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ORIGINAL ARTICLE

Programmed for Automatic Bone Disorder Clustering Based on Cumulative Calcium Prediction for Feature Extraction

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SUMMARY

Background: **The prediction of bone disorders varies between ortho-physicians. A precise bone disorder cataloging system is proposed based on a renewed method for estimating calcium value from a radiological image of the bone.**
Methods: **A deliberate method was employed, the binning technique, for the input image which divides the input image into non-overlapping blocks to obtain accurate calcium volume estimation. In this proposed approach, the input image undergoes two stages of the process. In stage 1, input image preprocessing is accomplished with median filtering to eliminate the unwanted noise and it increases the quality of the image. Further, the processed image is fed to the Otsu-thresholding-segmentation method to highlight the affected regions from the processed bone image. The LBP (Local Binary Pattern) is a technique implemented to pull out the feature vector alone from the input image. Calcium value is estimated from abnormal regions from the segmented bone image and with the help of extracted texture features, the calcium concentration is obtained. MSVM (Multi-class Support Vector Machine) technique is applied to categorize as normal, osteoporosis, and osteopenia. In stage 2, the entire input is divided into 4 x 4 bins and preprocessing, segmentation, feature extraction, and calcium estimation process were applied similar to stage I to each bin separately and the calcium values of all bins are added together.**
Results: **Finally, stage 1 and stage 2 calcium values are summed up to obtain a more precise calcium estimation of the input image the feature vectors which were pull-out from others. The result can prove that the proposed binning technique is best for the bone disorder classification system which attained the greater accuracy of 97.4% and sensitivity of 98.3% when compared with and without binning technique.**
Conclusions: **Validation of the results was performed with bone images, and these bone images were declared by the physician as bone disorder-affected images. The success rate of the bone disorder prediction is 80%.**
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KEY WORDS

bone conditions, calcium, bone mineral density, osteoporosis, osteopenia and feature extraction

INTRODUCTION

The chance of facing disorders in a better life probability is more due to the growth of the aging process. One of those disorders is a bone disorder that damages the volume of bone and causes bone disorders such as Osteopenia and Osteoporosis [13]. Bone degenerative disorder is defined as the reduction of low BMD (Bone

Mineral Density), and this is common with elder people. Low BMD is due to bone disorders, increasing the risk of bone cracks and brittleness and depresses a mechanical force on supporting normal body movement [5]. The examination of BMD is a vital method used for quick detection of osteoporosis bone disorders [3,11]. Bone Mineral Density investigation using DXA is one of the techniques for osteoporosis diagnosis [19]. T-Score is one of the bone density valuations using DXA. Based on World Health Organization values, T-score estimated for three classes such as regular bone density, osteopenia which leads to low bone density, and osteoporosis which leads to brittle bones [6]. However, the prediction of brittle bones using DXA is pricier and DXA is still having drawbacks that it cannot describe the bone microarchitecture. Generally, elder people may have a better chance to meet dentists for the treatment to compute the bone density using DXA. Oliveira et al. [15] projected that there is a relationship between the two bone conditions of the hip bone and mandibular bone. Hence, the calculation from mandibular bone information is more important in the early stage of prediction in osteoporosis [8,9]. Several approaches are established to predict osteoporosis by measuring the thickness of mandibular bone and also based on panoramic images of trabecular bone [2]. The structure of bone changes because of osteopenia, and osteoporosis is imaged as panoramic radiography images. Thus, the development of a specific recognition process is vital to extract the bone image in the specific region. The major correlation between the femoral neck and cortical width bone mineral density and spinal bone mineral density is anticipated [3]. Also, a BMD examination is conducted for the spine and the neck to calculate osteoporosis. Blake et al. [4] presented a trabecular structures extraction technique using morphological operations in the dental panoramic radiograph images. Eugene et al. [7] proposed a technique for detecting osteoporosis based on Weighted Fuzzy ARTMAP. Fourier method and segmentation method were used to extract features from the frequency of radiograph images and spatial domain of radiograph images.

Literature review

Sapthagirivasan & Anburajan [17] presented an osteoporosis analysis using trabecular features and support vector machine (SVM) for osteoporotic disorder prediction. At first, the input image is strengthened and then the features like delta, alignment, the solidity of spur and boundness were extracted. The Radial Bias Function classifies to recognize the images from the input side. The evaluation of the pinpointing capability is to spot input elements with stumpy bone mineral density values in fifty osteoporotic fractures on the femoral neck. Oliveira [15] and Widyaningrum [21] proposed panoramic images and integration of periapical for osteoporosis identification. In the feature extraction step, the shape and structure-based features of the porous bone are extracted from both images. From these extracted features from the bone, the important feature vectors are selected and it is used by the Decision Tree (DT) classifier to recognize the abnormal bone image. The valuation of osteoporotic disorder from bone radiograph images turns out to be the main task in image processing, and osteoporotic texture images and healthy subjects display a high degree of resemblance. It also increases the complexities during differentiating such textures. Zhang et al. [10] proposed analysis for characterization of the textured images to distinguish the normal patient from the pathologic patient. The GLCM feature extraction is used to extract texture features from the images.

