RESEARCH ARTICLE

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An Automatic Bone Disorder Classification Using Hybrid Texture Feature Extraction with Bone Mineral Density

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Abstract

A novel approach has been proposed to classify bone disorders for classifying the radiographic bone image as normal, Osteopenia and Osteoporosis. The proposed system consists of three major stages to predict the accurate bone disorder classification. In the first stage, image preprocessing is performed where bilateral filtering is applied to remove noise and to enhance the image quality. Then, the image is fed to Otsu based segmentation approach for segmenting the abnormal area of the bone image. In the second stage, Discrete Wavelet Transform (DWT) is used to the segmented image. Once the image gets segmented then, the Gray-Level Co-occurrence Matrix (GLCM) method is applied to extract the features in terms of statistical texture-based. Further the image which is applied to Principle Component Analysis (PCA) to reduce size of the feature vector. Besides, Bone Mineral Density (BMD) feature namely calcium volume is estimated from abnormal region in the segmented bone image and it is concatenated with the extracted texture features to obtain the final feature vectors. In the final stage, the Multi-class Support Vector Machine (MSVM) takes feature vectors as a inputto classify bone disorders. The simulation result demonstrates that the proposed system achieved the accuracy of 95.1% and sensitivity of 96.15%.

Keywords: Osteoporosis- Osteopenia- DWT (Discrete Wavelet Transform)- GLCM (Gray-Level Co-occurrence Matrix)

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Introduction

The risk of facing diseases in the better life expectancy is more due to the increase of aging process. One of those diseases is the bone disorder that losses the mass of bone and causes the bone diseases such as Osteopenia and Osteoporosis. These are major bone disorders (Oliveira et al., 2013; Ramkumar et al., 2018). The bone degenerative disease is described that the incident of low Bone Mineral Density (BMD) may commonly happen in elder people (Srikanth et al., 2015). The influences of these diseases enlarge the fractures risk, fragility and depressing mechanical force on sustaining normal body actions (Blake et al., 2007). The examination of BMD is an ultimate technique used for early detection of osteoporosis bone diseases (Arifin et al., 2005 ; Nakamoto et al., 2008) BMD examination with the help dual method X-ray absorptiometry (DXA) can be one of the techniques for osteoporosis diagnosis (White et al., 2002). T-scores are standardized scores of DEXA on each dimension for each type of bone. Using WHO standards, the T-score estimated for three categories such as normal bone density, low bone density which referred as osteopenia, and brittle bones which referred as osteoporosis (Gulsahi et al., 2009). Conversely, the prediction of bone disorders using DXA is comparatively more expensive especially in India, resolution and DXA is still a limitation since it cannot define the bone micro-architecture. The primary witness was the first time event of a fragility fracture occurs. Nonvertebral fractures are fragility fractures were some of the fractures are not including in this category such as toes, fingers and skull. The vertebral fractures are identified by radiographic image proof. Bisphosphonates are the most important class of medicine used for postmenopausal osteoporosis (Ian et al., 2018). Here they have been shown some prevention for fractures and also osteopenia is lacking slowly in patients (Sela et al., 2015)

In general, the elder people may have higher chance to meet dentists for the check-up to calculate the bone density using DXA (Oliveira et al., 2013). They insist that there is an association between the condition of hip bone and mandibular bone. Hence, the prediction of mandibularbone information is more important in early detection of osteoporosis (Juliastuti et al., 2016; Katsumata et al., 2014). Various techniques were developed to diagnosis osteoporosis by measuring the cross sectional width of mandibular bone and based on the panoramic image of trabecular bone and its pattern (Arifin et al., 2006; Sapthagirivasan et al., 2013). Slowly the structure of bone changes due to bone disorder such as osteopenia and osteoporosis that can be witnessed through panoramic radiography images. Therefore, the development of specific prediction process is required to extract the particular region from the bone image were

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the pattern changes comparatively.

