University of Shendi

X-RAY MEDICAL IMAGE CLASSIFICATION TECHNIQUE

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Abstract

Automatic classification has been on estimating a good selection of the appropriate class for a given image out of a set of pre-defined categories and it has representation techniques which are major aspect of automatic classification. The difficult of x-ray medical image classification is distribution training sample in training classes which convey unbalance training samples and at one class it is difficult to find a general features for that particular class because Intra class variability among these classes is high. Moreover, Visual similarity between images contained from different class makes inter-class similarity. To handle these problems, x-ray medical image feature extraction techniques should be studied to design x-ray medical image representation technique and evaluate this proposal technique compared with other representation techniques. X-ray medical image representation technique was designed and applied on 180 x-ray medical images from ImageCLEF 2005 dataset. It use an empirical study to compute an accuracy rate using a program code written in java which using classes to represent x-ray images using histogram equalization and applied java class for each image to compute 14 features. These features were fed to Support Vector Machine to establish a prediction model for this x-ray medical image representation technique. This x-ray medical image representation was evaluated using accuracy rate which obtained 83.426% at global level and it high compared with previous x-ray medical image representation at global level on same dataset.

Acknowledgment

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List of Abbreviation

ANNs	Artificial Neural Networks
BOW	Bag Of Visual Word
CBIR	Content Based Image Retrieval
CBMIR	Content Based Medical Image Retrieval
CCL	Connected Component Labelling
CLD	Color Layout Descriptor
DCT	Discrete Cosine Transform
ELM	Extreme Learning Machine
EHD	Edge histogram descriptor
FCM	Fuzzy C-Means Clustering
GLCM	Gray Level Co-Occurrence Matrix
HOG	Histogram of Edge Directions
IM	Invariant moment’s
IRMA	image retrieval medical applications
JSRT	Japanese Society Of Radiological Technology
KNN	K Nearest Neighbours
LBP	Local Binary Pattern
NSTF	Novel Shape-Texture Feature
OVA	One-Against-All
PACS	Picture Archiving And Communication Systems
PCA	Principal Component Analysis
PWC	Pair Wise Coupling

QBE	Query By Example
QBIC	Query By Image Content
RBF	Radial Basis Function
RWTH	Rheinisch-Westfaelische Technische Hochschule
ROI	Region Of Interest
SIFT	scale-invariant feature transform
SVM	Support Vector Machine
ZM	Zernike Moment Feature

Chapter 1

1.1 Introduction

The increasing amount of x-ray medical images requires new methods to archive and access this data. Conventional x-ray images databases allow for textual searches on the Meta data only. Often, the x-ray database scheme only holds references to the image data, which are stored as individual files on the file system. Sometimes, x-ray images contain information that cannot be conveyed by a textual description. Thus, Content Based Image Retrieval (CBIR) can be observed [1]. Denoting the analysis of data mining of large observational data sets in order to find unsuspected relationships and to summarize the data in ways that are better understandable to human observers [2]. CBIR aims at searching image databases for specific images that are similar to a given query image. Here, the search is based on the appearance of the images. Usually, a sample image is presented to the system, which answers this query by returning all similar matches. This concept is referred to as the Query By Example (QBE) paradigm which introduced by Niblack et al. when presenting the query by image content (QBIC) system in the early 1990s. Consequently, CBIR and the QBE paradigm do not directly aim at summarizing data. Rather, they are concerned with the understandable presentation of relevant extracts of a large set of data to a user [3]. There are several areas of application for CBIR systems. For instance, biomedical informatics compiles large image databases. In particular, medical images is increasingly acquired, transferred, and stored digitally. In large hospitals, several tera bytes of data need to be managed each year, so Content Based Medical Image Retrieval CBMIR computed numerical features from each image which stored within the database, then using the QBE approach which the same features are extracted from the query image and compared to the features stored within the database. The images that correspond to the most similar features are then retrieved from the database and presented to the user to answer his query [4]. In the past decade, quality of such a medical system and as in general, patient care system can be improved by successful categorization which uses information directly extracted from images. The goal of this challenge is to classify the images into pre-defined classes automatically and assigning correct labels to unseen test images [5]. It involves some basic principles such as representation where visual features of the image are extracted and generalized which trains and evaluates the classifier, adaptation and generalization [6]. The major aspect of automatic classification algorithm is image representation techniques. So, it needs different feature extraction techniques which have been utilized to represent medical X-ray images and it categorize into two group low level feature extraction and local patch-based image representation such as Bag of Words (BoW) [7]. Generally, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, faces) [8]. Extracting images features are generate on three levels, global, local and pixel level [9]. Also, low level feature extraction techniques are applied on different level of x-ray images such as Gray Level Co-Occurrence Matrix (GLCM)[10], Local Binary Pattern (LBP) [11], TAMURA [12], CASTELLI [13], WAVELET and CURVELET [14], Histogram of Edge Directions (HOG) and Invariant Moment's (IM). The evaluation of the representation performance is accuracy rate which are measured after created classification model by choosing one of state of the art supervised machine learning, it used as a classifier to evaluate the representation techniques. However more and more x-ray image representation techniques are generated, it still suffers from challenges. One of these open issues is unbalance of training sample and inter class similarity, additionally intra class variability.

1.2 Problem background

Compared with other classification domains, there are some particular difficulties when working on medical database such as intra class variability and inter class similarity which discussed as an open issue in [4] which are follows.

1.2.1 Intra class variability

It means differences between samples of the same visual class. This variability is complex and hard to describe as it stems from assignment of semantic category tags, and thus makes the problem of object class recognition significantly harder then problem of object instance recognition. In one x-ray images database class, it difficult to find a general features for that particular class because Intra class variability among these classes is high. Figure 1.1 shows some examples of high intra class variability within the class note the high visual variability among images even though they belong to the same category

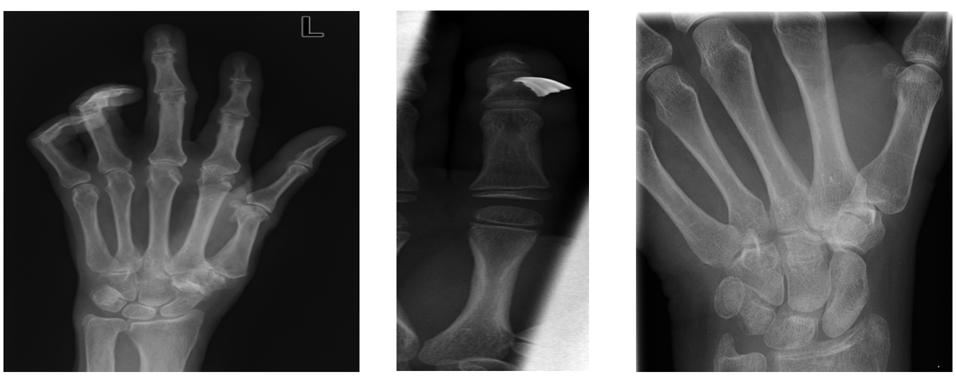

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Fig1.1 intra class variability in one class [4]

1.2.2 Inter-class similarity

Visual similarity between images contained from different class makes inter-class similarity. The similarity is evaluated through the same method that is used to compare the target image with the candidate image. High similarity would mean that the two images which in different class gloomy. Fig. 2 represents an example of inter-class similarity. These images belong to two categories which are differing in term of orientation and biological system.

Fig 1.2 inter class similarity between two classes [4]

1.3 Problem Statement

Compared with other classification domains there are difficulties when represent X-ray medical image features. High visual similarity between images in some classes was affects on its performance. In addition to that, intra class variability in one class. Depending on all problems, their needs for x-ray image classification technique.

1.4 Research Questions

Research questions helping on making a framework plane, it shows main steps should be worked to investigate objectives. One objective may take more than one question as showing later. Classification x-ray medical images means classify x-ray images in to predefine classes. To classify image base on its content should be extracted x-ray image contents. However different techniques were applied on this field, some these tools are applied to detect suitable x-ray image features. In one class there are variance between samples and similarity between samples in more than one class that need effective representation technique.

1- What x-ray image features techniques used to extracted content images?
2- How to solve inter class similarity and intra class variability?
3- How the proposed technique can approve?

1.5 Research Objectives

On content based x-ray medical image classification a lot of thesis investigated on how to extract x-ray medical image features. These features are used to represent x-ray medical image at different levels, global, local and pixel levels. So, the objectives achieve in this thesis are:

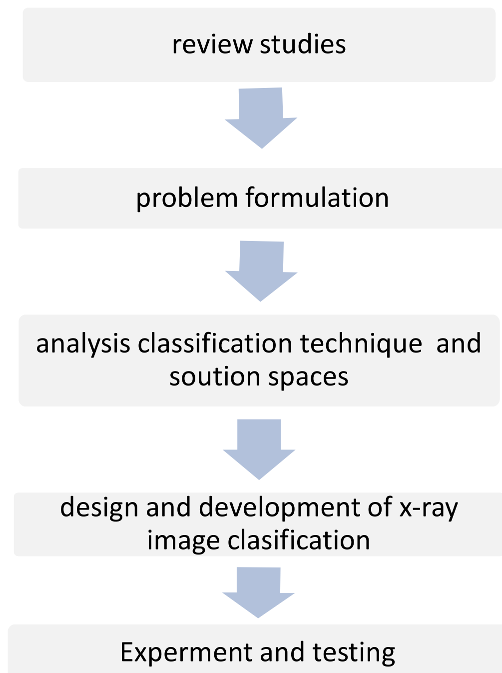
1- Taxonomy review of x-ray image feature extraction techniques
2- X-Ray medical image classification technique on global level.
3- Evaluation proposed techniques compared with other representation techniques.

1.6 Research Scope

In this study on x-ray medical image from ImageCLEF 2005 from IRMA group. It designed x-ray medical image classification technique which takes texture feature. This features extracted at global level. In preprocess x-ray medical image histogram equalization technique applied to increase contrasts and on this step detect object from image by using Connected Component Labeling technique. in classification step there are two step, firstly training phase which compute 14 haralick features from the co-occurrences matrix to fed SVM classifier to construct classification model then use this model to testing images in test phase was applied.

1.7 Research Methodology

The research framework started with literature review which focused on medical image content classification and retrieval. After determine problem formulations should be analyzed classification techniques in review. Depending on this phase there are algorithms and techniques give us solution space area. On this area we can implement and applying experiment and testing our solution.



1.8 Thesis outline

Regarding content-based x-ray image classification and retrieval x-ray image classification technique was affected on its performance. The remainder of this study is organized as follows. In chapter 2, we review various x-ray medical image visual features and their corresponding representation and matching techniques. In Chapter three research methodology which presents methodology to be adopted in continuing this research. Research procedures, operational framework, dataset, technique design, experiment and evaluation are included. Chapter four show the technique steps. Chapter five build x-ray medical image classification techniques at global level on ImageCLEF 2005 dataset, then compared it with previous studied. The thesis concludes with chapter six which state the conclusion of the research. Additionally, it explains the gap in the thesis and describes future works.

Chapter 2

2.1 Introduction

On the last years the rapid development of modern medical devices generate more and more medical images which need to designed medical image system to store X-ray medical image in computers and display it on high resolution monitor from dataset which requires techniques to index, analyze, and classification these X-ray images, one of these systems are Picture Archiving and Communication Systems (PACS) which have been developed in an attempt to provide economical storage, rapid retrieval of images, access to image acquired with multiple modalities, and simultaneous access at multiple site [15]. These systems main objective is to deliver the needed information to the right person at the right place on right time for efficient medical care [16]. to formulate this goal, publicly to deliver exactly image which stored in dataset, by searching image databases for specific images that are similar to a given query image depending on the image content, modality, body region, or pathology using query by example (QBE) paradigm to extract query image feature then compare it with stored feature in database to find the most similar feature will present to user [17]. Retrieving exactly image should be firstly classifying images dataset in to predefine classes to reduce search time, but this classification is complex for machine that led to use machine learning techniques. In this regard classification process includes image sensors, image preprocessing, image representation and object classification, in addition to that, the classification system consists of database that contain a predefined pattern that compares with detect object [18]. The classification process consists of following steps: Pre-processing phase to remove image noise and transformation image …etc. Also, Detection and extraction phase used techniques to extract image feature on three levels: global, local and pixel level

[19]. In addition, Training phase, Selection of the particular attribute which best describes the pattern. Lastly, Classification of the object which categorizes detected objects into predefined classes by using suitable method that compares the image patterns with the target patterns but to classify unlabeled image should study problem of effective representations for automatic image categorization. The representation technique should be flexible enough to cover a wide range of visually different classes, each with large within-category variations[17]. However there is unbalance between classes that let to makes many common classification methods unavailable. In addition to that, Visual similarities between some class's sometimes even skilled experts cannot find the differences between some classes visually. They may need to compare the images from different sources and refer to other medical. In several cases, medical similarities are far away from visual that make finding a general visual feature for one class is often very difficult because there is Variety in one class and difficulty to define discriminative visual features similarities.

2.2 Classification medical images:

Classification x-ray medical images means classify x-ray image into a predefined classes but Classification between the objects is easy task for humans but it has proved to be a complex problem for machines [20].

These classification processes have steps which applied on images dataset on offset to create images feature which compare with query image features on onset to return similarity images which stored on dataset previously. To make good classification, images enhancement techniques are applied to raise quality of images and researchers focused on the actual content of images that by applying several extracted features such as shape and texture then used classification techniques to obtain effective retrieval which have been proposed.

2.2.1 Image enhancement

Image enhancement techniques like Histogram equalization [21]. Publicly show that, it is applied to improve the quality of the image such as increasing the contrast of the image, which adjustment provides better gray intensities distribution on the histogram. Moreover this particular, [22] show these method can lead to better views of bone structure in X-ray images.

2.2.2 Features extraction

The feature is defined as a function of one or more measurements which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object and it can capture a certain visual property of an image either globally for the entire image or locally for regions or objects [23]. On the other hand, all features can be coarsely classified into low-level features and high-level features. Low-level features can be extracted directed from the original images, whereas high-level feature extraction must be based on low-level features [6]. Moreover, this low level features ware contains color, texture, shape and edge [23]. Color feature aren't necessary because X-ray are gray scale images. So, in next sections we review X-ray feature extraction.

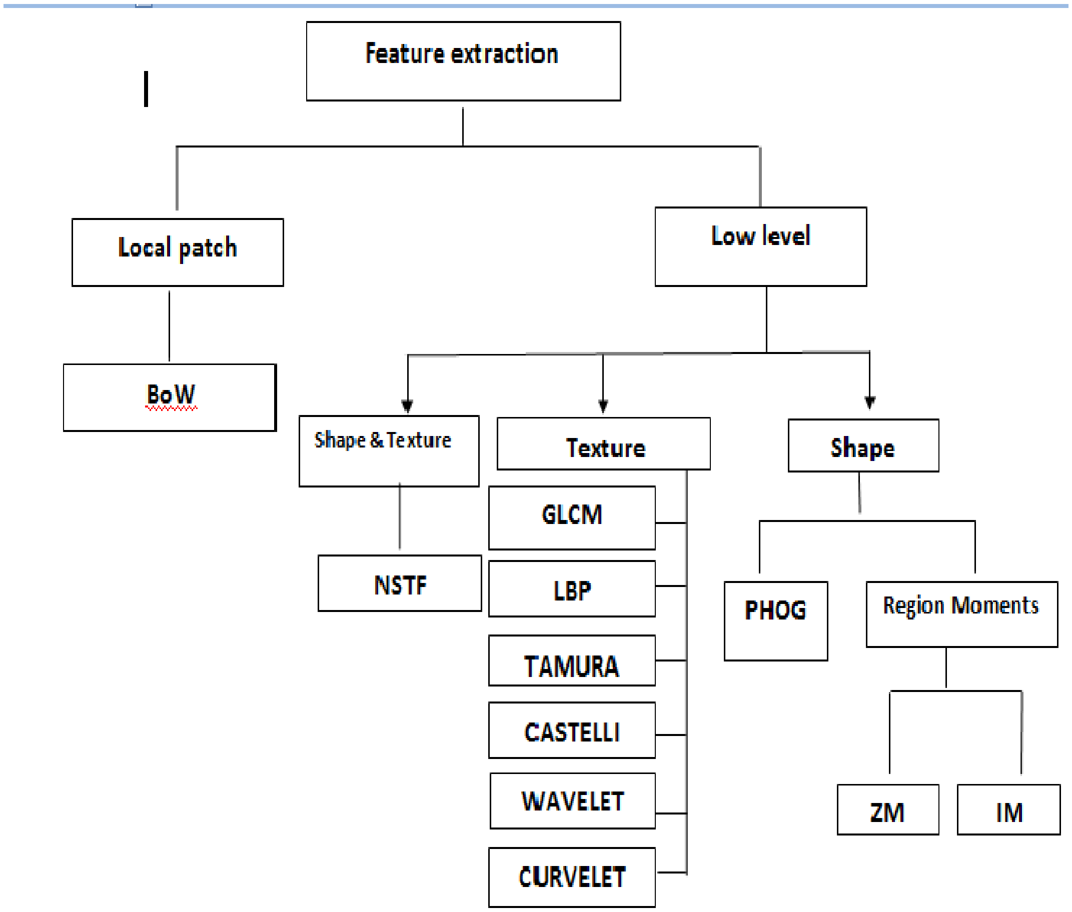


Fig 2.1. Feature extraction taxonomy on x-ray medical image.

2.2.2.1 Shape features:

Shape provides geometrical information of an object in an image [24]. Shape features are one-dimensional functions for shape representation, polygonal approximation, spatial interrelation feature, moments, scale-space methods and shape transform domains [25]. In this research, there are X-ray shape features extraction technique were applied which described in next sections.

