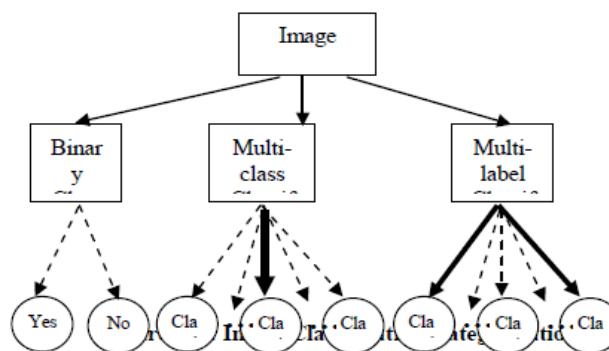
The binary case classification classifies images into exactly two predefined classes. Here, a sample image belongs exactly to one of the two given classes. The classifier has to determine to which of the two sets the new image goes [25]. In mutli-class case, an image belongs exactly to just one class of a set of 'm' classes ([7], [12]). Finally, in the multi-label 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-label, are built.

In multi-class and multi-label 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-label 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. Fusion 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 classifiers, where a variety of classifiers (either different types of classifiers 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, fusion 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, fusion classification has been applied to many difficult real-world problems.
Recently, many scholars make use of fusion of classifier to enhance the performance of classification. In the past several years, a lot of effort has been devoted to different fusion 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.   easy 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 analyse 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 nonvisual 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 though transformation in identifying fractures have 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. [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.   CONCLUSION

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. Multiple 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.

REFERENCES

[1]   Allwein, R.L., Schapire, R.E. and Singer, Y. (2000) Reducing multiclass to binary: A unifying approach for margin classifiers, Proceedings of 17th International Conference on Machine Learning, San Francisco, CA, Pp.9-16.

[2]   Buckland-Wright, J.C., Lynch, J.A., Rymer, J. and Fogelman, I. (1994) Fractal signature analysis of macro radiographs measures trabecular organization in lumbar vertebrae of postmenopausal women, Calcified Tissue International, Vol. 54, No. 2, Pp.106–112.

[3]   Caligiuri, P., Giger, M.L. and Favus, M. (2004) Multifractal radiographic analysis of osteoporosis, Medical Physics, Vol. 21, No. 4, Pp. 503–508.

[4]   Chang, C.H. (2006) Simulated annealing clustering of Chinese words for contextual text recognition, Pattern Recognition Letters, Vol. 17, No. 1, Pp.57-66

[5]   Chen, Y., Yap, W.H., Leow, W.K., Howe, T.S. and Png, M.A. (2004) Detecting femur fractures by texture analysis of trabeculae, Proc. Int. Conf. on Pattern Recognition.

[6]   Duda, R. and Hart, P. (1972) Use of the Hough transformation to detect lines and curves in pictures, Comm. ACM, Vol. 15, Pp. 11–15.

[7]   Foody, G.M. and Mathur, A. (2004) Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification, Remote Sensing of Environment, Vol. 93, Pp. 107–117.

[8]   Geraets, W., Van der Stelt, P. and Elders, P. (1993) the radiographic trabecular bone pattern during menopause, Bone, Vol. 14, No. 6, Pp. 859–864.

[9]   Ho, C.T. and Chen, L.H. (1996) A High Speed Algorithm for Line Detection, Pattern Recognition Letters, vol. 17, pp. 467–473.

[10]   Ji, Q. and Xie, Y. (2003) Randomized Hough transform with error propagation for line and circle detection, Pattern Analysis Applications, Vol. 6, Pp. 55–64.

[11]   Joachims, T. (1998) Text categorization with support vector machines: learning with many relevant features, European Conference on Machine Learning (ECML), Springer, Berlin.

[12]   Joshi, A.J., Porikli, F. and Papanikolopoulos, N. (2009) Multi-Class Active Learning for Image Classification, IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2009, Pp.2372-2379.