The significant correlation between the cortical width and femoral neck BMD and spinal BMD0020is proposed (Arifin et al., 2005). Also, BMD examination is conducted for the femoral neck and lumbar spine to predict bone disorder (osteoporosis) (Asano et al., 2006). Present a trabecular structures extraction technique using morphological operations in the dental panoramic radiographs images (Herumurti et al., 2010). They proposed a method for diagnosis osteoporosis based on "Weighted Fuzzy" ARTMAP. Fourier and segmentation techniques are used for extracting the features from the frequency and spatial domain of radiograph images (Gulsahi et al., 2009; Kavya et al., 2015). In the osteoporosis assessment, the selection of vital features from the trabecular pattern alone with anthropometric features is presented (Sela et al., 2015). In this paper, an automatic bone disorder classification is proposed using GLCM (Gray-Level Co-occurrence Matrix) with calcium value and MSVM (Multi-class Support Vector Machine). All Section two discusses the associated works and section three explains the stages involved in the proposed methodology. Followed by sections describes the results with discussion of the proposed technique and concludes the research paper.

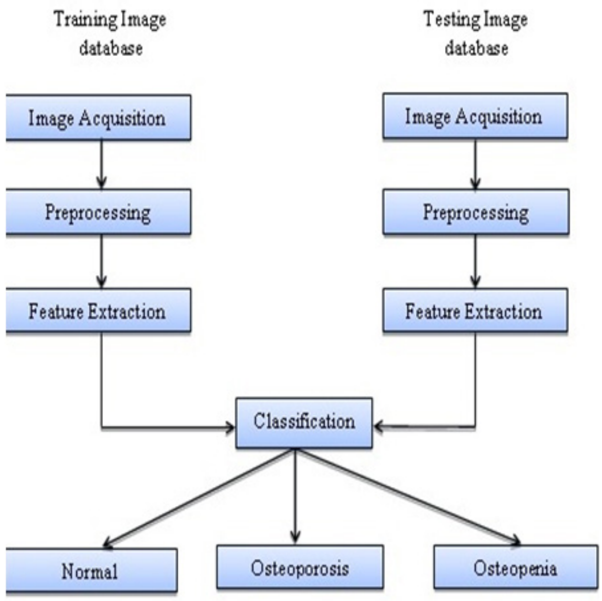


Figure 1. Defined Block Diagram of Proposed Automatic Bone Disorder Classification

Materials and Methods

This paper is an automatic bone disorder classification system is proposed for classifying the bone disorder such as osteopenia and osteoporosis. The proposed methodology consists of three important stages that include the preprocessing, feature extraction and classification. Initially, the method starts from preprocessing which is used to convert grayscale image and enhance the image using filtering technique, and convert it to binary image using segmentation technique. Then the features namely statistical texture-based features of disorders are extracted from segmented image and the texture features are used to predict the category of the bone disorder using machine learning classifiers. The defined block diagram of the proposed bone disorder classification is shown in Figure 1.

Conditioning of Image: Preprocessing

Image preprocessing techniques are essential to remove the noise and boost the quality of the raw input image. Before applying any image processing algorithm, preprocessing stage is the most significant to predict the abnormalities of the image without the effect of background image. In the proposed method, there are four important preprocessing such as resizing, gray-scale conversion, noise removal and segmentation. Figure 2, shows the defined block diagram of preprocessing technique. Further image resizing technique is used to resize the image into uniform size without loss of image quality. Then, the resized image is converted into gray-scale image because the complexity of gray-scale images is lower than the color images. These gray-scale images are used for further processing of noise removal and segmentation.

a) Noise Removal: Bilateral Filtering Method

A bilateral filter is dedicated to digital image to perform non-linearity, edge-preserving and noise-reducing smoothing filter. Bilateral filter replaces the intensity of each pixel in the image with a weighted average of intensity values from nearby pixels of the same image. Based on spatial and range domains of Gaussian distribution the weight is estimated based on the spatial and range domains of GD (Gaussian distribution). Considerably, the weights are depends on Euclidean distance of pixels and the radiometric differences which preserves sharp edges. Image enhancement, dynamic range compression, Image de-noising and illumination correction are the application of the bilateral filtering. The bilateral filtering is described by using following expressions. The Gaussian distance weight function in spatial domain is expressed as,

$$G_s(x,y)=e^{-\frac{x^2+y^2}{2\sigma_s^2}} \quad \text{(eqn.1)}$$

where, σ_s^2 is the spatial domain variance and its mean μ is zero, x and y are the distances between the center and neighboring pixels in the two directions.