2.2.2.1.1 *Histogram of Edge Directions*:

It captures general shape information in the image by using edge detection algorithms like canny edge which used to represent shape attribute for each image and image patches [6]. In the previous works extract X-ray images shape information by apply canny edge detector in [26]. In addition, apply canny edge detection method by [27]. on all databases of 600 sample images and 8 images are used for testing, each edge image is partitioned into 16 patches of equal size of 50×50 and each patch is partitioned into 4 concentric circular regions, with each circle consisting of equal number of pixels. Then mean and variance of each circular region is calculated to generate a feature vector. The size of each feature vector is 128 × 1 (64 means and 64 variances). This procedure is applied for entire database of the 600 sample images and 8 images are used for testing.

2.2.2.1.2 *Region Moments*:

Moments are very popular on region-based descriptors and one of it Zernike Moments (ZM) which does not require knowledge of the precise boundary of an object and Zernike basis function satisfies the orthogonal property, implying that the contribution of each moment coefficient to the underlying image is unique and independent, i.e. No redundant information overlaps between the moments [28]. ZM calculated on previous researches papers on x-ray medical images, so depending of it 6 moments calculate and Invariant Moment's (IM) features are 5 moments [29].

2.2.2.2 Texture:

Texture is a surface property which characterized by the spatial distribution of gray levels in a neighborhood, since texture shows its characteristics both by pixel co-ordinates and pixel values [11]. There are many approaches used for X-ray texture classification which extracted using Local Binary Pattern

(LBP), Gray Level Co-occurrence Matrix (GLCM) and Tamura Features. These methods of extracting texture features are explained in the following section.

2.2.2.2.1 *Local Binary Pattern*:

Local Binary Pattern (LBP) histogram are used for rotation invariant texture classification [30]. It is a simple yet efficient operator to describe local image pattern, and it has achieved impressive classification results on representative texture databases [31]. It Labels the pixels of input image by thresholding a neighborhood of each pixel with the center value and considering the results as a binary number [32].

The neighborhood is formed by a symmetric neighbor set of P pixels on a circle of radius.

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{p-1} s(i_n \quad i_c)2^n$$

Where n runs over the P neighbors of the central pixel, i_n and i_c are gray level values of the central pixel and the neighbor pixel, and s(x) is 1if x > 0 and 0 otherwise [32]. Also, D Unay applying these techniques by dividing images in 4x4 non-overlapping sub regions and concatenate the histogram obtaining 944 features per image [6]. In addition, total of 59×16=944 histogram bins are generated for feature vector in [33]. Also this technique finds 1062 dimensions in [34]. However the dimension of the final LBP histogram can be larger depending on the wavelet level. So this let to enhance it by building centre symmetric local binary patterns (CS-LBP) to find final dimension of the local WCS-LBP histogram which get 768 $(16 \times 3) \times 16$ sub-regions [35].

2.2.2.2.2 *Gray Level Co-occurrence Matrix*:

Gray Level Co-occurrence Matrix (GLCM) is created from a gray-scale image and it finds how often a pixel with a gray-level value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j and It is given by the relative frequency of the occurrences of two gray-level pixels i & j, separated by d pixels in the θ orientation, where d is the displacement and θ is the direction. The ‘d‘ can take values 1, 2, 3, etc., and θ can take values 0° (horizontal), 90° (vertical), 45° and 135° (diagonal) [18].

It extracts five important texture features at global levels:

$$\text{Energy}\ (d, \theta) = \sum_{x=1}^{Ng} f(x, y, d, \theta)$$

$$\text{Contrast}\ (d, \theta) = \sum_{x=1}^{Ng} \sum_{y=1}^{Ng} (i \quad j)^2 F(x, y, d, \theta)$$

$$\text{Correlation}\ (d, \theta) = \sum_{x=1}^{Ng} \sum_{y=1}^{Ng} \frac{(x-Mi)(y-Mi)F(x,y,d,\theta)}{\delta i\ \delta j}$$

$$\text{Homogeneity}\ (d, \theta) = \sum_{x=1}^{Ng} \sum_{y=1}^{Ng} \frac{1}{1+|x-y\,|} F(x, y, d, \theta)$$

Where Mi, Mj and δi and δj are mean and standard deviation of pixels value in raw (column) direction of the GLCM. It widely used to extract x-ray image texture features.

2.2.2.2.3 *Tamura Features*:

On this feature extracted technique H Tamura describing an image’s texture as properties and suggested coarseness, contrast, and directionality so these features are computed on a per-pixel basis [12].

2.2.2.2.4 *CASTELLI*:

Castelli used various texture features to describe image and properties encompass the global fractal dimension (computed using reticular cell counting), the coarseness, the gray-scale histogram entropy, some spatial gray-level statistics, and the circular Moran autocorrelation function. In all, they extracted 43 values from scaled images of fixed size (256×256 pixels) [13].

2.2.2.2.5 *Wavelets transform*:

A textural features extraction method, multi-resolution and non redundant representation of signals with an exact reconstruction capability, and forms a precise and uniform framework for the space–frequency analysis [36]. its good performance for piecewise smooth functions in one dimension, however wavelet is not suitable to capture more directional features in an image but since 2D images are irregular.

2.2.2.2.6 *CURVELET Transform*:

In 2000 Curvelet was developed, a type of the second generation Wavelets. As an extension of the Wavelet multi scale analysis framework which defined as an effective tool for finding curves at multiple resolution levels and it is well in dealing with linear singularities in 2D signals [36].

2.2.2.3 Shape and texture feature:

Getting visual features from image necessary using feature extraction for both shape and texture. So, there is rapid needing to get mix feature extraction for shape and texture like Novel Shape-Texture feature (NSTF) which overcomes the weakness of traditional features extraction methods, it has steps, firstly: justify gray level histogram by using histogram adjustment, then noise removal, thirdly edge and boundary extraction, and phase congruency computation [31].

2.2.3 Feature selection Principal Component Analysis:

It is a vector space transformation which used to reduce multidimensional datasets to lower dimensions for analysis, and they apply Principal Component Analysis (PCA) to reduce data dimensionality from 81 to 15 for each patch [37].

2.2.3 Machine learning techniques for X-ray classification:

The goal of X-ray image classification is to predict the relevance of one or more semantic concepts from a given vocabulary and distinguishing between multiclass classification, where images are associated with a single label, and multi-label classification, where an image can be related to more than one label which knows as image annotation, or image labeling [38].

Machine learning provides an effective way to automate the analysis and diagnosis for medical images and these techniques divide to Supervised and unsupervised machine learning techniques [19]. Supervised is learning the prediction function from data with given input and output which called training data and this data is a set of learning examples called instances, which contain information on previous observations [35]. Each instance i can be encoded by a vector of k attributes $x_i=(x_{i1},\dots,x_{ik})^T$ called input vector or feature vector. The matrix of all feature vectors X $=(x_1,\dots,x_n)^T$ is often called feature matrix. In addition, each instance is assigned with at least one label y_i, which is the output vector Y= $(Y_1,\dots,Y_n)^T$. Also, it has a lot of techniques like: Neural networks, Decision trees, and Support Vector Machines (SVMs). Unsupervised Learning refers to the problem of trying to find hidden structure in the unlabeled data and it has no measurements of outcome, to guide the learning process [39]. Grouping the sets of image data in such a way, that the similarity within a cluster should be maximized, and the similarity between different clusters must be minimized. These techniques include k-means and fuzzy c-means which used to apply unsupervised machine learning algorithm [19]. In a classification problem, the objective is to learn the decision surface that accurately maps an input feature space to an output space of class labels [38] Which are explained in the following sections.

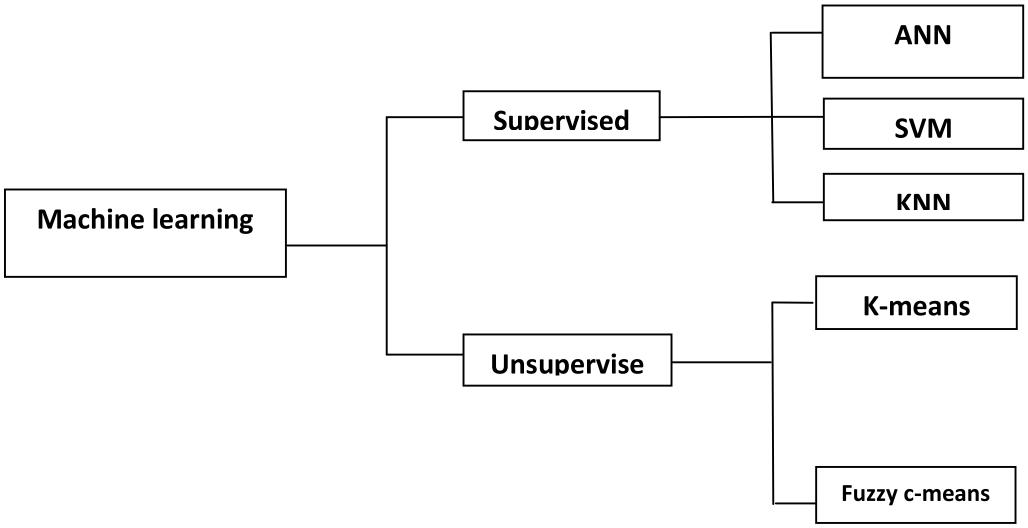


Fig 2.2 Machine learning technique taxonomy which applied on x-ray medical image classification.

2.3 A review on X-ray machine learning classification techniques:

This review coffers some of x-ray medical image representation and classification techniques on both supervised and unsupervised machine learning. Most paper applies Support Vector Machine, K Nearest Neighbor and fuzzy C-means.

2.3.1 Neural Networks:

Artificial neural networks (ANNs) techniques are used to solve classification and regression problems in real world applications [35]. The low level features of the segmented regions of the training set images are fed into the neural network classifiers, to establish the link between the low level image features and high level semantics [40]. It has a Several versions which are modeled, to name a few, feed forward neural net-work, Boltzmann machine, radial basis function (RBF) network, Kohonen self-organizing network, learning vector quantization, recurrent neural network, Hopfield network, spiking neural networks, and extreme learning machine (ELM); networks and most of them are inspired by biological neural [41]. However the low level features of the segmented regions of the training set images are fed into the neural network classifiers to establish the link between the low level image features and high level semantics.

Kalpathy-Cramer and Hersh Evaluated the performance of the two modality classifiers one for grey-scale images and the other for color images on CISMeF and the ImageCLEFmed2006 datasets with 51332 images depend on using GLCM, HOG and Edge orientation feature extracting techniques, A neural network-based scheme using a variety of low Level, The multi-layer perception architecture used a hidden layer of approximately 50-150 nodes which achieved an accuracy of > 95% [42]. However the confusion matrix suggests that the primary misclassification occur between the MRI and CT scan classes. This was expected because these classes are visually quite similar. Most of the misclassifications involved the “other” class with contained a set of miscellaneous images not belonging to the other five specific categories.

Pourghassem and Ghassemian in 2008 make Hierarchical medical image classification method including two levels using a perfect set of various shape and texture features on IRMA which contain 9100 image dividing to 40 classes. Also, FD, Major axis orientation, eccentricity, major and minor, GLCM and tessellation-based spectral feature are using to extracted feature and on each level of the hierarchical classifier, using a new merging scheme and multilayer perception (MLP) classifiers (merging-based classification), homogenous (semantic) classes is created from overlapping classes in the database, as a result it provides accuracy rate of 90.83% on 25 merged classes in the first level, the correct class is considered within the best three matches, this value will increase to 97.9% [43].

1.1 Support Vector Machine:

Briesemeister in 2012 declare SVM as a binary classification algorithm that tries to find a separating hyperplane between two classes such that margin between both classes is maximized [44]. Burges in 1998 assume that SVM is a set of kernel-based supervised learning methods used for classification and regression [38]. Wang and Summers show that these kernels means a matrix which encodes similarities between samples which is a weighting function in the integral equation used to calculate similarities between samples[35]. Rajam and Valli in 2013 conclude that there are two developed SVM multi class classifiers: 1) One-against-all (OVA) multi class classifier constructed N binary classifiers for N class and class sample as the positive example and remaining class samples as negative, 2) One-against-one (or) Pair Wise Coupling (PWC) constructs N*(N 1)/2 SVM binary classifiers for each pair of classes there is one classifier [4].

Reza Zare, Mueen et al construct four models classification on 11000 x-ray image on training data set and 1000 testing dataset of 116 classes Automatic classification using a bag of visual words models which extracted features on novel approach and represent an image by histogram of local patches on the basis of visual vocabulary [18]. Also, Mueen, Sapiyan Baba et al. in 2007 extracted three levels of features local, global and pixel on IRMA x-ray dataset with 10000 distributed 9000 training images under 57 labels and 1000 test images, that by using GLCM techniques and combine them in one big feature vector to gave it to classifier after used PCA to get information about distance between the pixels [45].

In addition to that, Rahman, Desai et al introduced representation image on the Probability estimation approach for multi-class support vector machines (SVMs) with low-level features GLCM, EHD, CLD, t-moment and MPEG-7 as inputs are represented as a vector of confidence or membership scores of pre-defined image categories on 11000 images from IRMA dataset, and the output based on several classifier combination and the probabilistic feature space are effective in terms of precision and recall compared to low level feature and feature vector contain valuable information due to their complex entry nature [6].

On 11000 X-Ray images with 116 categories On Image CLEF 2007 extracting features by using GLCM, LBP, Canny Edge and BoW model [46]. In addition, Qiu, Xu et al. (2006) applied SVM on Image CLEF 2005 with 9000 training images BLOB, LRPM, Texture extracted features and using SVM with RBF kernel [27]. GANESAN and SUBASHINI (2014) Divided 180 x-ray images from to 6 classes and used ZM, GLCM, PCA and DCT ex-tract features to feed SVM which has best accuracy 96.56 on ZM and GLCM extraction technique [47]. However there is unbalance between classes that appear on the size of each class in database that makes many common classification methods unavailable. In addition to that interclass similarity because to classify image in exact categories are hard to distinguish with the untrained eye but the basically differ in the orientation and the biological system and these medical images, sometimes even skilled experts cannot find the differences between some classes visually. In several cases, medical similarities are far away from visual that make finding a general visual feature for one class is often very difficult because there is Variety in one class and difficulty to define discriminative visual features similarities. Also, there is high intra-class variability because sparse categorization in large subset of IRMA code Categories in the database are not uniformly distributed that making training and consequently classification task very difficult.

Selvi and Kavitha Used similarity matching techniques and bag of visual words on local patch with a kernel based SVM on IRMA and constructed visual vocabulary by used clustering for training image to build histogram of the word frequency to feed the SVM [31]. However categorization is conduct on the entire image and this system handle only limited number of images categories in organ level and classification accuracy comparatively less. We know the SVM dealing with large dataset and if class has one or few images that led to miss classification. moreover, Mohammadi, Helfroush et al divided 4402 images from On IRMA dataset in to 21 class and extracting features by NSTF, LBP, GLCM, Moment Invariant, Region properties, Tamura, Entropy and Reformed Wavelet features extractions to fed SVM which getting high accuracy rate on combining NSTF, LBP and GLCM [32]. However NSTF effective and powerful combination of shape and texture feature but if the objects are shifted or rotated by using NSTF it may misclassification and NSTF better if using additional feature extraction. Unay, Soldea et al. applied The effect of principal component analysis based feature selection on the performance of local binary patterns on the ImageCLEF-2005-2008 Medical Annotation dataset, then used SVM with Gaussian radial basis function (RBF) [48]. However SVM maps data to a higher-dimensional space using kernel functions and performs linear discrimination in that space but there exists an error cost C which controls the trade-off between allowing training errors and forcing rigid margins. this C value creates a soft margin while permitting some misclassifications in addition to that the data is unbalanced meaning some classes have significantly larger share among data than others. Further-more, Avni, Greenspan et al. used 81098 images from image CLEF 2009, Gold Miner and Sheba Medical Center datasets with using local patch representation methodology (BoW) to explore the effects of various parameters on system performance, and show best outcome by using dense sampling of simple features with spatial content, and a non-linear kernel-based Support Vector Machine (SVM) classifier with three possible kernels: 1) the histogram intersection, 2) the Radial Basis Function and 3) the x^2 Kernels is ranked first by a small margin with accuracy However In cases where the class classification is local and relatively small (e.g. lesions) a global image representation can miss-detect the pathology and result in a misclassification of the image. Chest X-ray radiographs are the most common examination in radiology. The most common findings in chest x-rays include lung infiltrates, catheters and abnormalities of the size or contour of the heart. Distinguishing the various chest pathologies is a difficult task even to the human observer. Some classes have large intra-variability because sparse categorization in addition to that similar appearance of images although difference categorizes that led to problem in classification. Also, Awedh applied Hierarchical classification on IRMA 2005 dataset which contain 9000 images with 57 classes and using BoW to represent local patches so this hierarchical has tree level, for first level with 9 classes, second level with 29 classes and the third level with 57 classes [49].

Ko, Kim et al Improved medical image classification performance on X-ray images from IRMA 2007 with 2400 images dividing on 30 categories by applying local WCS-LBP feature extraction and using MSVM classifier showed high an average precision and recall performance but using random forests with a proposed local WCS-LBP which showed an average precision and recall performance approximately 4% and 3% better than the MSVM method [34]. However the depth of tree and the number of trees are important parameters of random forest so if increasing depth of the tree will increase performance but during experiment it increases the memory required to store trees and processing time increase linearly as number of trees increase. In addition to that using MSVM is not suitable when feature has high dimension and dataset over 1000 image so using WCS-LBP extract 768 dimensions that make a training task very time consuming.

Xue, You et al Classified a Chest X-ray image into two categories: frontal and lateral views on NLM with 8200 images and IRMA with 1867 images so using Image profile, Body size ratio, PHOG and CBSE features extractions [50]. However algorithms have been running on a portable computer (Mac Mini) connected to the x-ray machine workstation. Program listens to the workstation and automatically receives and processes (segments and classifies) x-ray DICOM images as they are acquired from patients. The frontal/ lateral view classification module will be added in front of the lung segmentation module. This automatic received and process with portable computer but what about journal article because sometimes caption and mention text information relating to the figure does not indicate if the figure is frontal or literal.