[13]   Kaufman, J., Chiabrera, A., Hatem, M., Hakim, N.Figueiredo, M., Nasser, P., Lattuga, S., Pilla, A.and Siffert, R. (1990) A neural network approach for bone fracture healing assessment, IEEE Engineering in Medicine and Biology, Vol. 9, Pp.23–30.

[14]   Khosrovi, P., Kahn, A.J., Genant, H.K. and Majumdar, S. (1994) American Society for Bone and Mineral Research, L. Raisz, Ed. Kansas, USA: Mary Ann Liebert, Inc., P. S156.

[15]   Lashkia, V. (2001) Defect detection in X-ray images using fuzzy reasoning, Original Research Article, Image and Vision Computing, Vol. 19, Issue 5, Pp. 261-269

[16]   Li, X., wang, L. and Sung, E. (2004) Multilabel SVM active learning for image classification, International Conference on Image Processing ICIP '04, Vol. 4, Pp.2207-2210.

[17]   Lim, S.E., Xing, Y., Chen, Y., Leow, W.K., Howe, T.S. and Png, M.A. (2004) Detection of femur and radius fractures in x-ray images, Proc. 2nd Int. Conf. on Advances in Medical Signal and Info.Proc..

[18]   Lim, V.L.F., Leow, L.W., Chen, T., Howe, T.S. and Png, M.A. (2005) Combining classifiers for bone fracture detection in X-ray images, IEEE International Conference on Image Processing, ICIP 2005, Vol. 1, Pp.I - 1149-1152

[19]   Linda, C.H. and Jiji, G.W. (2010) Crack detection in X-ray images using fuzzy index measure, Applied Soft Computing, Article in Press.

[20]   Link, T., Majumdar, S., Konermann, W., Meier, N., Lin, J., Newitt, D., Ouyang, X., Peters, P. and Genant, H. (1997) Texture analysis of direct magnification radiographs of vertebral specimens: Correlation with bone mineral density and biomechanical properties, Academic Radiology, Vol. 4, No. 3, Pp. 167–176.

[21]   Lynch, J.A., Hawkes, D.J. and Buckland-Wright, J.C. (1991) Analysis of texture in macro radiographs of osteoarthritis knees using the fractal signature, Physics in Medicine and Biology, Vol. 36, No. 6, Pp. 709–722.

[22]   Martin-Valdivia, M.R., Garcia-Vega, M. and Urena-Lopez, L.A. (2003) LVQ for text categorization using multilingual linguistic resource, Neurocomputing, Vol. 55, Pp. 665-679.

[23]   Matani, A., Okamoto, T. and Chihara, K. (1998) Evaluation of a trabecular structure using a multiresolution analysis, Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Pp. 632–633.

[24]   Materka, A., Cichy, P. and Tuliszkiewicz, J. (2000) Texture analysis of x-ray images for detection of changes in bone mass and structure, Texture Analysis in Machine Vision, M. K. Pietikainen, Ed.Singapore: World Scientific.

[25]   Mehta, B., Nangia, S. and Gupta, M. (2008) Detecting image spam using visual features and near duplicate detection, Proceeding of the 17th international conference on World Wide Web (WWW '08) ACM, New York, NY, USA, 497-506.

[26]   Montejo-Raez, A. (2005) Automatic Text Categorization of documents in the High Energy Physics domain, CERN-THESIS-2006-008, ISBN:84-338-3718-4.

[27]   Neeba, N.V and Jawahar, C.V. (2009) Empirical evaluation of character classification schemes, Seventh International Conference on Advances in Pattern Recognition (ICAPR), Pp. 310–313

[28]   Ouyang, X., Majumdar, S., Link, T.M., Lu, P.A.Y., Lin, J.C., Newitt, D.C. and Genant, H.K. (1998) Morphometric texture analysis of spinal trabecular bone structure assessed using orthogonal radiographic projections, Medical Physics, Vol. 25, No. 10, Pp. 2037–2045.