The Gaussian distance weight function in range domain is expressed as,

$$G_r(dL,da,db)=e^{-\frac{dL^2+da^2+db^2}{2\sigma_r^2}} \quad \text{(eqn.2)}$$

Figure 2. Block Diagram of Preprocessing Technique

Where, σ_r^2 is the range domain variance and the mean μ is zero. dL, da and db are differences of the three color channels between the center and neighboring pixels. These two domain Gaussians weight functions are joined to formulate the bilateral filter which is employed over every pixel in the image.

b) Segmentation: Otsu thresholding Algorithm

In image recognition, image segmentation is important and challenging problems. Image segmentation is a process of dividing or partitioning an image into important regions in the image. There are many applications of image segmentation process such as measure tissue volume, locate tumors, treatment planning, computer-guided surgery, locate objects and object recognition, etc. Otsu method is an automatic threshold selection region-based segmentation technique. It is a method of global thresholding which based on image's gray value. A method called Otsu method which required the estimation of gray-level histogram before starts the processing. Because of this method is one-dimensional the information of gray-level and it does not provide better segmentation response. Therefore, the two dimensional Otsu algorithm is used which considers both gray-level thresholds of the each pixel and its information of spatial correlation within the neighborhood.

Thresholding is a non-linear procedure which transforms from a gray-scale image into a binary image in which the both levels are considered for the pixels which using threshold value. In this process, categorizing of initial threshold value is based on gray scale and histogram of the image. In the proposed research, an enhanced Otsu's segmentation method is used to segment bone image efficiently based on the image histogram and global thresholding method. Initially, a threshold value is fixed and then each and every pixel value is compared with the fixed threshold value. Based on the comparative result the pixel is classified into two catalog methods such as foreground and background. The comparative result the pixel value leads the threshold value called foreground, if lags the considered as background.

Feature Extraction methods

Feature extraction is a challenging work to improve the resolution of the classification. In the proposed method, the feature extraction based on a hybrid technique in which two methods involved one is GLCM and the second is DWT alone with these methods to reduce the feature vector PCA incorporated. A final feature vector is obtained by concatenating the hybrid feature vector with calcium value which is estimated from the image. Figure 3 demonstrate that the process of proposed feature extraction techniques.

a) Decomposition Techniques

b) To decomposition the image a mathematical tool used for feature extraction.

Extract specific features by using wavelet coefficient from bone images. Here, we scaled and shifted versions of some fixed mother wavelets functions. They offer localized frequency information about a function of a signal, which is used for classification for the bone disorders. By using DWT, a function can be represented in terms of multi-scale representation. Different levels of resolution can be analyzed for an input function. The input image is process by two functions h (n) and g (n) filters for x and y axis. Further it is in row representation of the original image. Four sub-band (LL, LH, HH, HL) transform achieved from images at each scale. By using wavelet coefficients, calculation make for the LL sub-band using haar wavelet function.

c) Data Decorrelation Techniques

The Data Decorrelation is achieved through Principal Components Analysis (PCA) is commonly used dimensionality reduction techniques. For the given data-set, this technique calculates the linear lower-dimensional representation for the data-set using the variance of the reconstructed data is conserved. In the PCA technique, the reduction feature vectors are obtained from the wavelets limiting the feature data-sets by the PCA that produces a supervised cataloging algorithm. Therefore, PCA is to reduce the dimensionality of the wavelet coefficients that increases resolution and becomes accurate classifier.

d) Texture Analysis Techniques

The process of texture analysis prefomed through statistical texture-based features extracted from the essential wavelet selected from PCA using GLCM (Gray Level Co-occurrence Matrix). Hence this can called also as GLSDM (Gray Level Spatial Dependence Matrix). Here feature extraction is a statistical-based technique that can define the spatial association between pixels of different gray levels of the image.

e) Final feature vector

The selected region has converted to binary format using segmentation technique. The results of binary information used for further classification and analysis.