Classification of solitary pulmonary nodules in chest x-ray images applied by Al Gindi, Attiatalla et al. for diagnosis of early-stage lung cancer in x-ray lung images problem, solving it by a computer-aided diagnosis so a novel model for automatic classification of pulmonary lung nodules calculated Features for grayscale, shape, invariant moment, gradient, and texture features for the nodules, by using Public Database by Japanese Society of Radiological Technology (JSRT) which contain a set of 247 chest x-ray images, high classification accuracy over 100% by applying Curvelet Decomposition 50% Training Set and 50% Testing Set [36].

In lung x-ray image, the lung region may contain a tumor, hence being highly significant whereas the surrounding area does not contain significant information from medical diagnosis perspective so Camlica, Tizhoosh et al. detected the salient regions of images during training and folded the data to reduce the effect of irrelevant regions and used LBP to extracted features on smaller image areas and consequently classification by SVM on IRMA 2009 dataset with 14410 x-ray images, as a result, SVM needed 141.17 second training time and 92:51 testing time without salient and 53 millisecond per image for on-line quires. The SVM who's saliently needed 60:36 seconds training time, 52:56 seconds testing time and for online queries 30 milliseconds per image [33]. However folding image blocks are most critical part of pre-processing but if we consider the deletion of non-salient blocks altogether. This may be particularly of interest in non-medical cases where the scene may contain irrelevant information along with objects of interest and investigate the feasibility and potential effect of folding blocks not necessarily just folding rows and columns.

On COREL and IAPR Bhattacharya, Rahman et al. selected 5000 generic image database with manually assigned semantic categories and on IMAGE-

CLEF with 2400 medical image database with different modalities and examined body parts, to represent images in a new feature space based on both supervised multi-class SVM and unsupervised FCM clustering based algorithms should be extracted features by CLD, MPEG-7and EHD features extraction, in addition, using SVM with RBF kernel getting high accuracy [51]. However selection of natural clusters same as semantic categories on FCM led to poor performed compared with the SVM on using Euclidean based similarity measure on global CLD and EHD feature vector. In addition to that that similarity between images from different classes that because classify image in exact categories are hard to distinguish with the untrained eye but the basically differ in the orientation and the biological system. Categories in the database are not uniformly distributed that making training and consequently classification task very difficult.

On the area of determining a Breast cancer Antony and Ravi applied new approach to determine the classification of mammographic image which contain various features like space, distance, circumscribed masses and micro calcification, to classifying mammographic images created on the Region of Interest (ROI) On DoD BCRP with 750 samples and MIAS with 322 samples and DDSM with 2640 samples databases to classify the image increase quality of image to normalize it by using histogram equalization, and computing intensity features from shape features, region features such as 'Solidity', 'Eccentricity', 'Convex Area', 'Orientation', 'Perimeter', 'Major Axis Length', 'Minor Axis Length' which are extracted to compute volumetric values. Using SVM was getting high accuracy when using k-means clustering [52].

on different medical image modality Dimitrovski, Kocev et al. Used the modality classification on databases from the Image CLEF competitions in 2011, 2012 and 2013 with 9496 images, described by four visual and one textual features, and combinations thereof, so using local binary patterns, color and edge directivity descriptors, fuzzy color and texture histogram and scale-invariant feature transform (and its variant opponent SIFT) as visual features and the standard bag-of-words textual representation coupled with TF-IDF weighting, as a result, best per-forming features for modality classification are the SIFT and opponent SIFT features [53].

Ganesan and Subashini selected 250 X-ray images dividing on six different classes, retrieving similar X-ray images based on the content of the query image required average filter to Pre-processing of X-Ray images for noise reduction and enhancement, then Image texture features were extracted by GLCM to feed classifier, in addition, City block distance method is used as the metric for retrieving the top three similar images from the image database based on the feature vector of the query image, as a result BPNN classifier gave a classification high accuracy [54]. However dataset contain 250 images it is small data volume and they work at all data not internal classes in addition to that if using LBP feature with GLCM giving good result but Still the dealing with big data challenges.

2.3.2 K-Nearest Neighbors:

Wieland and Pittore in 2014 state The K Nearest Neighbors (KNN) classification model classifies for each unlabeled instance its k nearest neighbors in the multi-dimensional feature space spanned by a set of training instances and assigns a class value according to the majority of a particular class within this neighborhood [55]. Müller, Michoux et al. Suppose that A be a set of labeled feature vectors and B be a set of unlabeled feature vectors then the class label of each vector B_i can be said to be equal to the majority class label of the k vectors in A closest to B_i Also, any object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small) [56]. If k = 1, then the object is simply assigned to the class of its nearest neighbor.

on global level Mueen, Sapiyan Baba et al. extract texture and edge feature took k=3 that given 53% accuracy rate, then, getting information from GLCM and canny edge on local level 63%. Lastly down scaled image (15x15) to get pixel information with 78%. But combining three levels in big vector after resize 490 by apply PCA [18]. Also, Zare, Seng et al. (2013) took K=9 on global level and fed classification method from LBP & BOW feature extraction however consider individual classes, classification task was difficult [6]. In addition, Gueld, Keysers et al. (2004) used two choices k=1, k=5 but No different because 1NN better for EUCLIDEAN and 5NN was better too [56]. However find general rule to determine best setting for k are hard to construct.

Awedh apply Hierarchical classification on IRMA 2005 dataset which contain 9000 images with 57 classes and using BoW to represent local patches so this hierarchical has tree level, for first level with k= 9 classes, second level k= 29 classes, and the third level k=57 classes with accuracy of 86% [49].

moreover, Fesharaki and Pourghassem build hierarchical classification on a novel 2158 medical X-ray images in 18 classes, using shape features in the first level, then on next levels combining shape and texture features or texture features only used to split the overlapped classes in smaller classes in a row for forming all the classes, alone and using K-NN classifier, as a result, obtained 93.6% accuracy [28].

on ImageCLEF2005 dataset with 9000 images of 57 classes using GLCM to extract texture feature and Histogram of Oriented Gradient (HOG) for shape feature extraction, in addition, SURF was used for the 4 level of feature extraction, reducing feature vector by PCA, also using K-NN classifier getting accuracy result achieved 89.32% and 92.99% for the respective 80 and 90 % of training images . Srinivas and Mohan in 2013 apply Retrieval of medical images on IRMA with 12000 images by using multi-feature extraction method depend on similarity measures to compare the query image with database images so to extract feature vectors using canny edge an patch on mean and variance and Euclidean distance similarity measure gives 97% precision and 86% recall [26].However in this paper they used similarity measures in comparing query image with database images but if they classify data among features were done by machine learning algorithm like SVM and K-NN and building histogram for similarity matching by any technique reduce search space because searching the similarity in all dataset take a lot of time and is very expensive if the database huge the retrieval very hard. Lehmann, Güld et al. in 2005 selected Data mining methods on medical image databases using several steps, firstly, automatic categorization, using DCT, Canny Edge, CASTELLI and TAMURA, all on 6231 images from all kind of modalities, separated into 81 classes with at least 5 samples per class is analyzed, As a result, it gave accuracy of 98% within the ten best matches is sufficient for most applications [14]. However there is misclassification because the large categorization which has enough reference have 85% recognition rate whereas image from small classes and the class which have small size led to inhomogeneous and misclassify. There is intra-class variability increase because grouping sparse category (all radiograph are coded with plain radiography, cornel posterior anterior direction, body region abdomen and musculoskeletal bio system) in to larger superset. By the way inter-class similarity means image have similar appearance although it is differ in IRMA code for mammographic that were acquired in crania caudal and oblique orientation inspecting the confusion matrix reveals other cases.

2.3.3 K-means clustering

K-Means or Hard C-Means clustering is basically a partitioning method applied to analyze data and treats observations of the data as objects based on locations and distance between various input data points and Partitioning the objects into mutually exclusive clusters (K) is done by it in such a fashion that objects within each cluster remain as close as possible to each other but as far as possible from objects in other clusters [57].

Antony and Ravi (2015) Determining a Breast cancer by used new approach to determine the classification of mammographic image which contain various features like space, distance, circumscribed masses and micro calcification, to classifying mammographic images created on the Region of Interest (ROI) On DoD BCRP with 750 samples and MIAS with 322 samples and DDSM with 2640 samples databases to classify the image increase quality of image to normalize it by using histogram equalization, and computing intensity features from shape features, region features such as 'Solidity', 'Eccentricity', 'Convex Area', 'Orientation', 'Perimeter', 'Major Axis Length', 'Minor Axis Length' which are extracted to compute volumetric values. Using SVM was getting accuracy 96% but this accuracy up to 99 % when using k-means clustering [52].

Also, Ray and Sasmal introduced an efficient clustering of x-ray images based on various levels of image features global, local and pixel depending on extracted features by GLCM and canny edge for texture and shape features on 150 x-ray images consists of five different classes of x-ray images such as knee, hand, skull, backbone, and chest. Best classification given by K-means + Hierarchical clustering techniques individual Backbone 92% [58].

2.3.4 Fuzzy C-means:

Fuzzy C-Means clustering method extended from Hard C-Mean clustering method which is an unsupervised clustering algorithm that is applied to wide range of problems connected with feature analysis, clustering and classifier [59].

design.Rajam and Valli Reviewed this algorithm based on an iterative optimization of a fuzzy objective function. it provides a promising solution to the clustering problem and the degree of membership of a data item to a cluster is between [0, 1], in addition, for a given query image the output of the FCM is the membership value of the image with each of the K classes and The query image belongs to the class for which the membership value is high [35].

To determine a Breast cancer Antony and Ravi using new approach to determine the classification of mammographic image which contain various features like space, distance, circumscribed masses and micro calcification, to classifying mammographic images created on the Region of Interest (ROI) On DoD BCRP with 750 samples and MIAS with 322 samples and DDSM with 2640 samples databases to classify the image increase quality of image to normalize it by using histogram equalization, and computing intensity features from shape features, region features such as 'Solidity', 'Eccentricity', 'Convex Area', 'Orientation', 'Perimeter', 'Major Axis Length', 'Minor Axis Length' which are extracted to compute volumetric values. By applying this fuzzy c-means, it increases accuracy over 98% [52].

2.4 Comparison of the various works:

The field of classification medical image has been an active research area. Growth on classify X-ray medical images in to predefine class using machine learning techniques, Table1. Summarized performance of technique on different medical image dataset like IRMA, Gold miner, Sheba Medical Center, JSRT, NLM and different X-ray mammographic dataset. We observed that number of images under studding from dataset has not unique measures, number of predefine class too.

Classification X-ray processing has a lot of phases begin with removing Noise from image by applying many techniques like Gaussian filter. Secondly, extract image feature, we observed that, there are two mainly type of feature extraction: low level method and local patch. In low level method initially canny edge method applied on image database, also HOG and region moment with its types like IM and ZM. Then texture feature extraction like LBP and GLCM which are widely used. In LBP histogram contain information about distribution of local micro-patterns like edges, spots and flat areas. Also, on BoW approach, extraction local patch to construct codebook that by applying SIFT descriptor and represent image in a histogram, this BOW is good local patch extraction features method. Above all choosing feature extraction methods to built a feature vector has a large dimensionality which reduced by applying PCA which used to fed classifier.

Supervised and Unsupervised techniques used as classification techniques, like NN, KNN, SVM, Fuzzy c-mean, K-mean. although medical images are not complex comparable with general color image which contain a lot of detail, and x-ray is gray scale image, we observed in some cases on the review paper are miss classification if the class has one or a few images and sparse categorization on dataset led classifier to high intra-class variability, in addition inter-class similarity when classify image in exact category and this category are not uniformly distributed that making consequently classification task very difficult.

Above all summarized we observed that extraction feature BOW model very good method to extract exactly batch then chose machine learning algorithm but Random forests still need high cost so depend on comparison algorithms the SVM are common used and it give high accuracy rate.

Table 2.1 review on x-ray medical image classification and representations.

Paper name	Paper Date	dataset	No of classes	No of images	Feature extraction	Machine learning	Accuracy rate
Automatic classification of medical X-ray images using a bag of visual words	2013	Image CLEF 2007	116	12000	BoW SIFT	SVM	high
Multilevel Feature Extraction and X-ray Image Classification	2007	IRMA x-ray dataset	57	10000	GLCM PCA	K-NN and SVM	high

RADIOGRAPHIC MEDICAL IMAGE RETRIEVAL SYSTEM FOR BOTH ORGAN AND PATHOLOGY LEVEL USING BAG OF VISUAL WORDS	2014	IRMA database			BoW	multimodal PLSA and SVM	Very high
Automatic categorization of medical images for content-based retrieval and data mining	2005	IRMA	81	6231	DCT CASTELLI TAMURA	simple nearest neighbor	high
Medical image retrieval with probabilistic multi-class support vector machine classifiers and adaptive similarity fusion	2008	IRMA	116	1100 0	GLCM EHD CLD t-moment MPEG-7 PCA	SVM	high

NOVEL SHAPE-TEXTURE FEATURE EXTRACTION FOR MEDICAL X-RAY IMAGE CLASSIFICATION	2012	IRMA	21	4402	NSTF, LBP GLCM, Moment Invariant Region properties, Tamura, Entropy Reformed Wavelet , PCA	SVM	Very high
Automatic Annotation of X-ray Images: A Study on Attribute Selection	2010	Image CLEF -2005 -2008	58 196	1267 7	LBP PCA	SVM	high
AUTOMATIC CLASSIFICATION OF MEDICAL X-RAY IMAGES	2013	Image CLEF 2007	116	1100 0	LBP GLCM Canny Edge BoW	SVM KNN	high

X-ray Categorization and Retrieval on the Organ and Pathology Level, Using Patch-Based Visual Words	2011	imagCLEF 2009 Gold Miner Sheba Medical Center	196	15000 66000 98	BoW SIFT PCA	SVM	Very high
Comparison of Global Features for Categorization of Medical Images	2004	IRMA	81	6335	DCT CASTELLI TAMURA Edge structure	k-NN	Very high
A Learning-Based Similarity Fusion and Filtering Approach for Biomedical Image Retrieval Using	2011	six different datasets from Image CLEF (2005- 2010)	30	5000	EHD CLD FCTH CEDD	SVM	High

SVM Classification and Relevance Feedback							
AN AUTOMATIC CLASSIFICATION SYSTEM APPLIED IN MEDICAL IMAGES	2006	Image CLEF 2005		1000 0	Blob LRPM PCA	SVM	high
Medical Image Classification Using Multi-Vocabulary	2015	IRMA 2005	57 29 9	9000	BoW PCA	SVM K-NN	Very high
x-ray image classification using random forests with local wavelet based cs-local binary pattern	2011	IRMA 2007	30	2400	WCS-LBP	Random forests SVM	High
medical x-ray image hierarchical classification using a merging and splitting scheme in feature space	2013	IRMA	18	2158	IM GLCM ZM	MLP K-NN	Vey high

Medical Image Indexing and Retrieval using Multiple Features	2013	IRMA	8	1200 0	Canny edge detection mean & variance patch based	KNN	High
Chest X-ray Image View Classification	2015	NLM IRMA	2	8200 1867	Image profile Body size ratio PHOG CBSE	SVM	Very high
A Comparative Study for Comparing Two Feature Extraction Methods and Two Classifiers in Classification of Early-stage Lung Cancer Diagnosis of chest x-ray images	2014	JSRT		247	CURVELET WAVELET	SVM	Very high
CLASSIFICATION OF MEDICAL X-RAY IMAGES FOR AUTOMATED	2014	IRMA	6	180	ZM GLCM PCA	SVM	high

ANNOTATION					DCT		
Medical Image Classification via SVM using LBP Features from Saliency-Based Folded Data	2015	IRMA 2009	193	1441 0	LBP	SVM	high
Image Representation and Retrieval Using Support Vector Machine and Fuzzy C-means Clustering Based Semantical Spaces	2006	IMAGE-CLEF	22	2400	CLD MPEG-7 EHD	SVM	high
A New Approach to Determine the Classification of Mammographic Image Using K-Means Clustering Algorithm	2015	DoD BCRP MIAS DDSM		930 437 2683	solidity eccentricity convex area orientation perimeter major axis length minor axis	k-means SVM Neuro Fuzzy Fuzzy C Meanss KMeans	Very high

					length	Clustering	
Improving the Annotation Accuracy of Medical Image in ImageCLEFmed2005 Using K-Nearest Neighbor (KNN) Classifier	2015	ImageCLEF2005	57	9000	SURF PCA GLCM PHOG	K-NN	Very high
Automatic Image Modality Based Classification and Annotation to Improve Medical Image Retrieval	2007	ImageCLEFmed2006 CISMeF	6	50000 1332	GLCM PHOG Edge orientation	A-NN	Very high
Improved medical image modality classification using a combination of visual and textual features	2015	IMAGECLEF 2011 2012	18	2012	LBP CEDD MPEG-7	SVM	High

		2013	31 31	2001 5483	EHD FCTH WAVELET SIFT OSIFT		
Content-based medical image classification using a new hierarchical merging scheme	2008	IRMA	40	9100	-PCA -FD - Major axis orientation, eccentricity, major and minor - GLCM - tessellation-based spectral	MLP	High

					feature -		
A New Approach for Clustering of X-ray Images	2010	BRNS	5	150	GLCM CANNY EDGE	K-means + Hierarchical clustering	High
A Content Based Approach to Medical X-Ray Image Retrieval using Texture Features	2014	mammographic database	6	250	GLCM	BPNN SVM	High

2.5 Open issue and Conclusion:

This chapter reviews the various methods which used to classify X-ray image into predefine classes construct feature vector to feed machine learning algorithm which used to classify X-ray image. From the above survey, it is concluded that for classify image in to exactly class efficient low level or local patch extraction techniques were applied firstly then chooses machine learning algorithm to classify it. To obtain good retrieval image result must apply feature extraction and machine learning with high accuracy rate all that before indexing process. Although ANN technique is efficiently handles noisy inputs and computation rate is high however it is difficult on choosing the type of network architecture, poor semantically, it requires a large amount of training data. Also, SVM technique provides a good generalization capability, Simple to manage decision rule complexity and Error frequency additionally, it contains non linear transformation however SVM structure difficult to understand, determination of optimal parameters is not easy when there is nonlinear separable training data and it does not take the class distribution into consideration and ability to correctly classify unknown samples may be impaired. Fuzzy properties are described by identifying various stochastic relationships however output is not good without prior knowledge. Theoretically, KNN is the simplest of all machine learning algorithms, However the imbalance problem that the number of positive samples for a given object class is seriously less than that of negative ones; the complexity problem that the computational cost grows quadratic ally with the number of object classes. Also, intra-class variability and inter class similarity affected on classification performance so designing good representation technique should guarantees increasing in accuracy rate which a measurement of performance.