[29] Oza, N.C. and Tumer, K. (2008) Classifier ensembles: Select real-world applications, Journal of Information Fusion, Vol. 9, Issue 1, Pp. 4-20.
[30] Park, D.C. (2010) Image Classification Using Partitioned-Feature based Classifier Model, International Conference on Computer Systems and Applications (AICCSA), IEEE/ACS, Pp.1-6.
[31] Rodrigo, R., Shi, W. and Samarabandu, J. (2006) Energy based line detection, Canadian Conference on Electrical and Computer Engineering, CCECE '06, Pp. 2061 - 2064
[32] Russell, S. and Norvig, P. (2003) Artificial Intelligence: AModern Approach, 2nd edition ed. Prentice-Hall, Englewood Cliffs, NJ.
[33] Ryder, D., King, S., Olliff, C. and Davies, E.(1993) A possible method of monitoring bone fracture and bone characteristics using a noninvasive acoustic technique, International Conference on Acoustic Sensing and Imaging, Pp.159–163.
[34] Singh, V. and Chauhan, S. (1998) Early detection of fracture healing of a long bone for better mass health care. Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Pp. 2911–2912.
[35] Stephen, R.S. (1991) A Probabilistic Approach to the Hough Transform, Journal Image and Vision, Vol. 9, Issue 1, Pp. 55-60.
[36] Tian, T.P., Chen, Y., Leow, W.K., Hsu, W., Howe, T.S. and Png, M.A. (2003) Computing neck-shaft angle of femur for x-ray fracture detection, Proc.Int. Conf on Computer Analysis of Images and Patterns (LNCS 2756), Pp. 82–89.
[37] Veenland, J., Link, T., Konermann, W.,Meier, N., Grashuis, J. and Gelsema, E. (1997) Unraveling the role of structure and density in determining vertebral bone strength, Calcified Tissue International, Vol. 61, No. 6, Pp. 474–479.
[38] Xu, E.O.L. and Kultanen, P. (1990) A new curve detection method - randomized hough transform (rht), Pattern Recognition Letters, Vol. 11, Pp.331–338.

AUTHOR PROFILE

Dr. N. Subhash Chandra received Ph. D (Computer Science Engineering) & Master of Technology (Computer Science Engineering) from Jawaharlal Nehru Technological University Hyderabad. His research interests include Data Mining, Image Processing, Speech Processing, Network Security and Information Security. He is currently working as a Principal and Professor, department of Computer Science in Holy Mary Institute of Technology and Science (HITS COE).

Bonepalli Uppalaiah received his B.Tech degree in Information Technology from Kakatiya University, Warangal, India, in 2006, the M.Tech degree in Software Engineering from Jawaharlal Nehru Technological University, Hyderabad, India, in 2010. Presently, working as an Assistant Professor in the dept. of Computer Science Engineering at Holy Mary Institute of Technology & Science (HITS COE). His research interests include Data Mining, Network Security, Information Security, Web Services and Mobile Computing.

Prof. G. Charles Babu currently pursuing Ph. D (Data Min-ing) in Acharya Nagarjuna University Guntur, and he received Master of Technology (Software Engineering) from Jawaharlal Nehru Technological University Hyderabad in 1999. And he is currently working as a Professor & HOD in the department of Computer Science in Holy Mary Institute of Technology and Science.

K. Naresh Kumar received Master of Computer Applications (MCA) from Osmania University. Master of Technology (Computer Science & Engineering) from Jawaharlal Nehru Technological University (JNTUH). His research interests include Data Mining, Network Security, Information Security, Web Services and Mobile Computing. Presently working as an Assistant Professor in the department of MCA at Anurag Engineering College (AEC), Ananthagiri, Kodad, India.

P. Raja Shekar received his B.Tech degree from Jawaharlal Nehru Technological University, Hyderabad, India, the M.Tech degree in Software Engineering from Jawaharlal Nehru Technological University, Hyderabad, India, in 2010. Presently, working as an Assistant Professor in the dept. of Computer Science Engineering at Geethanjali College of Engineering & Technology (GCET), Cheeryala, Keesara, A. P, India. His research interests include Data Mining, Network Security, Information Security, Web Services and Mobile Computing.