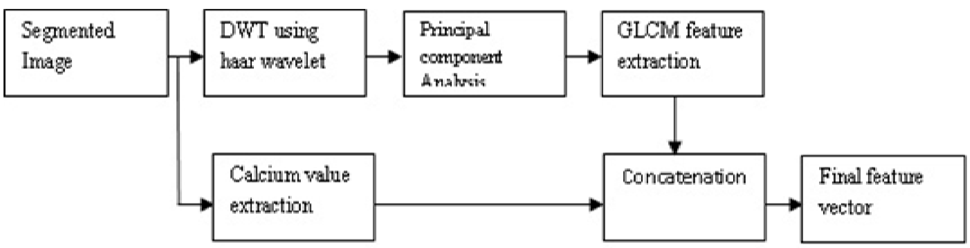
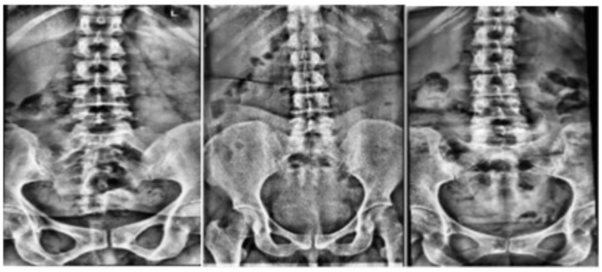
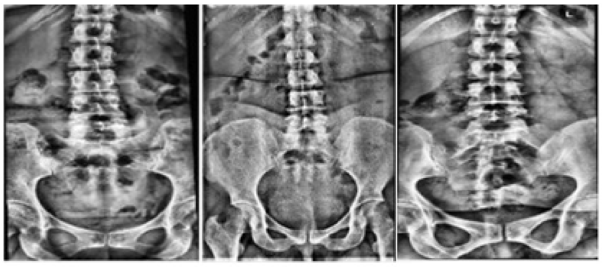


Figure 3. Block Diagram of Feature Extraction Process



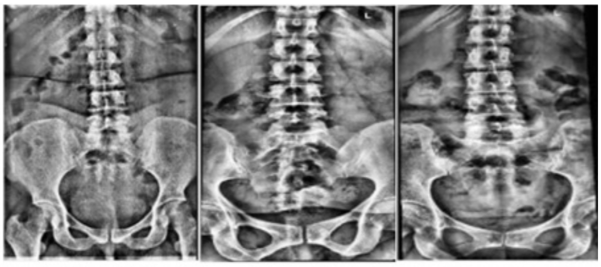
(a) (b) (c)

Figure 4. Input Bone-RBG Images (a) Normal (b) Osteopenia (c) Osteoporosis



(a) (b) (c)

Figure 6. Noise Removed Bone Images (a) Normal (b) Osteopenia (c) Osteoporosis



(a) (b) (c)

Figure 5. Resized and Grayscale Bone Images (a) Normal (b) Osteopenia (c) Osteoporosis

From this, features such as energy, contrast, homogeneity, correlation are extracted.

Classification using Support Vector Machine (SVM)

The machine learning algorithms are used as the classifiers for the image classification in which trained based on the image features as dataset. In general, the classifiers are categorized into two type's namely supervised or unsupervised learning algorithms. The support vector machine is characterized as supervised learning method. This has a great advantage in the accuracy. The accuracy is achieved through practices with more numbers of examples of same kind. Thereby the input as processed with a great knowledge of its input types, so the accuracy improves considerable with other algorithms. The instance of inputs were classified and labeled based on the clustering data like normal, osteopenia and osteoporosis.

Results

`The simulation of automatic bone disorder classification system is carried out using MATLAB. It is widely used software for abnormal detection from various humans part images obtained from various tools. In this simulation, totally 90 X-ray images have been used in which 60 images are taken for training phase and remaining 30 images are taken testing and validation. The image processing techniques consists of following techniques such as image pre-processing, image segmentation, and feature extraction from image and classification technique. The main advantage in resizing of the images is to compare the bone image with an appropriate image with same size. Hereby, they can produce high accuracy output on bone features. It replaces the intensity of each pixel in the image with a weighted average of intensity values from nearby pixels from the same image. This pixel weight is estimated based on the spatial and range domains of Gaussian distribution. Moreover, the weights are depends on both radiometric and Euclidean distance of pixels the differences which preserves sharp edges. The image has been processed to the core (Image denoising, dynamic range compression, illumination correction and image enhancement) with the help of the bilateral filtering. The bilateral filtering is described by the (section 2.1.a) expressions.