Chapter 3 Research methodology

3.1 Introduction

This chapter presents methodology to be adopted in continuing this research. Research procedures, operational framework, dataset, technique design, experiment and evaluation are included.

3.2 Research Design and Frame work

To conducted problem of interclass similarity and intra class variability we should design anew classification technique. Firstly, earning x-ray medical dataset to implement classification technique, and then preprocessing all x-ray medical images under experiments. After that, training phase which training samples under classes are chosen to extracted texture features and fed it to SVM classifier which used as a prediction model to testing phase.

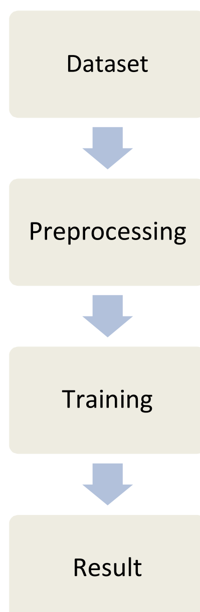


Figure 3.1 Flowchart of the proposed classification technique

3.2.1 Dataset

Image retrieval medical applications (IRMA) group from Rheinisch-Westfaelische Technische Hochschule (RWTH) University Hospital of Aachen, Germany. It consists of medical radiographs collected randomly from daily routine work at the Department of Diagnostic Radiology. The quality of radiographs varies considerably and there is a high intra class variability and inter-class similarity among classes. In order to establish a ground truth, the images were manually classified by expert physicians using the IRMA code [60]. Sample images from the database together with textual labels and their complete code are given in fig3.2. This dataset is available to researcher and to get it should be first download the request from IRMA website and after agreement it will be available but in every publishing paper should make acknowledgement for them.

Fig. 3.2 Sample images and the corresponding textual labels from IRMA code [6]

3.2.2 Preprocessing

This procedure begins with enhancement phase as a first phase which applied on all images using histogram equalization techniques which applied to improve the quality of the image such as increasing the contrast of the image. This contrast adjustment provides better gray intensities distribution on the histogram. The method is useful in images with backgrounds and foregrounds that are both bright or both dark.

Second phase segmentation process which done to find the region of interest (ROI). The ROI is found by segmenting the biggest region in the image. Connected Component Labeling (CCL) is applied for this purpose. CCL scans an image and groups its pixels into components based on pixel connectivity. Third phase is feature extraction and this procedure was done by applying special texture tools. It is a full 14 haralick texture feature factors to describe images texture properties.

3.2.3 Training

The training phase consists begin with determine image samples which used to construct a predictor model using SVM classifier. SVM constructed model and evaluated it in the training phase itself to ensure that the best possible accuracy rate is attained for every individual class in the database.

3.2.4 Result

The model generation used to test phase and use accuracy rate to measure the performance. This accuracy measurement was used as a measurement in previous researches.

Table 3.1 the operational framework for the research:

Research question	Objective	Contribution
1-What x-ray image features techniques used to extracted content images?	1-Taxonomy review of x-ray image feature extraction techniques	1-Review on x-ray image feature extraction 2-Review on x-ray image classification and annotation
2-How to solve inter class similarity and intra class variability?	2-X-Ray medical image representation technique on global level.	3-Design and create x-ray medical images representation technique and apply it on at global level
3-How we can approve proposed technique?	3-Evaluation proposed techniques compared with other representation techniques	4-Experiment framework

Chapter 4

4.1 Introduction:

Medical images are key component in diagnosis and preventive medicine [6]. However these computerize system manages valuable resources it need effective and accurate automatic medical image retrieval application which using automatic image classification by mapping images into pre-defined classes which involves basic principles like representation images visual features where these features are extracted and generalization in training and evaluate the classifier in testing. This representation techniques categorized to (i) low-level image representation (ii) patch passed image representation. The crucial role in image processing is extracted low level visual features which include color, texture and shape [61]. But on x-ray images color are not necessary because it is grayscale. So on these techniques we extracted texture features because textures has a useful prosperities for x-ray image description which gained throw texture analysis and observation. A basic stage to collect such features through texture analysis process is texture feature extraction which extracted in several methods, using statistical, structural, and model-based and transform information, in which a well-known method is using a Gray Level Co-occurrence Matrix (GLCM) [29].

4.2 Methodology:

The main purpose of this research was made a methodology consist of two steps training phase and testing phase. In training phase, the texture features are extracted from all training images, and SVM classifier is trained on the extracted features to create a classification model. This model is used to classify the test images into the predefined classes in the testing phase.

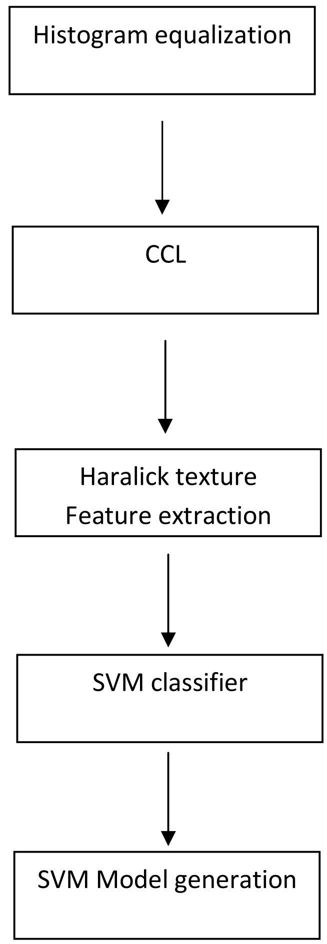


Figure 4.1 Flowchart of the technique steps

4.2.1 Histogram equalization:

It is an image enhancement techniques is applied to improve the quality of the image by increasing contrast of the image to provide better gray intensities distribution on the histogram. In our technique we apply histogram equalization. It is a technique for adjusting image intensities to enhance contrast [62]. Let f be a given image represented as a $m_r$by $m_c$matrix of integer pixel intensities ranging from 0 to L 1. L is the number of possible intensity values, often 256.

Let p denote the normalized histogram of f with a bin that for each possible intensity. So

$$p_n = \frac{\text{number of pixels with intensity n}}{\text{total number of pixels}} \qquad n = 0,1, \ldots \ldots, l \quad 1$$

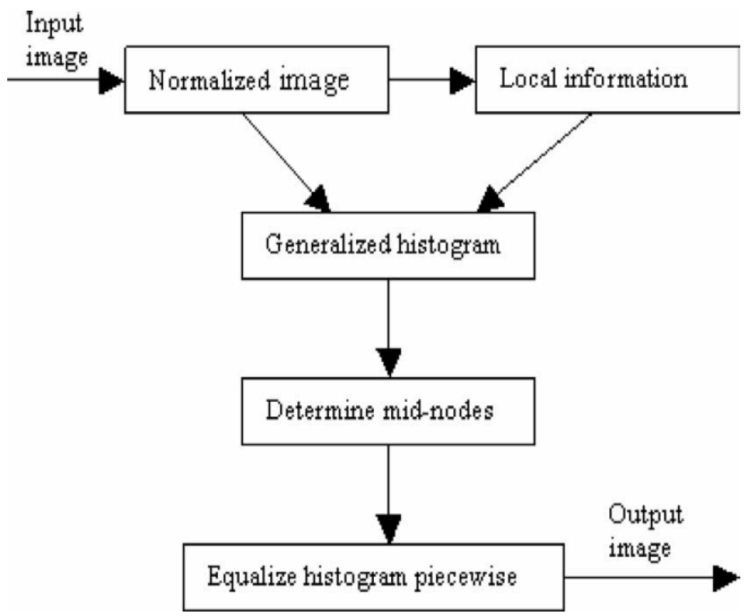


Figure 4.2 Histogram equalization flowchart [20]

4.2.2 Connected Component Labeling:

Connected component labeling is an important problem appearing in different fields of research. It is the assignment of a unique label to each non-zero element on a 2D grid in such a way that all non-zero neighbors get the same label that by consider x-ray image as 2D cases with four neighbors (north, south, east and west) [63]. A pixel $p \in S$ is said to be connected to $q \in S$ if there is a path from p to q consisting entirely of pixels of S. CCL techniques by assuming that region pixels have the value 0 (black) and that background pixels have the value 255 (white). It can scan the image to find an unlabeled 0, then assign a label L to all of its 0 neighbors and if there are no more unlabeled 0 pixels should be stop to rescan image.

4.2.3 Feature extraction:

It is second component of our techniques which play basically role in the performance of any image classification. In our technique we extract texture features because it contains important feature. Tuceryan and Jain [64]divided feature extraction methods to four main categories, namely: structural, statistical, model-based and transform domain. In our technique we choose statistical methods which represent the texture indirectly according to the non-deterministic properties that manage the distributions and relationships between the gray levels of an image [65]. So we apply Haralick Texture Features which introduce in 1973, Haralick [66] introduced the co-occurrence matrix and his texture features and he proposed two steps for texture feature extraction: the first is computing the co-occurrence matrix and the second step is calculating texture feature base on the co-occurrence matrix. Haralick extracted fourteen texture features from GLCM for an image. To compute co-occurrence matrix should be determine gray level in new converted matrix from original image

4.2.3.1 Angular second moment (ASM) feature:

The ASM is known as uniformity or energy. It measures the uniformity of an image. When pixels are very similar, the ASM value will be large.

$$ASM = \sum_{i,j=0}^{N-1} \{p(i,j)\}^2$$

4.2.3.2 Contrast feature:

Contrast is a measure of intensity or gray-level variations between the reference pixel and its neighbor. In the visual perception of the real world, contrast is determined by deference in the color and brightness of the object and other objects within the same field of view.

$$CTR = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i,j=1}^{N} p(i,j) \right\}, \qquad |i-j| = n$$

When i and j are equal, the cell is on the diagonal and i   j = 0. These values represent pixels entirely similar to their neighbor, so they are given a weight of

0. If I and j differ by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, the contrast is increasing and the weight is 4. The weights continue to increase exponentially as (i j) increases.

4.2.3.3 Entropy Feature:

Entropy is a difficult term to define. The concept comes from thermodynamics; it refers to the quantity of energy that is permanently lost to heat every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term can be understood as amount of irremediable chaos or disorder. The equation of entropy is:

$$E = -\sum_{i,j=0}^{N-1} p(i,j)\ x \log(p(i,j))$$

4.2.3.4 Variance Feature (INERTIA):

Variance is a measure of the dispersion of the values around the mean of combinations of reference and neighbor pixels. It is similar to entropy, answers the question 'What is the dispersion of the difference between the reference and the neighbor pixels in this window?'

$$INR = \sum_{i,j-0}^{N-1} \{i - j\}^2 x\ p(i,j)$$

4.2.3.5 Correlation Feature:

Correlation feature shows the linear dependency of gray level values in the co-occurrence matrix. It presents how a reference pixel is related to its neighbor, 0 is uncorrelated, 1 is perfectly correlated.

$$COR = \sum_{i,j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}$$

Where μ_i, μ_j and i, σ_j are the means and standard deviations of p_x and p_y.

$$\sigma_i = \sum_{i,j=0}^{N-1} (i-\mu_i)^2 p(i,j)$$

$$\sigma_j = \sum_{i,j=0}^{N-1} (j-\mu_j)^2 p(i,j)$$

4.2.3.6 Inverse Difference Moment (IDM) Feature:

IDM is usually called homogeneity that measures the local homogeneity of an image. IDM feature obtains the measures of the closeness of the distribution of the GLCM elements to the GLCM diagonal.

$$IDM = \sum_{n=0}^{N-1} \frac{1}{1+(i-j)^2} p(i,j)$$

IDM weight value is the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal.

4.2.3.7 Sum Average Feature:

$$\sum_{i=0}^{2N-2} i p_{x+y}(i)$$

4.2.3.8 Sum Variance Feature:

$$\sum_{i,j=0}^{N-1} (i-\mu_i)^2 p(i,j)$$

4.2.3.9 Sum Entropy Feature:

$$\sum_{i=0}^{2(N_g-1)} p_{x+y}(i) log_{x+y}(i) \quad (11)$$

4.2.3.10 Difference Variance Feature:

$$\sum_{i=0}^{N_g-1} (i \quad f'_a)^2 p_{x-y}(i) \quad (12)$$

Where:

$$p_{x-y}(k) = \sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} pd, \theta(i,j) \quad , k = |i \quad j| = \{0, 1, 2, \ldots\ldots, (N_g \quad 1)\} \quad (13)$$

$$f'_a = \sum_{i=0}^{N_g-1} i . p_{x-y}(i) \quad (14)$$

4.2.3.11 Difference Entropy Feature:

$$\sum_{i=0}^{N_g-1} p_{(x-y)}(i) log p_{x-y}(i) \quad (15)$$

4.2.3.12 Information Measures of Correlation Feature1:

$$\frac{HXY - HXY1}{max(HX, HY)} \quad (16)$$

4.2.3.13 Information Measures of Correlation Feature2:

$$(1 \quad exp[\quad 2(HXY^2 \quad HXY)])^{\frac{1}{2}} \quad (17)$$

4.2.3.14 Max Correlation Coefficient:

Square root of the second largest value of Q

$$Q(i,j) = \sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(j)} \quad (18)$$

4.3 Model generation modules:

After extracted texture features should be create model generation that by make a label of every image have been identified firstly, and then extract visual features from the entire training set. these extracted features as well as the label of every image in the dataset are fed into classifier to construct the classification model. Based on empirical results and several classification applications in same domain, Support Vector Machine (SVM) is very attractive for image classification as its aim to find the best hyperplane separating relevant and irrelevant vectors maximizing the size of margin. This optimum hyperplane has maximum margin towards the sample objects, that is, the greater the margin, the less the possibility that any feature vector will be misclassified.

4.3.1 Support Vector Machine:

Support vector machine (SVM) is a computer algorithm that learns by example to assign labels to objects [67]. But it introduced firstly in 1998 by Burges [68] as algorithm with a set of kernel-based supervised learning methods used for classification and regression. Wang and Summers explored these kernels in [38]showing it means a matrix which encodes similarities between samples which is a weighting function in the integral equation used to calculate similarities between samples. Rajam and Valli in [35]discussed that SVM was first designed for binary classification and it developed the two SVM multi class classifiers: 1) One-against-all (OVA) multi class classifier constructed N binary classifiers for N class and class sample as the positive example and remaining class samples as negative, 2) One-against-one (or) Pair Wise Coupling (PWC) constructs N*(N 1)/2 SVM binary classifiers for each pair of classes there is one classifier.

Chapter 5

5.1 Introduction

Image classification is one of the major aspects of CBIR and it has a known steps. All steps have huge techniques which created to formulate special purposes. In this chapter, wherein an effort has been made to create x-ray medical image representation technique and it selects of the appropriate class for a given image out of a set of pre-defined classes using SVM classifier as a supervision machine learning technique. Its task started with preprocessing phase. Histogram equalization was used as increasing contrast technique and determining ROI by using CCL segmentation technique. then extracting texture feature by applying haralick texture feature extracted tools. After that, using this features as input to a discriminative support vector machine classifier to construct a classification model. The experimental results were based on ImageCLEF 2005 medical database. The classification performance was evaluated on the entire dataset at global level. It was also compared with other classification techniques with various image classifications on the same database. The comparison results showed that superior performance has been achieved especially for classes with less number of training images. The proposed classification technique is evaluated on a database consisting of 180 medical X-ray images of 6 classes. It provides accuracy rate of 83.426%.

5.2 Environment setup

The utilized images in this thesis are chosen from an IRMA database [69]. In our task, to evaluate the proposed technique and to compare it with other features, 6 classes are selected. In addition to that, to evaluate this technique needing a program which was written by java using image processing code to enhancing x-ray images, determine ROI and extract features. Also, used libsvm-3.21 library under Ubuntu 14.04.5 LTS with Hard disk size: 25 GB, processor: Intel(R) Core(TM) i5-3330 CPU @ 3.00GHz and RAM : 4 GB.

5.3 Experiment

Image classification technique is major aspect of automatic image classification technique. Here, supervised learning approach is used to classify x-ray images. It consists of sequences phases. Firstly, earning x-ray medical image dataset was not easy and it isn't available on internet. It was available after acceptant from RWTH University Hospital of Aachen, Germany which was opening dataset and make it available to download. After that X-ray images are pre-processed using histogram equalization technique. However this technique increased contrast, it increased image volume too. The segmentation process is done to find the region of interest (ROI) which is found by segmenting the biggest region in the image. Connected Component Labeling (CCL) is applied for this purpose. CCL scans an image and groups its pixels into components based on pixel connectivity. It make labeling by just giving a pixel a particular value, all pixels in the gray-scale region have the label '1'. Pixels in the next gray-scale degree region have the label '2' and so on. The black was the background, has the label '0'. This, the problem is to 'label' connected regions in an image. By note, the CCL decrease volume. Then the features are extracted by applying haralick texture features extraction tools.

Training phase starting by selected adequate number of training samples that because supervised classification algorithms require adequate number of training samples to determine model parameters. But training sample size has crucial role in accuracy estimated for resulted. So at each class we take 5 training samples. The extracted features are fed into the SVM classifier which constructed classification model. This model used to test classification technique taking the rest of images. It gives accuracy by computes it as a ratio of number of images classified correctly over the size of test dataset.

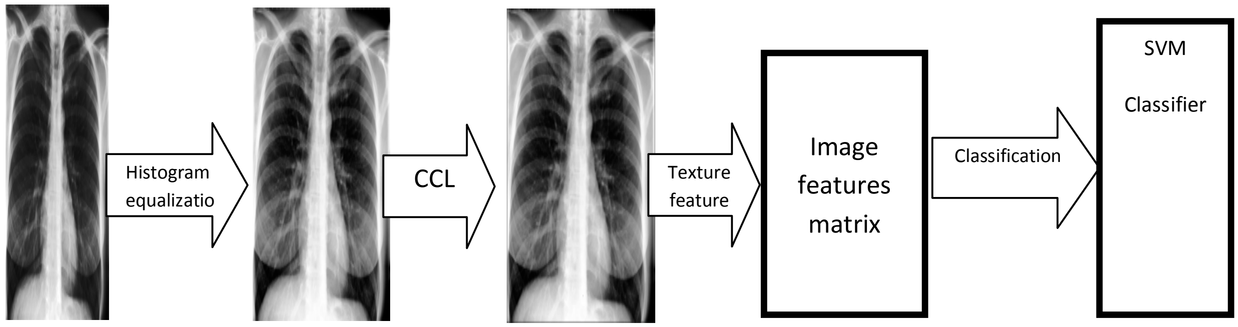


Fig 5.1. Classification technique steps.

5.3.1 Preprocessing phase:

The accuracy of image classification technique depends mainly on good choosing for image preprocessing to getting good representation for images. In this phase, histogram equalization technique enhances x-ray images contrast and making its objects clear. Determine image object CCL good technique and to describe property of x-ray images we choose its texture because image texture depends on the scale or resolution at which it is displayed. In this study, extracted texture feature are made at global level. Texture feature contains important information regarding underlying structural arrangement of surfaces in an image. Haralick features are well texture extraction tools which introduced by haralick et al in 1973 and haralick Features describe the correlation in intensity of pixels that are next to each other in space. Haralick proposed fourteen measures of textural features which are derived from the co-occurrence matrix a well known statistical technique for texture feature extraction. It contains information about how image intensities in pixels with a certain position in relation to each other occur together. Main question how this technique work and what haralick feature. These questions depend on co-occurrence matrix. To create it from natural image we dealing with image as a matrix. Firstly, Determine gray level in new converted matrix which by converted original image to 0, 1, 2 and 3 gray level. 0 value for all pixel value from 0 to 63, 1 for pixel from 64 to 127, 2 for pixel from 128 to 191 and last gray level was 3 for pixels from 192 to 255 pixel values. After that, count the matrix in d direction. Here, Ɵ directions are 0, 45, 90 and 135 directions. Then count matrix in exactly Ɵ direction. Then count transformation matrix to use it procedure Sum of count matrix + transform matrix. Normalize (probability) of Sum matrix was very important step in created co-occurrence matrix. In this study, 14 haralick texture features used to full description of x-ray properties which took by applying java classes.

5.3.2 Training phase

This phase took 5 samples for each class. We took with 14 features for each image sample to feed it to SVM classifier to create a predictor model. SVM constructs binary classification from a set of training samples belong to class labeled $y_i \in (+1,\ \ 1)$ SVM used hyperplanes to separate two classes. SVM selected hyperplane that cause the largest separation among the decision function values for the borderline example of two classes. For multi-class classification problems where classes are more than two classes, in [70] there are general approaches, one against one and one against all to make a classification prediction model. Here one against all approaches is applied. Classifier is calculated from each class versus all classes.

5.4 Result and discussion:

In this section, the experiment is conduct to evaluate performance of classification technique on ImageCLEF 2005 medical dataset. This dataset contain x-ray images from a lot of biological system examined. Here, selected main body region which segmented to 6 main body regions.

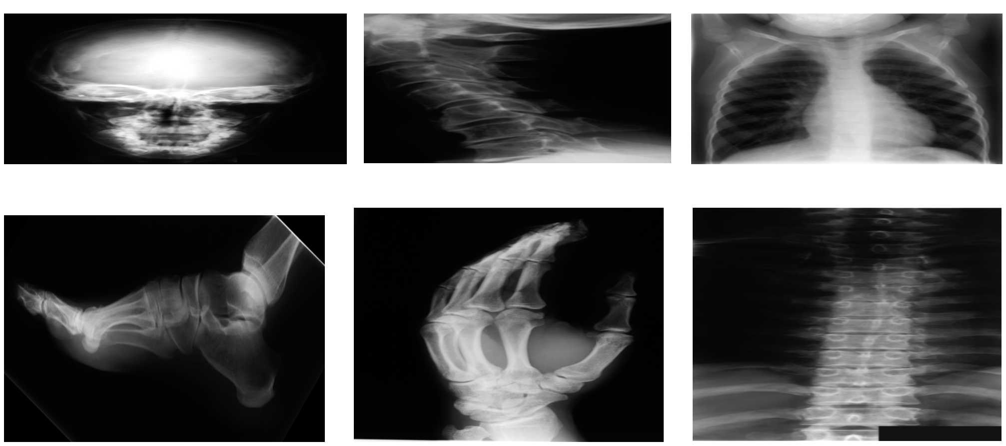


Fig 5.2. 6 classes from ImageCLEF 2005.

5.4.1 Classification result:

A library of SVM (LIBSVM) software package has been utilized to perform representation based classification on 180 X-ray images from ImageCLEF 2005 medical image dataset. As a result of applied classification technique with SVM classifier on balance classes at global level get high accuracy compared with previous representation techniques on same database. Our technique has 83.43% accuracy rate.

5.4.2 Discussion:

The classification task is difficult task because unbalance of training data as well as the existing high intra class variability and inter class similarity between x-ray images in some classes. To show the performance of the proposed approaches, other experiments with various image classification techniques were conducted on same dataset ImageCLEF 2005. However, the accuracy is obtains from all previous experiments at global level which are used as a measurement. It used to compare classification results in the average accuracy, that is:

$$\text{Average accuracy (Correctness rate)} = \frac{No.of\ images\ classified\ correctly}{size\ of\ test\ dataset}$$

Their experiments done to deal with intra class variability and inter class similarity problems. As presented in tabel1, the result obtained from purely classification techniques which clearly in [21] A.mueen and zainudeen applying GLCM, canny edge feature extraction techniques at global level which getting t accuracy rate about 65% with KNN classifier. However KNN classifier is good classifier but there are number of images from these classes was misclassified within the sub-region itself. Further investigation on misclassified images and related classes shows that most of them are suffering from high inter-class similarities and intra class variability. It is observed that for those classes referring to the same sub-body region which are visually similar and the numbers of training images are not distributed uniformly, and then SVM or any other classifier would be bios to classify images in to exact category with a bigger number of training images. In addition to that, a lot of classification techniques suffers from all these issues, in [18] extracted texture using GLCM and shape using HOG at global level. It also gets 61.22% accuracy rates with KNN. And in [71] low accuracy rate with global by extracted texture using GLCM and both classifier KNN with 52.88 and SVM with accuracy 53.84.

Table 5.1 Image representation techniques used in various studies on ImageCLEF 2005

Paper	Accuracy	Image representation technique	Classifier
[21]	65.95 70.45	GLCM, Canny Edge and Pixel value	KNN SVM with RBF
[18]	61.2	GLCM, HOG and PCA	KNN
[71]	52.88 53.84	GLCM and PCA	KNN SVM

However, classification tasks are challenged when it deals with real-life constraints of content-based image classification in medical domain. The database used in this study is ImageCLEF 2005 [72] which was provided by the image retrieval medical applications (IRMA). As a result of investigated in previous classification techniques, good classification technique depend on good techniques in preprocessing and classifier. So, key advantages of high classification accuracy depend on less number of labeled training x-ray images. At state earlier, main challenges of database are unbalanced number of training data. To highlight these problems, haralick features factors are applied on 180 images from ImageCLEF 2005. It was segmented to 6 classes. On balanced training sampled are better than unbalance. Firstly, for each class we take 5 training samples for each class. All images were preprocessing using histogram equalization for each images, then segmentation process by applying connected component labeling are applied to detect ROI. Then texture feature tool are applied on each images, we used haralick feature extracted which creates fourteen features. Each image has a one features vector labeled with (+1, -1). After that, LIBSVM software packages used make training phase.

To dealing with this LIBSVM, should be installed g++ firstly to computer. Then download LIBSVM. After extract it, we change the current directory to libsvm directory.

cd libsvm-3.22

after that build SVM-train, SV-predict and SVM-scale

make

```
  @ubuntu:~/Downloads/libsvm-3.18$ make
g++ -Wall -Wconversion -O3 -fPIC -c svm.cpp
g++ -Wall -Wconversion -O3 -fPIC svm-train.c svm.o -o svm-train -lm
g++ -Wall -Wconversion -O3 -fPIC svm-predict.c svm.o -o svm-predict -lm
g++ -Wall -Wconversion -O3 -fPIC svm-scale.c -o svm-scale
```

Data format file must be in special format

<label> <index1>:<value> <index2>:<value2> <index3>:<value3> ...

...

...

...

where

<label> is the target value that has to be a number

<index>:<value> is a feature value. <index> has to be an integer starting from 1 and <value> is a real number.

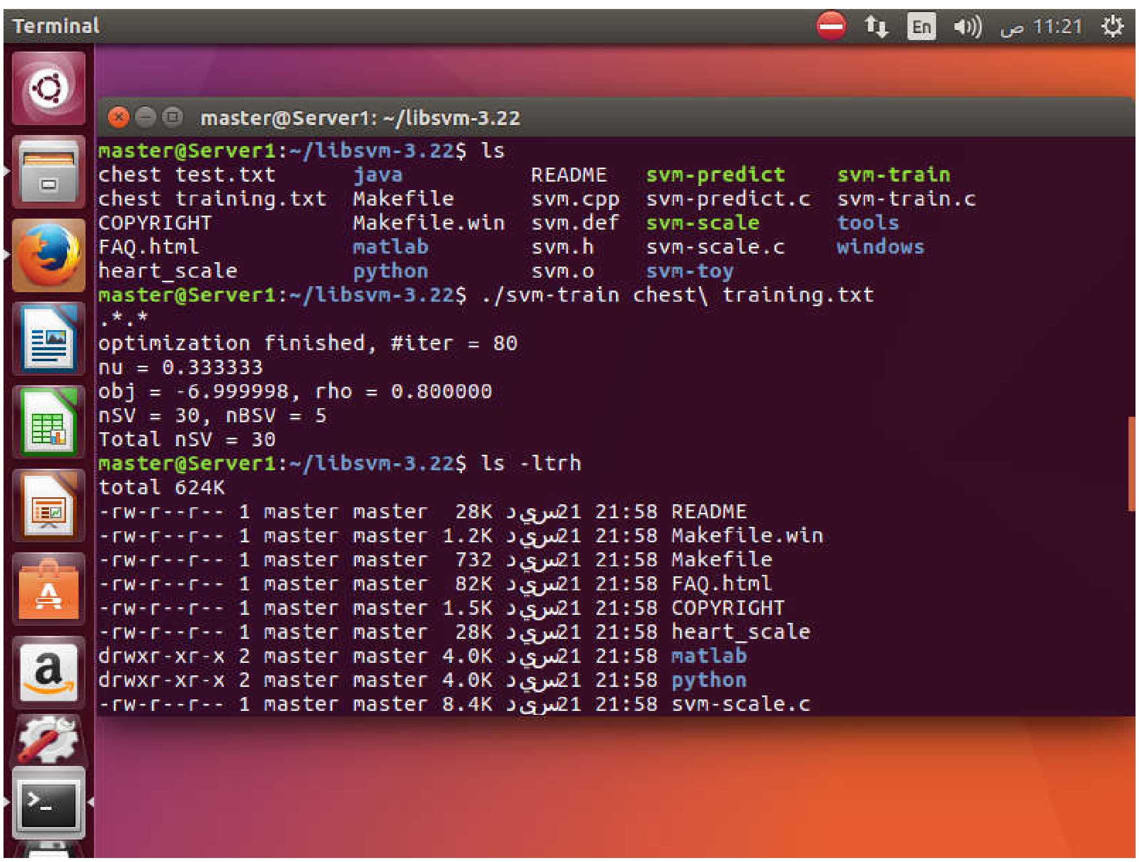
For example chest training file format

```
1.000000 1:0.06067 2:1.60892 3:348953.82885 4:25798.73780 5:0.89884 6:44.64422 7:131.63365 8:3.07588 9:3.23247 10:1.51622 11:0.58299
1.000000 1:0.02983 2:2.08137 3:1027373.44999 4:23863.54185 5:0.82749 6:43.09563 7:215.08442 8:3.72924 9:4.09757 10:1.88146 11:0.80329
1.000000 1:0.03385 2:1.52083 3:932304.26581 4:24114.81573 5:0.86894 6:43.23557 7:196.61044 8:3.55619 9:3.77718 10:1.40052 11:0.69729
1.000000 1:0.03076 2:3.71385 3:1031602.93020 4:23787.97349 5:0.85932 6:42.79402 7:200.69482 8:3.60369 9:3.87512 10:3.48359 11:0.76352
1.000000 1:0.02819 2:2.83942 3:1186232.77626 4:23603.96216 5:0.83462 6:42.78851 7:207.50838 8:3.73725 9:4.06280 10:2.62953 11:0.77329
-1.000000 1:0.05510 2:3.90503 3:377663.02072 4:25415.60052 5:0.88578 6:44.63223 7:137.01202 8:3.15270 9:3.31847 10:3.68268 11:0.65235
-1.000000 1:0.02703 2:1.77653 3:1136390.88298 4:23673.35479 5:0.82236 6:42.94879 7:205.95052 8:3.73016 9:4.06252 10:1.56640 11:0.8517
-1.000000 1:0.02778 2:4.08071 3:785665.05420 4:23944.81471 5:0.80068 6:43.18993 7:177.36143 8:3.56313 9:4.03439 10:3.67116 11:0.96598
-1.000000 1:0.01709 2:2.92415 3:1163582.69196 4:23624.46103 5:0.70388 6:42.81447 7:211.61906 8:3.86666 9:4.56465 10:2.33422 11:1.1130
-1.000000 1:0.02865 2:2.11440 3:670346.85223 4:24343.54606 5:0.77984 6:43.51131 7:165.40031 8:3.53480 9:4.07296 10:1.79593 11:0.96277
-1.000000 1:0.02485 2:1.89813 3:1194160.06505 4:23639.77769 5:0.76561 6:42.87577 7:211.63290 8:3.78606 9:4.31079 10:1.52634 11:1.0363
```

Training data

./svm-train training_set_file

In our experiment training set file are chest, head, hand, foot, neck and spine. This command will generate a model file (.model). here for example we take chest training.model, with details in terminal1.



Notes:

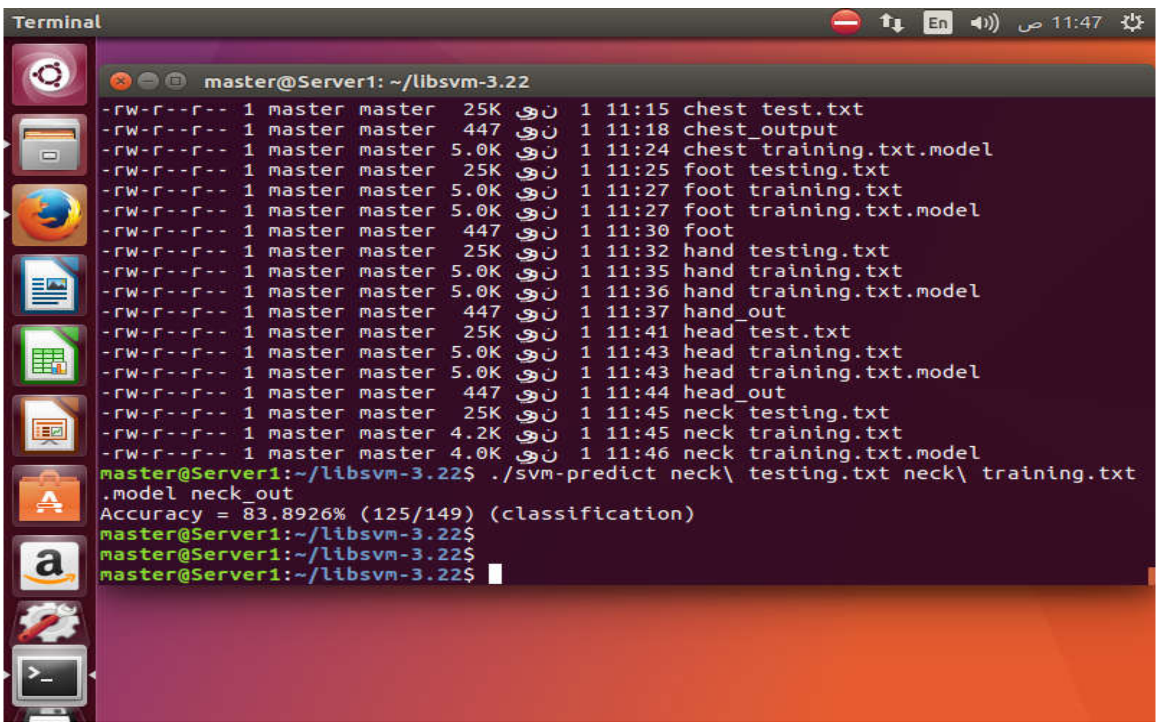
- iter is the number of iterations
- Nu is the fraction of errors and support vectors.
- Obj is the optimal objective value o the problem.
- Rho is the bias value in the decision function.
- nSV and nBSV are numbers of support vectors and bounded support vectors in each class.
- Total nSV is the total number of support vectors in each class.