Otsu method is an automatic threshold selection region-based segmentation technique. It is a method of global thresholding which depends on gray-scale value of the image. Otsu technique needs the estimation of gray-level histogram. The one-dimensional otsu algorithm considers only the information of gray-level and it does not provide better segmentation response. Therefore, the two dimensional Otsu algorithm is used which considers both gray-level thresholds of the each pixel and its information of spatial correlation within the neighborhood The results of each stages results are demonstrated for three types of images are normal, are Osteopenia and osteoporosis. The raw input bone images of normal, osteopenia and osteoporosis are shown in Figure 4.(a-c)

Then, all the images are resized into 384×256 fixed image size and converted into grayscale image from RGB images which is shown in Figure 5 (a-c)

The Figure 6, demonstrates that the noise removed images using bilateral images which improve the contrast and quality of the images. These noise removed images are fed to the Ostu based segmentation which segments the abnormal area such black spot which are considered as porous in the image.

Figure 7, shows that the segmentation results of all three categories such as normal condition, osteopenia and osteoporosis images. Based on the intensity point's accounts (i.e pixel) in each statistics, groupings are cataloged into Ist order and IInd order statistics condition. GLCM is a technique of extract the second order statistical image's texture-based features. Two dimensional histogram from GLCM contains component in which $(i, j)^{th}$ is the event of frequency where i that arises with j. In the function of distance "d=1" and "$\Theta=0^o$" angle (horizontal), (along the positive diagonal "$\Theta=45^o$", vertical "$\Theta=90^o$" and along the negative diagonal

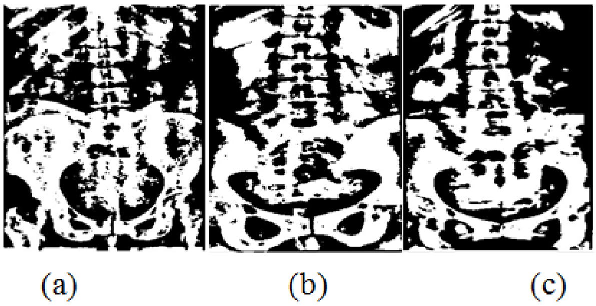


Figure 7. Segmented Bone Images (a) Normal (b) Osteopenia (c) Osteoporosis

"ϴ=135°" and i and j were gray scaled. In this approach, GLCM is generated. Some important texture-based features obtained from the LH and HL sub-bands of the first five levels of wavelet decomposition are as follows contrast, correlation, energy, homogeneity, variance, mean and standard deviationare.

a) Contrast

It is defined as the measure of local variance in the GLCM which is expressed as,

$$\text{Contrast}=\sum_{i,j}(i-j)^2 P_{d,\theta}(i,j) \quad \text{(eqn. 3)}$$

b) Correlation

Correlation is states that as the measures of correlation degree of a pixel over its neighbor for the entire image. It range varies from -1 to 1.

$$\text{Correlation}=\sum_{i,j}\frac{(i-\mu_x)(j-\mu_y)P_{d,\theta}(i,j)}{\sigma_x\sigma_y} \quad \text{(eqn. 4)}$$

c) Energy

Energy is defined as the measure of the amount of pixel pair repetitions. It measures the uniformity of an image.

$$\text{Energy}=\sum_{i,j}(P_{d,\theta}(i,j))^2 \quad \text{(eqn. 5)}$$

d) Homogeneity

Homogeneity is defined as the measures of the closeness of the distribution diagonal of the GLCM elements to the GLCM. It is also called as Inverse Difference Moment (IDM).

$$\text{Homogeneity}=\sum_{i,j}\frac{P_{d,\theta}(i,j)}{1+|i-j|} \quad \text{(eqn. 6)}$$

Where, $P_{d,\theta}(i,j)$ is the probability of computing the pixel with I as a gray-level positioned at the distance d and θ is from the pixel with j as s gray-level, μ_x, μ_y; σ_x, σ_y are the mean and variance of $P_{d,\theta}$ respectively. There are four important preprocessing such as resizing, gray-scale conversion, noise removal and segmentation. The first pre-processing step is to set a predominate size to all three types of images such as normal, osteoporosis and osteopenia. Image orientation and noise level differing in large scale between colored images and grey-scale images. In this context, color image will have high noise ratio in terms of color wave length differ one color to another color. All three type of image such as normal, osteoporosis and osteopenia whose color orientation was changes to grey-scale. The effect of noise ratio reduces noticeably. Unwanted areas were ruled out such as edges of the images, apart from bone images etc. Segmentation processed applied to three types of images such as normal, osteoporosis and osteopenia .The medical images which are difficult to understand, thereby in this stage is required to get better image quality which makes the segmentation more accurate. It will make the bone disorder image for the subsequent two process segmentation and feature extraction.

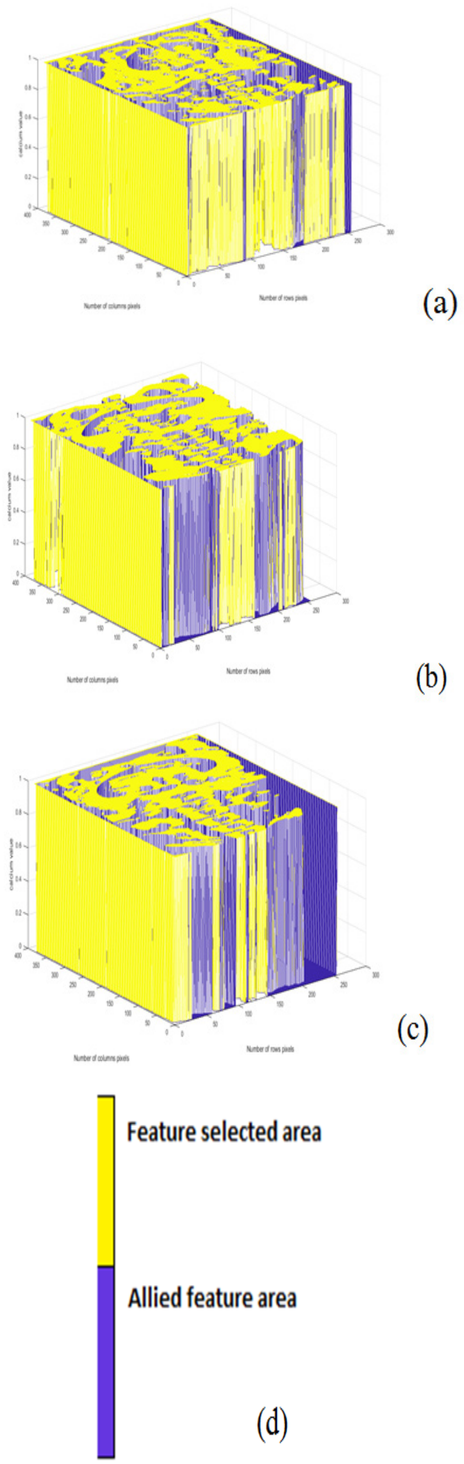


Figure 8. 3D Dimensional Plot of Segmented Image (a) Normal, (b) Osteopenia and (c) Osteoporosis (d) Color identity.

Table 1. Calcium Value Estimation

Types of images	Calcium value (g/cm^2)
Normal	14.4277
Osteopenia	13.1247
Osteoporosis	12.6077

Table 2. Three Classes Confusion Matrix

Classes	Normal	Osteopenia	Osteoporosis	Total
Normal	9	1	0	10
Osteopenia	1	7	1	9
Osteoporosis	0	2	9	11
Total	10	10	10	30

Three Dimensional Plot Of Segmented

The three dimensional representation provide a different predication on the texture features. Also it highlights the calcium intensity areas with the affected areas with respected to the 3-axises. Figure 8, illustrates the 3D plot of the segmented image.

Calcium Value Estimation

The volume of calcium values are estimated for the three types of segmented bone images. These values are one of the parameters which are concatenated with the feature sets for both training and testing phases. Table I demonstrate that the estimated calcium values (g/cm^2) for three categories of images. In statistical features texture-based analysis are estimated from the statistical distribution of examined combinations of intensities at identified positions relative to each other in the image. The methodology calculates a variety of statistical features along with BMD (Bone Mineral Density) such calcium volume is calculated from the binary preprocessed region. The threshold value of bone density values is estimated by Gaussian distribution. BMD is also known as bone mineral content (BMC) which is divided by the predicted area from the scanned image. Calcium volume=BMC/area (g/cm^2). From this equation, the volume of calcium is estimated for all the normal, Osteoporosis and Osteopenia images. These calcium values are concatenated with a hybrid feature vector to attain the final feature vector of the image. Further, the final feature vector is fed to the Multiclass Support Vector Machine (MSVM) is a classifier for training and testing the performance in the classifying of the bone image into three categories normal, Osteoporosis and Osteopenia images.