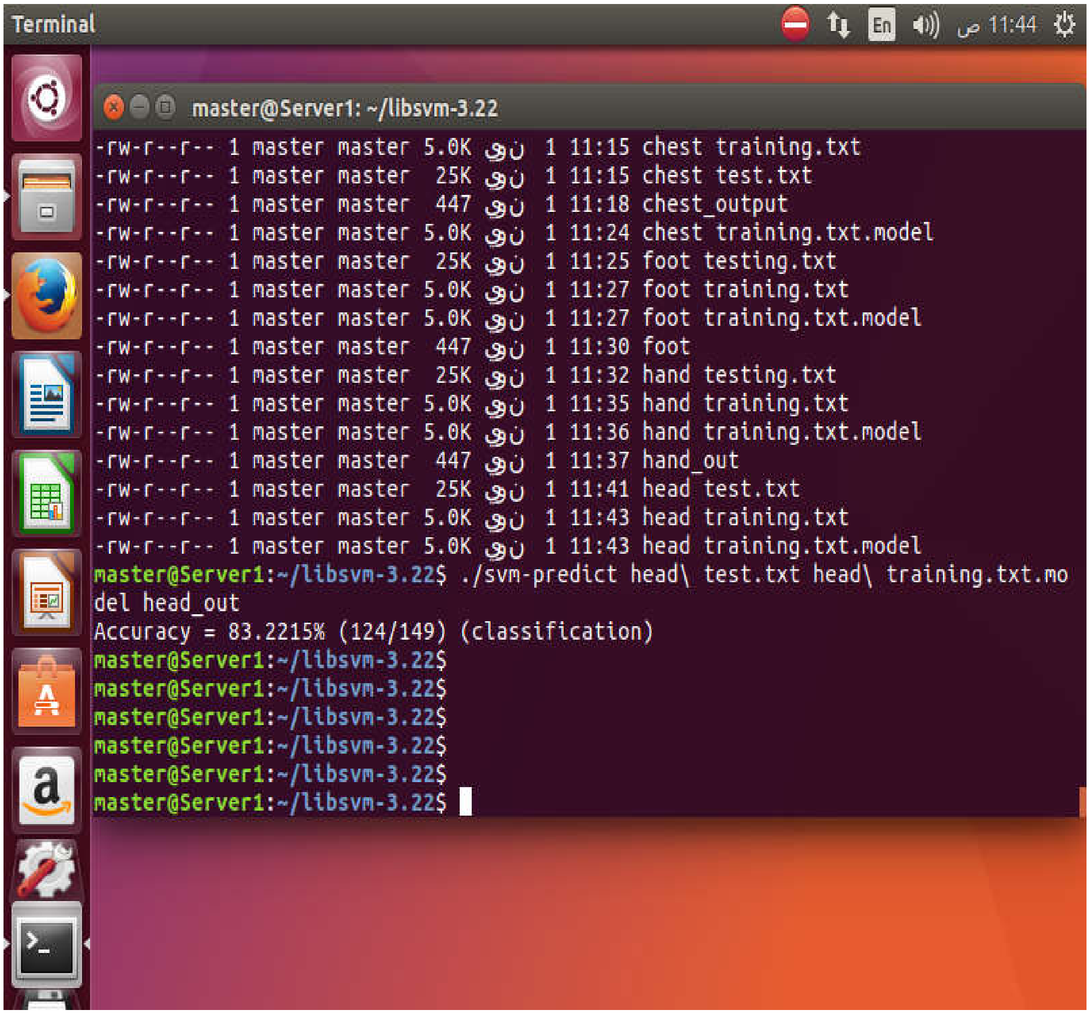
Testing data

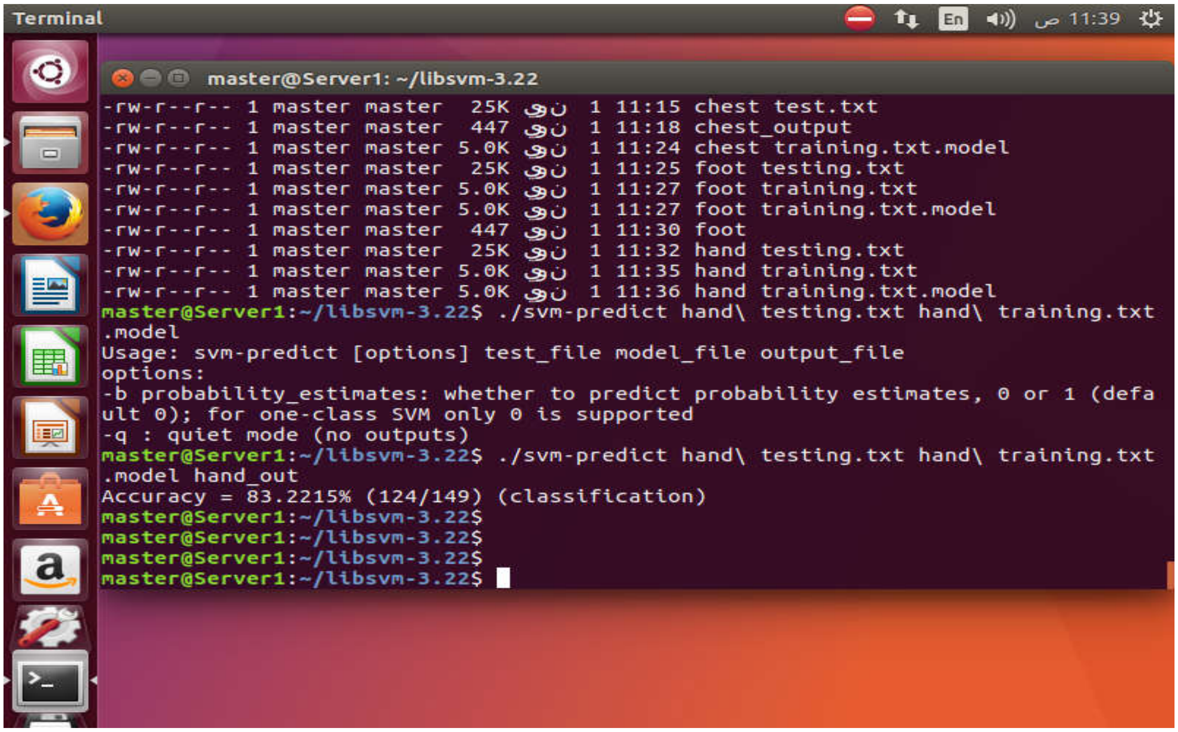
./svm-predict test_file model_file output_file

For example in testing chest.

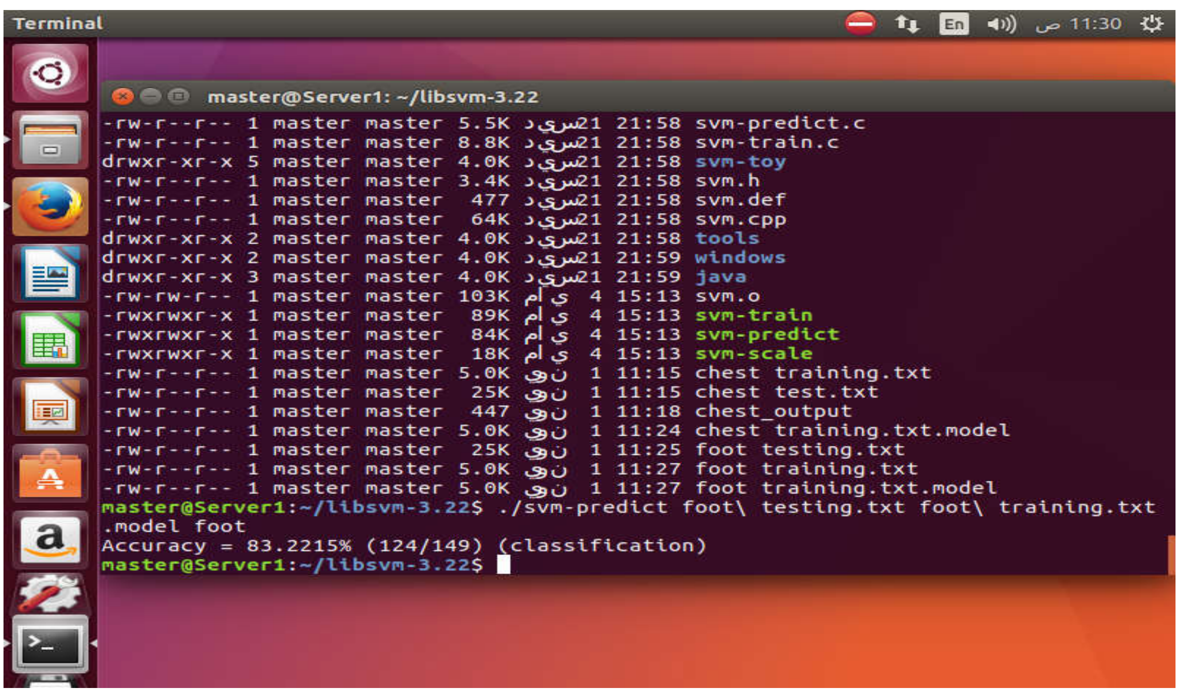
./svm-predict chest test.txt chest training.model output. As a result, next terminals show outputs



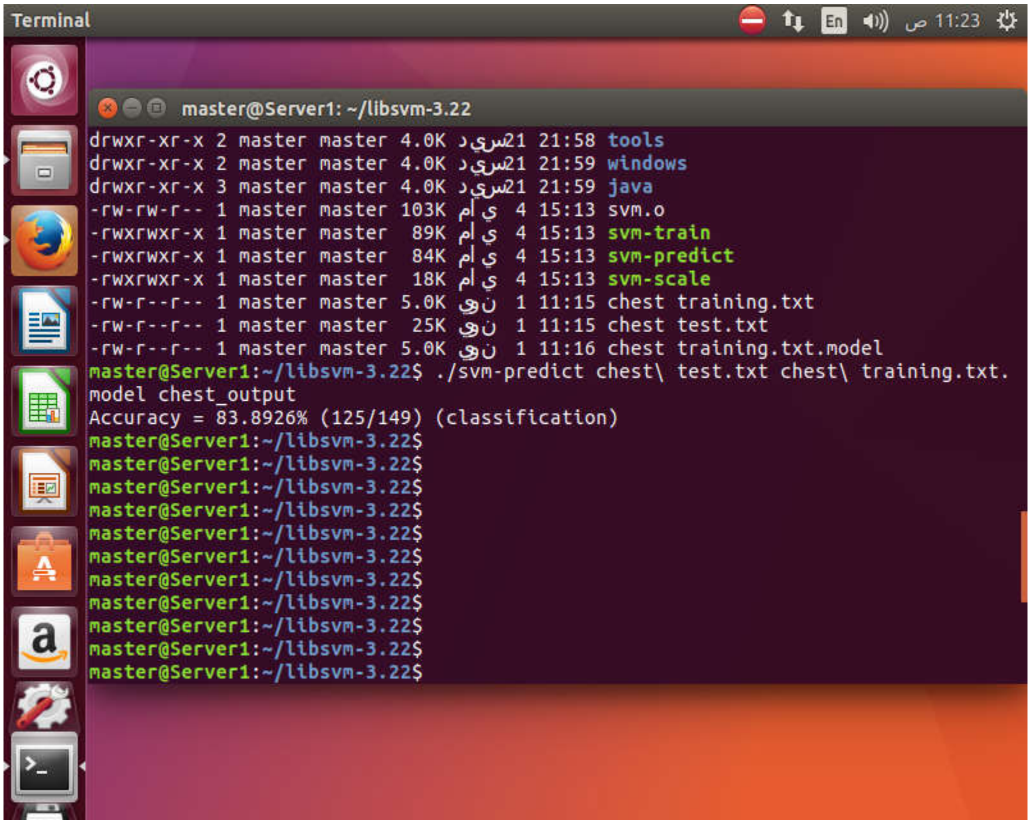

Terminal
11:44 ص
En
master@Server1: ~/libsvm-3.22
-rw-r--r-- 1 master master 5.0K نوف 1 11:15 chest training.txt
-rw-r--r-- 1 master master 25K نوف 1 11:15 chest test.txt
-rw-r--r-- 1 master master 447 نوف 1 11:18 chest_output
-rw-r--r-- 1 master master 5.0K نوف 1 11:24 chest training.txt.model
-rw-r--r-- 1 master master 25K نوف 1 11:25 foot testing.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:27 foot training.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:27 foot training.txt.model
-rw-r--r-- 1 master master 447 نوف 1 11:30 foot
-rw-r--r-- 1 master master 25K نوف 1 11:32 hand testing.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:35 hand training.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:36 hand training.txt.model
-rw-r--r-- 1 master master 447 نوف 1 11:37 hand_out
-rw-r--r-- 1 master master 25K نوف 1 11:41 head test.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:43 head training.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:43 head training.txt.model
master@Server1:~/libsvm-3.22$ ./svm-predict head\ test.txt head\ training.txt.mo
del head_out
Accuracy = 83.2215% (124/149) (classification)
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$

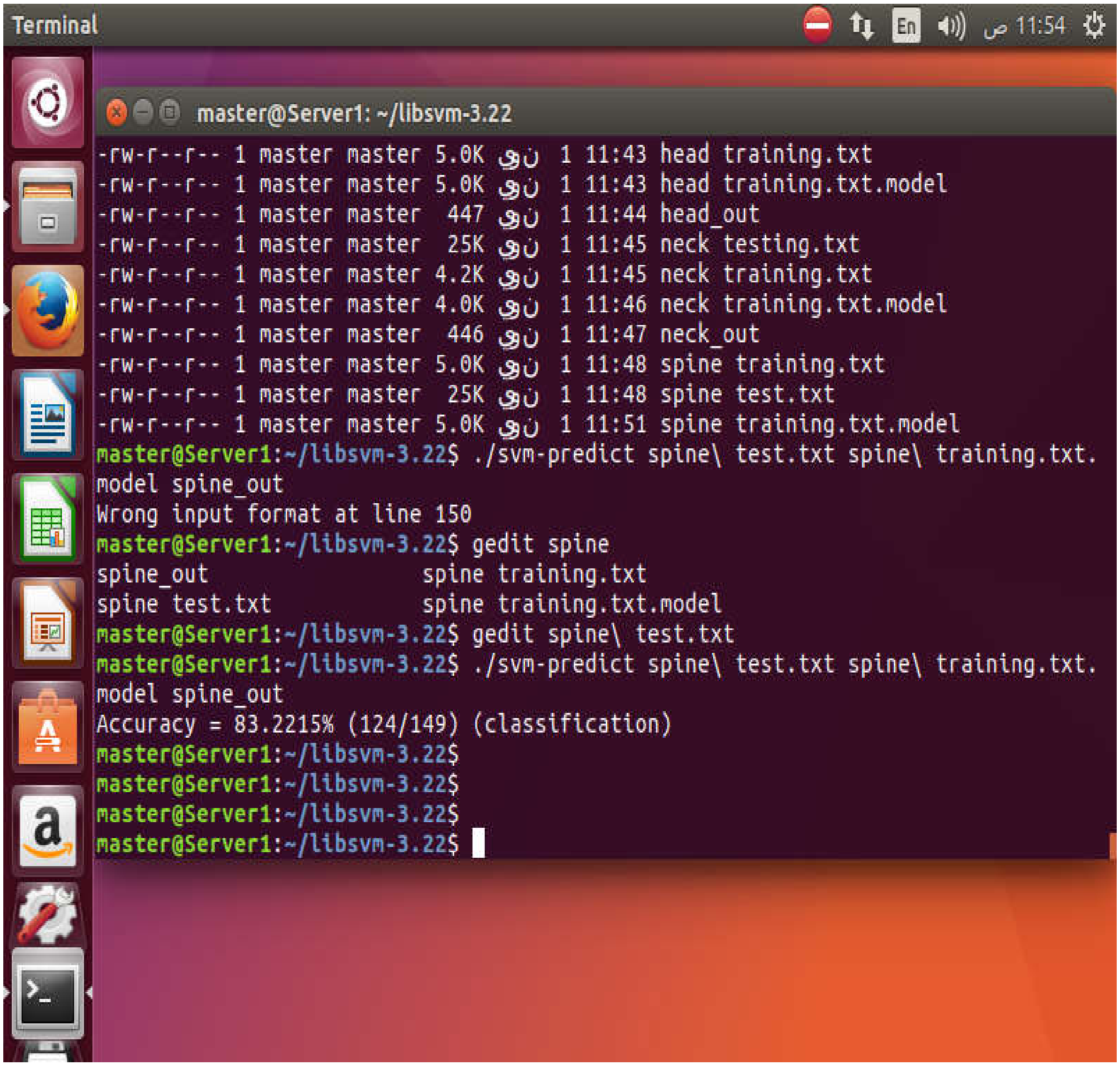


Terminal
En
11:39 ص
master@Server1: ~/libsvm-3.22
-rw-r--r-- 1 master master 25K يون 1 11:15 chest test.txt
-rw-r--r-- 1 master master 447 يون 1 11:18 chest_output
-rw-r--r-- 1 master master 5.0K يون 1 11:24 chest training.txt.model
-rw-r--r-- 1 master master 25K يون 1 11:25 foot testing.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:27 foot training.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:27 foot training.txt.model
-rw-r--r-- 1 master master 447 يون 1 11:30 foot
-rw-r--r-- 1 master master 25K يون 1 11:32 hand testing.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:35 hand training.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:36 hand training.txt.model
master@Server1:~/libsvm-3.22$ ./svm-predict hand\ testing.txt hand\ training.txt .model
Usage: svm-predict [options] test_file model_file output_file
options:
-b probability_estimates: whether to predict probability estimates, 0 or 1 (default 0); for one-class SVM only 0 is supported
-q : quiet mode (no outputs)
master@Server1:~/libsvm-3.22$ ./svm-predict hand\ testing.txt hand\ training.txt .model hand_out
Accuracy = 83.2215% (124/149) (classification)
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$



Terminal
En
11:30 ص
master@Server1: ~/libsvm-3.22
-rw-r--r-- 1 master master 5.5K ديس21 21:58 svm-predict.c
-rw-r--r-- 1 master master 8.8K ديس21 21:58 svm-train.c
drwxr-xr-x 5 master master 4.0K ديس21 21:58 svm-toy
-rw-r--r-- 1 master master 3.4K ديس21 21:58 svm.h
-rw-r--r-- 1 master master 477 ديس21 21:58 svm.def
-rw-r--r-- 1 master master 64K ديس21 21:58 svm.cpp
drwxr-xr-x 2 master master 4.0K ديس21 21:58 tools
drwxr-xr-x 2 master master 4.0K ديس21 21:59 windows
drwxr-xr-x 3 master master 4.0K ديس21 21:59 java
-rw-rw-r-- 1 master master 103K ماي 4 15:13 svm.o
-rwxrwxr-x 1 master master 89K ماي 4 15:13 svm-train
-rwxrwxr-x 1 master master 84K ماي 4 15:13 svm-predict
-rwxrwxr-x 1 master master 18K ماي 4 15:13 svm-scale
-rw-r--r-- 1 master master 5.0K يون 1 11:15 chest training.txt
-rw-r--r-- 1 master master 25K يون 1 11:15 chest test.txt
-rw-r--r-- 1 master master 447 يون 1 11:18 chest_output
-rw-r--r-- 1 master master 5.0K يون 1 11:24 chest training.txt.model
-rw-r--r-- 1 master master 25K يون 1 11:25 foot testing.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:27 foot training.txt
-rw-r--r-- 1 master master 5.0K يون 1 11:27 foot training.txt.model
master@Server1:~/libsvm-3.22$ ./svm-predict foot\ testing.txt foot\ training.txt .model foot
Accuracy = 83.2215% (124/149) (classification)
master@Server1:~/libsvm-3.22$


Terminal
ص 11:23
En
master@Server1: ~/libsvm-3.22
drwxr-xr-x 2 master master 4.0K ديس21 21:58 tools
drwxr-xr-x 2 master master 4.0K ديس21 21:59 windows
drwxr-xr-x 3 master master 4.0K ديس21 21:59 java
-rw-rw-r-- 1 master master 103K ماي 4 15:13 svm.o
-rwxrwxr-x 1 master master 89K ماي 4 15:13 svm-train
-rwxrwxr-x 1 master master 84K ماي 4 15:13 svm-predict
-rwxrwxr-x 1 master master 18K ماي 4 15:13 svm-scale
-rw-r--r-- 1 master master 5.0K نوف 1 11:15 chest training.txt
-rw-r--r-- 1 master master 25K نوف 1 11:15 chest test.txt
-rw-r--r-- 1 master master 5.0K نوف 1 11:16 chest training.txt.model
master@Server1:~/libsvm-3.22$ ./svm-predict chest\ test.txt chest\ training.txt.
model chest_output
Accuracy = 83.8926% (125/149) (classification)
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$
master@Server1:~/libsvm-3.22$



In table2. The accuracy individual classes was 83.426%. Although the training samples are equals five samples for each class, accuracy are differs each from other depending on choosing samples themselves. In addition to that, little number of samples was affected. If we compare accuracy of chest and hand, the hand accuracy less than chest because it has a lot off hand parts (image objects). To illustrate these issues, consider images taken from different body regions. For instance, 'chest' and its sub-body regions are well defined classes that are dominated by high-frequency textures features and thus cannot be confused with other classes. On the different, 'hand' class contains bigger number of sub-body regions as compared with chest, and therefore it presents high intra class variability and inter-class similarity in certain classes within this category which would affect classification performance. This ambiguity is due to features across images that do not often entail a semantic relationship between them.

Table 5.2. Balance training samples

Class name	Accuracy
Chest	83.89%
Foot	83.22%
Hand	83.12%
Head	83.22%
Neck	83.89%
Spine	83.22%
Total	83.426%

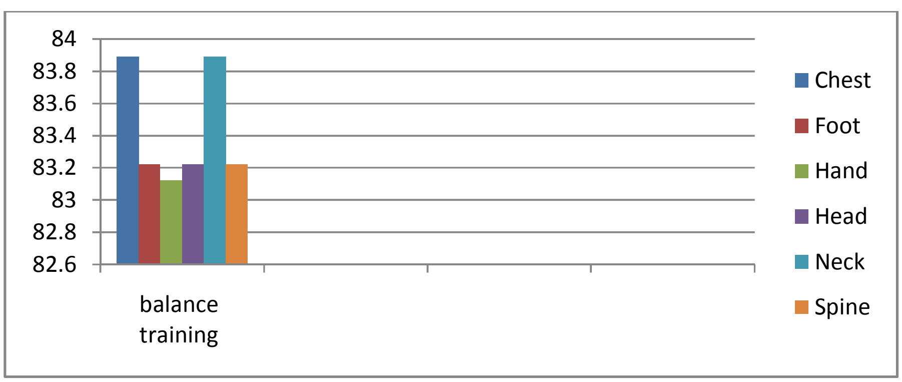


Fig 5.4 Classification on balance training sample

This technique also applied on unbalance training sample. These samples have same classification technique. Each class has accuracy differ from other Table 3 show that, the total accuracy is 82.72%. These accuracy has high different between classes. Foot has 79.5% accuracy which was low compared with spine because on the foot images contains objects differ from one foot training sample to another foot training samples. This variability between image objects affected on its accuracy and if numbers of image sample aren't enough as a training sample for prediction model accuracy will enhance which clearly in spine class. So, number of training samples affected on class accuracy.

Table 5.3. Representation on unbalance classes

Class name	Accuracy
Chest	84.03%
Foot	79.5%
Hand	84.87%
Head	78.57%
Neck	84.48%
Spine	84.87%
Total	82.72%

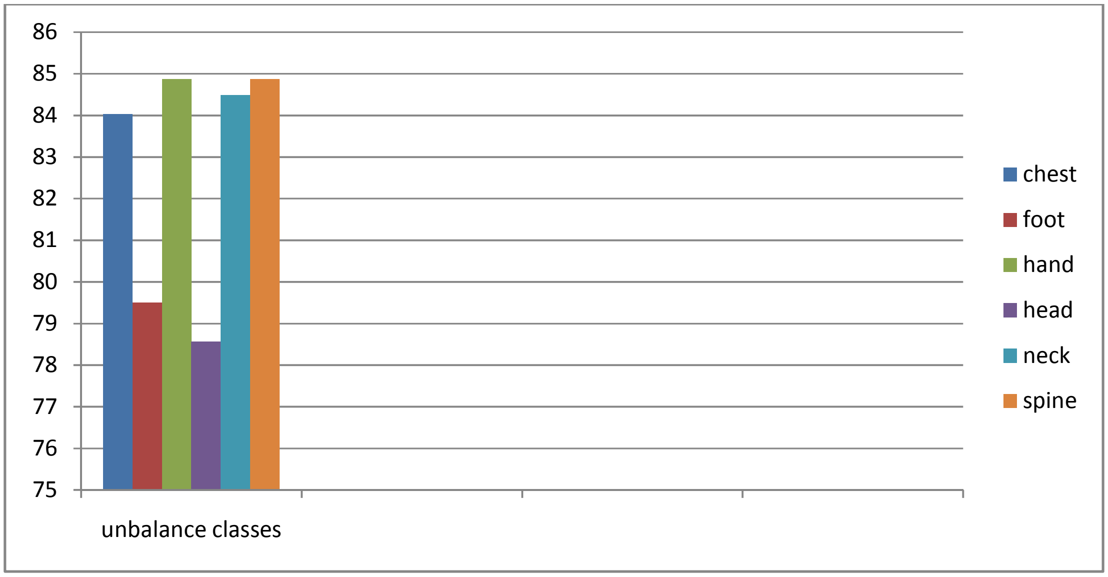


Fig 5.5. Representation on unbalance training data

Chapter 6

6.1 Introduction:

This chapter presents the conclusions from this thesis. In section 6.1, we provide a summary of the thesis. Future work is proposed in section 6.2.

6.2 Conclusion:

In this thesis, we have studied, analyzed, designed and implemented the x-ray medical image representation technique. As we have seen from the results obtained by many works in the literature, it is difficult to obtain high accuracy for every individual class because of the problem of intra-class variability and inter-class similarity in a large medical database. All the results obtained are average classification accuracy on the entire dataset. This is not an accuracy that has been achieved in every individual class. To address this issue, we proposed an x-ray medical image representation technique. At first, we studied content based x-ray image retrieval and classification, specially x-ray image classification and representation. Then, we chose x-ray image representation using texture feature which applied by haralick texture features tools to implement. Experiment showed that haralick texture feature at global level on x-ray image is high accuracy rate compared with previous techniques which applied on same dataset. Several steps are produce to create this x-ray image representation technique. It begins with preprocess step which produce at every image. It produced by applying histogram equalization to increase image contract. Additionally, CCL are applied to detect ROI. Second step, extract texture features to feed SVM classifier which predict classification model to measure accuracy rate. In this work, the feature database of six different classes of X-ray images namely chest, head, neck, hand, arm and spine which applied on 180 x-ray image which segmented to 6 classes.

In this technique five sample for training. As compared with previous technique on same dataset and on global level, experimental results show that 180 x-ray images from 6 classes which attain a higher accuracy rate 83.426%.

6.3 Future work

Following the investigations described in this thesis, the main lines of the research re-mains open and a number of projects could be taken up:

- Applying additional segmentation technique to detect lunch cancer and determine fraction depend on image content
- Contribute shape feature and make multi level feature extracted.
- BoW is used for local patch-based image representation.

References

1. Smeulders, A.W., et al., *Content-based image retrieval at the end of the early years.* IEEE Transactions on pattern analysis and machine intelligence, 2000. **22**(12): p. 1349-1380.
2. Hand, D.J., H. Mannila, and P. Smyth, *Principles of data mining*. 2001: MIT press.
3. Müller, H., et al., *A review of content-based image retrieval systems in medical applications—clinical benefits and future directions.* International journal of medical informatics, 2004. **73**(1): p. 1-23.
4. Zare, M.R., A. Mueen, and W.C. Seng, *Automatic classification of medical X-ray images using a bag of visual words.* IET Computer Vision, 2013. **7**(2): p. 105-114.
5. Jain, A.K., R.P.W. Duin, and J. Mao, *Statistical pattern recognition: A review.* IEEE Transactions on pattern analysis and machine intelligence, 2000. **22**(1): p. 4-37.
6. Zare, M.R., W.C. Seng, and A. Mueen, *Automatic Classification of medical X-ray Images.* Malaysian Journal of Computer Science, 2013. **26**(1): p. 9-22.
7. Rui, Y., T.S. Huang, and S.-F. Chang, *Image retrieval: Current techniques, promising directions, and open issues.* Journal of visual communication and image representation, 1999. **10**(1): p. 39-62.
8. ping Tian, D., *A review on image feature extraction and representation techniques.* International Journal of Multimedia and Ubiquitous Engineering, 2013. **8**(4): p. 385-396.
9. Marée, R., et al. *Biomedical image classification with random subwindows and decision trees*. in *International Workshop on Computer Vision for Biomedical Image Applications*. 2005. Springer.
10. Soh, L.-K. and C. Tsatsoulis, *Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices.* IEEE Transactions on geoscience and remote sensing, 1999. **37**(2): p. 780-795.
11. Ojala, T., M. Pietikainen, and T. Maenpaa, *Multiresolution gray-scale and rotation invariant texture classification with local binary patterns.* IEEE Transactions on pattern analysis and machine intelligence, 2002. **24**(7): p. 971-987.
12. Tamura, H., S. Mori, and T. Yamawaki, *Textural features corresponding to visual perception.* IEEE Transactions on Systems, Man, and Cybernetics, 1978. **8**(6): p. 460-473.
13. Castelli, V., et al., *Progressive search and retrieval in large image archives.* IBM Journal of Research and Development, 1998. **42**(2): p. 253-268.
14. Lehmann, T.M., et al., *Automatic categorization of medical images for content-based retrieval and data mining.* Computerized Medical Imaging and Graphics, 2005. **29**(2): p. 143-155.
15. Winter, A. and R. Haux, *A three-level graph-based model for the management of hospital information systems.* Methods of Information in Medicine, 1995. **34**(4): p. 378-396.
16. Niblack, C.W., et al. *QBIC project: querying images by content, using color, texture, and shape*. in *IS&T/SPIE's Symposium on Electronic Imaging: Science and Technology*. 1993. International Society for Optics and Photonics.
17. Kamavisdar, P., S. Saluja, and S. Agrawal, *A survey on image classification approaches and techniques.* International Journal of Advanced Research in Computer and Communication Engineering, 2013. **2**(1): p. 1005-1009.
18. Mueen, A., M.S. Baha, and R. Zainuddin, *Multilevel Feature Extraction and X-ray Image Classi cation.* Journal of Applied Sciences, 2007: p. 1224-1229.
19. Nowak, E., F. Jurie, and B. Triggs. *Sampling strategies for bag-of-features image classification*. in *European conference on computer vision*. 2006. Springer.
20. Cheng, H. and X. Shi, *A simple and effective histogram equalization approach to image enhancement.* Digital signal processing, 2004. **14**(2): p. 158-170.
21. Mueen, A., R. Zainuddin, and M.S. Baba, *Automatic multilevel medical image annotation and retrieval.* Journal of digital imaging, 2008. **21**(3): p. 290-295.
22. Choras, R.S., *Image feature extraction techniques and their applications for CBIR and biometrics systems.* International journal of biology and biomedical engineering, 2007. **1**(1): p. 6-16.

23. Saber, E. and A.M. Tekalp, *Integration of color, edge, shape, and texture features for automatic region-based image annotation and retrieval.* Journal of Electronic Imaging, 1998. **7**: p. 684-700.
24. Yang, M., K. Kpalma, and J. Ronsin, *A survey of shape feature extraction techniques*. 2008, IN-TECH.
25. Rajam, I.F. and S. Valli, *Content-Based Image Retrieval Using a Quick SVM-Binary Decision Tree–QSVMBDT*, in *Advances in Digital Image Processing and Information Technology*. 2011, Springer. p. 11-22.
26. Srinivas, M. and C.K. Mohan. *Medical Image Indexing and Retrieval Using Multiple Features*. in *Proceedings of CIIT conference*. 2013.
27. Ganesan, S. and T. Subashini, *Classification of medical x-ray images for automated annotation.* J. Theor. Appl. Inf. Techno!, 2014. **63**(3).
28. Fesharaki, N.J. and H. Pourghassem, *Medical x-ray image hierarchical classification using a merging and splitting scheme in feature space.* Journal of medical signals and sensors, 2013. **3**(3): p. 150.
29. Haralick, R.M. and K. Shanmugam, *Textural features for image classification.* IEEE Transactions on systems, man, and cybernetics, 1973. **3**(6): p. 610-621.
30. Guo, Z., L. Zhang, and D. Zhang, *A completed modeling of local binary pattern operator for texture classification.* IEEE Transactions on Image Processing, 2010. **19**(6): p. 1657-1663.
31. Mohammadi, S.M., M.S. Helfroush, and K. Kazemi, *Novel shape-texture feature extraction for medical X-ray image classification.* Int J Innov Comput Inf Control, 2012. **8**: p. 659-76.
32. Unay, D., et al. *Automatic annotation of X-Ray images: a study on Attribute Selection*. in *MICCAI International Workshop on Medical Content-Based Retrieval for Clinical Decision Support*. 2009. Springer.
33. Camlica, Z., H.R. Tizhoosh, and F. Khalvati. *Medical image classification via svm using lbp features from saliency-based folded data*. in *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on*. 2015. IEEE.
34. Ko, B.C., S.H. Kim, and J.-Y. Nam, *X-ray image classification using random forests with local wavelet-based CS-local binary patterns.* Journal of digital imaging, 2011. **24**(6): p. 1141-1151.
35. Rajam, F. and S. Valli, *A survey on content based image retrieval.* Life science journal, 2013. **10**(2): p. 2475-2487.
36. Gindi, A., T.A. Attiatalla, and M.M. Sami, *A Comparative Study for Comparing Two Feature Extraction Methods and Two Classifiers in Classification of Earlystage Lung Cancer Diagnosis of chest x-ray images.* Journal of American Science, 2014. **10**(6): p. 13-22.
37. Mensink, T., *Learning Image Classification and Retrieval Models*. 2012, Université de Grenoble.
38. Wang, S. and R.M. Summers, *Machine learning and radiology.* Medical image analysis, 2012. **16**(5): p. 933-951.
39. Liu, Y., et al., *A survey of content-based image retrieval with high-level semantics.* Pattern recognition, 2007. **40**(1): p. 262-282.
40. Subbulakshmi, C. and S. Deepa, *Medical dataset classification: a machine learning paradigm integrating particle swarm optimization with extreme learning machine classifier.* The Scientific World Journal, 2015. **2015**.
41. Kalpathy-Cramer, J. and W. Hersh. *Automatic image modality based classification and annotation to improve medical image retrieval*. in *Medinfo 2007: Proceedings of the 12th World Congress on Health (Medical) Informatics; Building Sustainable Health Systems*. 2007. IOS Press.
42. Pourghassem, H. and H. Ghassemian, *Content-based medical image classification using a new hierarchical merging scheme.* Computerized Medical Imaging and Graphics, 2008. **32**(8): p. 651-661.
43. Briesemeister, S., *Interpretable machine learning approaches in computational biology*. 2012, Ph. D. dissertation, Universität Tübingen.
44. Joachims, T., *Making large-scale SVM learning practical*. 1998, Technical Report, SFB 475: Komplexitätsreduktion in Multivariaten Datenstrukturen, Universität Dortmund.
45. Rahman, M.M., B.C. Desai, and P. Bhattacharya, *Medical image retrieval with probabilistic multi-class support vector machine classifiers and adaptive similarity fusion.* Computerized Medical Imaging and Graphics, 2008. **32**(2): p. 95-108.
46. Qiu, B., C.S. Xu, and Q. Tian. *An automatic classification system applied in medical images*. in *Multimedia and Expo, 2006 IEEE International Conference on*. 2006. IEEE.