The machine learning algorithms are used as the classifiers for the image classification in which the image features as been trained and these images were features considered as dataset. Therefore, the model is constructed in the training phase and is used to recognize the pattern during the testing phase. The binary SVM classifier is treated as fundamental classifier for multiclass problem which is mapped into couple of class problems based on divide and conquer technique. For N different classes, binary classifiers N × (N-1)/2 are required for the class classification. In this paper, Multiclass Support Vector Machine (MSVM) has been used for classifying the three types of bone classes such as normal, osteopenia and osteoporosis. In order to classify the three classes, the requirement was binary classifiers N × (N-1)/2 that are six binary classifiers are used as base learners. Each image is fed to all six binary classifiers as a training image, a unique ID is created from each classifiers. In order to calculate the entries a binary comparison is performed for all the six classifiers. Here, +1,-1 and 0 is entered as three different classes such as normal condition,osteopenia and osteoporosis. In the same way calculation performed for all six binary classifiers and the corresponding entries are accounted. Multiclass SVM is a collection of multiple binary classifiers are applied to train input image and also to classify the random input images. In the test phase, the test images are fed to the system which is classified using Multiclass SVM based on the training feature sets. In the performance evaluation, the confusion matrix is a specific table layout that permits visualization of the performance of an algorithm, usually a supervised learning one. Table II shows that the confusion matrix of the three classes. Each column of the matri x represents the cases in a predicted class, while each row represents the occurrences in an actual class.

In the proposed methodology, the data has been separated into two sets in which 65% of the input data sets are used for the training phase and left over 35% of the input data sets were used for testing phase. The performance of the automatic bone disorder classification is evaluated using accuracy, sensitivity and specificity. The following equations (Ian et al., 2018; Juliastuti et al., 2016; Katsumata and Fujita, 2014) were used calculate the sensitivity, specificity and accuracy. Accuracy is described as the quality of the classification algorithm which considers the true positives, false positives and false negatives. The measurement of sensitivity and specificity done is by calculating only the positive and negative cases respectively. TP represents the true positives, TN represents the true negatives, FP is the false positives and FN denotes the false negatives.

$$\text{Sensitivity}=\frac{TP}{TP+FN} \quad \text{(eqn. 7)}$$

$$\text{Specificity}=\frac{TN}{TN+FP} \quad \text{(eqn. 8)}$$

$$\text{Accuracy}=\frac{(TP+TN)}{(TP+FP+TN+FN)} \quad \text{(eqn. 9)}$$

Table 3. Performance Comparison

Technique	Accuracy	Sensitivity	Specificity
Multi-class SVM (Proposed)	95.1%	96.15%	89.00%
Probabilistic Neural Network (PNN) Srikanth et al., (2016)	94.3%	88.2%	94.2%

From each class, 10 images are taken for validating the proposed method using multiclass SVM. Based on these classification results, the performance evaluation parameters attain the 95.1% of accuracy, 96.15% of the sensitivity and 89% of specificity. These results verified the best performance of the proposed methodology. The classification and validation results are illustrated in Table III.

Discussions

In conclusion, this paper, a novel feature extraction technique based bone disorder classification system is proposed. The bone disorders were causing due to lack of vitamins and minerals. Noticeably there are few parameters which are directly proportional to the bone disorders; Calcium makes a huge impact on bone disorders. Thereby the input images were classified based on the disorder condition and calcium values were extracted from the input images. Bilateral filtering is used to eliminate the noise that is unwanted areas such as shape edges etc. Based on this concept the quality of image can be improved. The Otsu based segmentation is employed to segment the abnormal area in the bone image. This technique has more advantages over other segmentation processes such as clustering. Then, a hybrid feature extraction approach is applied to the segmented image for extracting the texture-based features using integration of DWT with GLCM. The feature reduction is achieved by using PCA and it is concatenated with the calcium value of each bone image. MSVM is used to classify the image to three bone disorders such as normal, Osteopenia and osteoporosis image. The simulation result shows that the proposed framework obtained the accuracy of 93.33% and sensitivity of 96.15% which much greater exiting method. This proposed frame work can contribute for the bone disorder patients a lot.

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