47. Selvi, S.M. and C. Kavitha, *Radiographic medical image retrieval system for both organ and pathology level using bag of visual words.* Int J Eng Sci Emerg Technol, 2014. **6**(4): p. 410-416.
48. Avni, U., et al., *X-ray categorization and retrieval on the organ and pathology level, using patch-based visual words.* IEEE Transactions on Medical Imaging, 2011. **30**(3): p. 733-746.
49. Awedh, M., *Medical Image Classi cation Using Multi—Vocabulary.* Asian Journal of Applied Sciences, 2015. **8**(1): p. 71-78.
50. Xue, Z., et al. *Chest x-ray image view classification*. in *Computer-Based Medical Systems (CBMS), 2015 IEEE 28th International Symposium on*. 2015. IEEE.
51. Bhattacharya, P., M. Rahman, and B.C. Desai. *Image representation and retrieval using support vector machine and fuzzy c-means clustering based semantical spaces*. in *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*. 2006. IEEE.
52. Antony, S.J.S. and D.S. Ravi, *A New Approach to Determine the Classification of Mammographic Image Using K-Means Clustering Algorithm.* International Journal of Advancements in Research & Technology, 2015. **4**(2).
53. Dimitrovski, I., et al., *Improved medical image modality classification using a combination of visual and textual features.* Computerized Medical Imaging and Graphics, 2015. **39**: p. 14-26.
54. Ganesan, S. and T. Subashini, *A content based approach to medical X-Ray image retrieval using texture features.* International Journal of Computers & Technology, 2014. **12**(7): p. 3742-3748.
55. Wieland, M. and M. Pittore, *Performance evaluation of machine learning algorithms for urban pattern recognition from multi-spectral satellite images.* Remote Sensing, 2014. **6**(4): p. 2912-2939.
56. Gueld, M.O., et al. *Comparison of global features for categorization of medical images*. in *Medical Imaging 2004*. 2004. International Society for Optics and Photonics.
57. Ghosh, S. and S.K. Dubey, *Comparative analysis of k-means and fuzzy c-means algorithms.* International Journal of Advanced Computer Science and Applications, 2013. **4**(4).
58. Ray, A. and K. Sasmal, *A new approach for clustering of X-ray images.* 2010.
59. Gong, M., et al., *Fuzzy c-means clustering with local information and kernel metric for image segmentation.* IEEE Transactions on Image Processing, 2013. **22**(2): p. 573-584.
60. Lehmann, T.M., et al. *The IRMA code for unique classification of medical images*. in *Medical Imaging 2003*. 2003. International Society for Optics and Photonics.
61. Patil, M.S.S., M.A. Junnarkar, and M.D. Gore, *Study of Texture Representation Techniques.* image, 2014. **3**(3).
62. Rafael Gonzalez, C., E.R. Woods, and L.S. Eddins, *Digital Image processing using MATLAB*. 2004, 2nded. PublishingHouseofElectronicsIndustry.
63. Kalentev, O., et al., *Connected component labeling on a 2D grid using CUDA.* Journal of Parallel and Distributed Computing, 2011. **71**(4): p. 615-620.
64. Hoffman, R. and A.K. Jain, *Segmentation and classification of range images.* IEEE transactions on pattern analysis and machine intelligence, 1987(5): p. 608-620.
65. Tuceryan, M. and A.K. Jain, *Texture analysis.* Handbook of pattern recognition and computer vision, 1993. **2**: p. 235-276.
66. Pham, T.A., *Optimization of texture feature extraction algorithm.* Computer Engineering Department of Electrical Engineering, Faculty of Electrical Engineering, Mathematics and Computer Science Delft University of Technology, 2010.
67. Noble, W.S., *What is a support vector machine?* Nature biotechnology, 2006. **24**(12): p. 1565-1567.
68. Burges, C.J., *A tutorial on support vector machines for pattern recognition.* Data mining and knowledge discovery, 1998. **2**(2): p. 121-167.
69. Lehmann, T.M., et al. *Content-based image retrieval in medical applications: a novel multistep approach*. in *Electronic Imaging*. 1999. International Society for Optics and Photonics.
70. Hsu, C.-W. and C.-J. Lin, *A comparison of methods for multiclass support vector machines.* IEEE transactions on Neural Networks, 2002. **13**(2): p. 415-425.
71. Abdulrazzaq, M. and S.A. Noah, *Improving the Annotation Accuracy of Medical Images in Image CLEF med 2005 Using K-Nearest Neighbor (kNN) Classifier.* Asian Journal of Applied Sciences, 2015. **8**(1): p. 16-26.

72. Clough, P., et al. *The CLEF 2005 cross–language image retrieval track*. in *Workshop of the Cross-Language Evaluation Forum for European Languages*. 2005. Springer.

Appendices

Histogram equalization java code:

```
import java.awt.image.BufferedImage;

import java.awt.image.WritableRaster;

import java.io.File;

import java.io.IOException;

import javax.imageio.ImageIO;


/**

 *

 * @author Windu Purnomo

 */

public class HistogramEq{

   public int[][] getRGB(File file) throws IOException{

      BufferedImage buf = ImageIO.read(file);

      int width = buf.getWidth();

      int height = buf.getHeight();

      int size = width * height;

      int c = 0, counter = 0;

      int [][] rgb = new int[3][size];

      for(int i = 0; i<width; i++){

         for(int j = 0; j<height ; j++){

            c = buf.getRGB(i,j);

            rgb[0][counter] = (c&0x00ff0000)>>16;

            rgb[1][counter] = (c&0x0000ff00)>>8;

            rgb[2][counter] = c&0x000000ff;

            counter++;
```

```
        }
    }
    return rgb;
}

public float [] RGB2GS (File file) throws IOException{
    BufferedImage buf = ImageIO.read(file);
    int width = buf.getWidth();
    int height = buf.getHeight();
    int size = width * height;
    int c = 0, counter = 0, r, g, b;
    float [] grayScale = new float[size];
    for(int i = 0; i<width; i++){
        for(int j = 0; j<height ; j++){
            c = buf.getRGB(i,j);
            r = (c&0x00ff0000)>>16;
            g = (c&0x0000ff00)>>8;
            b = c&0x000000ff;
            grayScale[counter] = (float) (0.3 * r + 0.59 * g + 0.11 * b);
            counter++;
        }
    }
    return grayScale;
}

public int [] histogram(float[] grayScale){
    int [] pixNum = new int [256];
    int size = grayScale.length;
```

```
    for(int c = 0; c<256; c++){
        int sum = 0;
        for(int i = 0; i<size; i++) if(grayScale[i]==c) sum++;
        pixNum[c] = sum;
    }
    return pixNum;
}

//CDF = Cumulative Distributif Function
public int [] getCDF(int [] histogram){
    int [] cdf = new int [256];
    int cum = 0;
    for(int i = 0; i<256; i++){
        cum += histogram[i];
        cdf[i] = cum;
    }
    return cdf;
}

public int getMinCDF(int [] cdf){
    int minCDF = 257;
    for(int i = 0; i<256; i++){
        if(cdf[i]<minCDF && cdf[i]!=0) minCDF = cdf[i];
    }
    return minCDF;
}

public int getMaxCDF(int [] cdf){
```

```
    int maxCDF = 0;
    for(int i = 0; i<256; i++){
        if(cdf[i]>maxCDF) maxCDF = cdf[i];
    }
    return maxCDF;
}

public float[] equalization(int [] cdf, int pictSize){
    int min = getMinCDF(cdf);
    float e [] = new float[256];
    System.out.println("minimum: "+min);
    System.out.println("pictSize: "+pictSize);
    for(int i = 0; i<256; i++){
        e[i] = (float)((((float)cdf[i]-min)/(float)pictSize)*255);
    }
    for(int i = 0; i<256; i++){
        if(e[i]<0) e[i]=0;
        if(e[i]>255) e[i]=255;
    }
    return e;
}

public float [] picEqualized(float [] grayScale, float [] equalization, int w, int h){
    int size = w*h;
    float [] newGS = new float[size];
    int counter = 0;
    for(int i = 0; i<w; i++){
        for(int j = 0; j<h; j++){
```

```
            newGS [counter] = equalization[(int)grayScale[counter]]; //convert
            counter++;
        }
    }
    return newGS;
}

public void drawImage(float [] newGS, int w, int h)throws IOException{
    int size = w*h;
    int counter = 0;
    BufferedImage im = new BufferedImage(w,h,BufferedImage.TYPE_BYTE_GRAY);
    WritableRaster raster = im.getRaster();
    for(int i = 0; i<w; i++){
        for(int j = 0; j<h; j++){
            raster.setSample(i, j, 0, newGS[counter]);
            counter++;
        }
    }
    ImageIO.write(im, "PNG", new File("a.png"));
}

public static void main (String args[]) throws IOException{
    HistogramEq he = new HistogramEq();
    File file = new File("3370.png");
    BufferedImage x = ImageIO.read(file);
    int width = x.getWidth();
    int height = x.getHeight();
    int size = width * height;
```

```
        float grayScale [] = new float[size];
        int histogram [] = new int[256];
        int cdf [] = new int[256];
        float equalized [] = new float[256];
        float picEqualized [] = new float[size];

        grayScale = he.RGB2GS(file);
        histogram = he.histogram(grayScale);
        cdf = he.getCDF(histogram);
        equalized = he.equalization(cdf, size);
        picEqualized = he.picEqualized(grayScale, equalized, width, height);
        he.drawImage(picEqualized, width, height);
        int counter = 0;
    }
}
```

Connected Component Labeling

```
import java.awt.Color;

import java.awt.Graphics;

import java.awt.image.BufferedImage;

import java.io.File;

import java.util.ArrayList;

import java.util.HashMap;

import java.util.List;

import java.util.Map;

import javax.imageio.ImageIO;

public class CCL

{

 private int[][] _board;

   private BufferedImage _input;

   private Graphics inputGD;

   private int _width;

   private int _height;

   private int backgroundColor;

  public Map<Integer, BufferedImage> Process(BufferedImage input, int bgColor)

   {

           backgroundColor = bgColor;

       _input = input;

       _width = input.getWidth();

       _height = input.getHeight();

       _board = new int[_width][];

       for(int i = 0;i < _width;i++)

           _board[i] = new int[_height];

  Map<Integer, List<Pixel>> patterns = Find();
```

```
        Map<Integer, BufferedImage> images = new HashMap<Integer, BufferedImage>();
inputGD = _input.getGraphics();
        inputGD.setColor(Color.BLUE);
        for(Integer id : patterns.keySet())
        {
            BufferedImage bmp = CreateBitmap(patterns.get(id));
            images.put(id, bmp);
        }
        inputGD.dispose();
        return images;
    }
  protected boolean CheckIsBackGround(Pixel currentPixel)
    {
            // check if pixel color is backgroundColor (white).
        //return currentPixel.color.getAlpha() == 255 && currentPixel.color.getRed() == 255 &&
currentPixel.color.getGreen() == 255 && currentPixel.color.getBlue() == 255;
            return currentPixel.color == backgroundColor;
    }
    private static int Min(List<Integer> neighboringLabels, Map<Integer, Label> allLabels) {
            if(neighboringLabels.isEmpty())
                    return 0; // TODO: is 0 appropriate for empty list
            int ret = allLabels.get(neighboringLabels.get(0)).GetRoot().name;
            for(Integer n : neighboringLabels) {
                    int curVal = allLabels.get(n).GetRoot().name;
                    ret = (ret < curVal ? ret : curVal);
            }
            return ret;
    }
       private static int Min(List<Pixel> pattern, boolean xOrY) {
            if(pattern.isEmpty())
```

```
            return 0; // TODO: is 0 appropriate for empty list
            int ret = (xOrY ? pattern.get(0).x : pattern.get(0).y);
        for(Pixel p : pattern) {
            int curVal = (xOrY ? p.x : p.y);
            ret = (ret < curVal ? ret : curVal);
        }
        return ret; }
private static int Max(List<Pixel> pattern, boolean xOrY) {
        if(pattern.isEmpty())
            return 0; // TODO: is 0 appropriate for empty list
        int ret = (xOrY ? pattern.get(0).x : pattern.get(0).y);
        for(Pixel p : pattern) {
            int curVal = (xOrY ? p.x : p.y);
            ret = (ret > curVal ? ret : curVal);
        }
        return ret; }
private Map<Integer, List<Pixel>> Find()
{
    int labelCount = 1;
    Map<Integer, Label> allLabels = new HashMap<Integer, Label>();
    for (int i = 0; i < _height; i++)
    {  for (int j = 0; j < _width; j++)
       {    Pixel currentPixel = new Pixel(j, i, _input.getRGB(j, i));

           if (CheckIsBackGround(currentPixel))
           {     continue; }
           List<Integer> neighboringLabels = GetNeighboringLabels(currentPixel);
           int currentLabel;
           if (neighboringLabels.isEmpty())
```

```
            {
                currentLabel = labelCount;
                allLabels.put(currentLabel, new Label(currentLabel));
                labelCount++;
            }
            else
            {
                currentLabel = Min(neighboringLabels, allLabels);
                Label root = allLabels.get(currentLabel).GetRoot();
                for (Integer neighbor : neighboringLabels)
                {
                    if (root.name != allLabels.get(neighbor).GetRoot().name)
                    {
              allLabels.get(neighbor).Join(allLabels.get(currentLabel));
                    } } }
                }

            _board[j][i] = currentLabel;
        } }
    Map<Integer, List<Pixel>> patterns = AggregatePatterns(allLabels);
    return patterns;    }
private List<Integer> GetNeighboringLabels(Pixel pix)
{
    List<Integer> neighboringLabels = new ArrayList<Integer>();
    for (int i = pix.y - 1; i <= pix.y + 2 && i < _height - 1; i++)
    {
        for (int j = pix.x - 1; j <= pix.x + 2 && j < _width - 1; j++)
        {
            if (i > -1 && j > -1 && _board[j][i] != 0)
```

```
        {
            neighboringLabels.add(_board[j][i]);
        } } }
            return neighboringLabels;
}
private Map<Integer, List<Pixel>> AggregatePatterns(Map<Integer, Label> allLabels)
{
  Map<Integer, List<Pixel>> patterns = new HashMap<Integer, List<Pixel>>();

  for (int i = 0; i < _height; i++)
  {
    for (int j = 0; j < _width; j++)
    {
      int patternNumber = _board[j][i];

      if (patternNumber != 0)
      {
        patternNumber = allLabels.get(patternNumber).GetRoot().name;

        if (!patterns.containsKey(patternNumber))
        {
          patterns.put(patternNumber, new ArrayList<Pixel>());
        }

        patterns.get(patternNumber).add(new Pixel(j, i, _input.getRGB(j, i)));
      } } }
      return patterns;
}
```

```
 private BufferedImage CreateBitmap(List<Pixel> pattern)
 {
    int minX = Min(pattern, true);
    int maxX = Max(pattern, true);
    int minY = Min(pattern, false);
    int maxY = Max(pattern, false);
   int width = maxX + 1 - minX;
    int height = maxY + 1 - minY;
    BufferedImage bmp = new BufferedImage(width, height, BufferedImage.TYPE_INT_ARGB);
for (Pixel pix : pattern)
    {
       bmp.setRGB(pix.x - minX, pix.y - minY, pix.color); //shift position by minX and minY
    }
    inputGD.drawRect(minX, minY, maxX-minX, maxY-minY);
    return bmp;
 }

 public static String getBaseFileName(String fileName) {
        return fileName.substring(0, fileName.indexOf('.'));
 }
 public static String getFileNameExtension(String fileName) {
        return fileName.substring(fileName.indexOf('.') + 1);
 }
 public BufferedImage getProcessedImage() {
        return _input;
 }
// Sample usage:
 // java org.ml.ccl.CCL images/one.png
 // java org.ml.ccl.CCL images/two.png -5000269
```

```
public static void main(String[] args) {
        if(args.length == 0) {
                System.err.println("Usage: CCL imageFile [bgColor]");
                return; }
        CCL ccl = new CCL();
        try {
int bgColor = 0xFFFFFFFF; // white default background color
                if(args.length == 2) {
                        bgColor = Integer.decode(args[1]);
                }
                BufferedImage img = ImageIO.read(new File(args[0]));
                // TODO: Obtain background color.
                // An attempt to obtain bg color automatically: Center of image.
                System.out.println("image bg color: " + img.getRGB(img.getWidth()/2,
img.getHeight()/2));
                Map<Integer, BufferedImage> components = ccl.Process(img, bgColor);
                String format = getFileNameExtension(args[0]);
                for(Integer c : components.keySet()) {
                        //ImageIO.write(components.get(c), format, new File(getBaseFileName(args[0])
+ "-component-" + c + "."  + format));
                }
                ImageIO.write(ccl.getProcessedImage(), format, new File(getBaseFileName(args[0]) +
"-processed" + "." + format));
        }
      catch(Exception ex) {
        } } }
```

Haralick feature extraction code:

```
import de.lmu.ifi.dbs.jfeaturelib.features.Haralick;
import de.lmu.ifi.dbs.utilities.Arrays2;
```

```
import ij.process.ColorProcessor;

import java.io.InputStream;

import java.io.IOException;

import java.net.URISyntaxException;

import java.util.List;

import javax.imageio.ImageIO;

/**

 * This is is a very basic Class that demonstrates the usage of a descriptor

 * with plain Java without the commandline exctractor.

 *

 * @author Franz */


public class HaralickDemo {

public static void main(String[] args) throws IOException, URISyntaxException {

       // load the image

       InputStream stream = HaralickDemo.class.getClassLoader().getResourceAsStream("5ffs-
processed.png");

       ColorProcessor image = new ColorProcessor(ImageIO.read(stream));

 //initialize the descriptor

       Haralick descriptor = new Haralick();

       //run the descriptor and extract the features

       descriptor.run(image);

     //  obtain the features

       List<double[]> features = descriptor.getFeatures();

      //  print the features to system out

       for (double[] feature : features) {

           System.out.println(Arrays2.join(feature, ", ", "%.5f"));

       } } }
```