The feed-forward Neural Network (NN) classifier is used to detect the osteoporosis image from the normal image. Davidowitz and Kotick [8] presented a scheme that consists of the purpose of the (Region of Interest) ROI in the image by DXA. The proposed feature extraction from ROI is classified based on the bone conditions.

To balance the offset on the ROI, the least value of intensity is used. In the feature extraction stage, the features are extracted using the fraction of intensity values and the ROI total area. Then, these features are fed to the ANN for the clustering of normal and abnormal BMD detection.

Research methodology

In this paper, an automatic bone disorder classification system using calcium estimation from the image is proposed for classifying bone disorders such as osteoporosis and osteopenia. The proposed methodology contains two stages which include three important processes such as preprocessing, segmentation, and calcium estimation. Initially, the method starts from preprocessing which is used to convert gray-scale images. To enhance the image, filtering technique is used to convert it to a binary image using segmentation technique. Then, the features specifically like texture-based features and segmented images were extracted and calcium values are estimated. Finally, stage 1 and stage 2 calcium values are summed up to obtain a more precise calcium estimation of the input image the feature vectors which were extracted from others.

The result can prove that the proposed binning technique is best for the bone disorder classification system which attained greater accuracy, when compared with and without binning technique. The block diagram of the proposed system is shown in Figure 1.

Stage 1: Processes

In stage 1, the entire input is applied to preprocessing, segmentation, feature extraction, and calcium estimation process.

Preprocessing

Image preprocessing techniques are essential to remove the unwanted quantities of so-called noise and boost the feature of the raw input image. Before applying any image processing algorithmic steps, the preprocessing stage is the most significant to predict the abnormalities of the image without the effect of a background image. The digital bone disorder images are medical images that are difficult to understand; hence, 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 2 processes: segmentation and feature extraction. In the proposed method, there are four important preprocesses such as resizing of the image, converting it into a gray-scale image, noise removal, and segmentation. Image resizing is used to resize the image into uniform size without loss of image quality. Then, the image is converted to a gray-scale image that reduces the difficulties in the image then the colored images and these gray-scale images are used for further processing of noise removal and segmentation. A median filter is applied to processing images, and it is a robust method to remove the impulsive noise [14]. It is a computationally rigorous operation, and it is also difficult to implement it in real-time application. The median filter is superior to the mean filter of conserving productive detail in the image. The filter cogitates all pixels of the image in turn and checks nearby neighbors to decide whether or not the same is representative of its ambiances. In that case, substitute the pixel value with the median of the neighboring pixel values. The median is estimated by first sorting the entire pixel values of the images from the surrounding neighborhood into numerical ascending order and substituting the pixel being considered with the middle pixel value. In case the neighborhood pixel contains the same values then the average of the two middle pixel values is considered. The median filter uses spatial filtering operation, so it uses a 2-D mask which is applied to each pixel of the input image. To apply the mask means to the center pixel of the image, evaluating the covered pixel brightness and determining which brightness value is the median value. The median value is found by placing the brightness pixel value in ascending order and selecting the center value of a pixel. The median value obtained will be the value for that pixel in the output image. Here, in the proposed technique, noise from the input image is detached; the processing steps are as follows, Step 1: Binning size is set as 3 x 3 for the input image, Step 2: Sort the pixel based on its value from the particular window in ascending order and discover the median pixel value p, Step 3: The original pixel p is replaced by the median of those pixels in the 3 x 3 neighborhood, Step 4: Above steps are repeated for all windows of the test image.

Otsu thresholding segmentation

In image recognition, image segmentation is the most important process. It is defined as the progression of dividing an input image into significant and equal portions. There are more applications to carry out image segmentations such as measuring locate objects, locate tumors, treatment planning, tissue volume, computer-guided surgery, object recognition, and a lot more. Otsu method is an automatic threshold selection region-based segmentation technique [21]. It is a method, whose threshold value only depends on the image's gray value. This method required the estimation value of the gray-level histogram required before starting the processes. The one-dimensional contains the information of gray-level, and it does not give a better segmentation response. Therefore, the 2D Otsu algorithm is used which considers both gray-level thresholds of each pixel and its information of spatial correlation within the neighborhood. In the paper, enhanced Otsu's segmentation technique is deployed to segment bone images capably using the global thresholding method and image histogram. All pixel in the input image is compared with this onset value. If the pixel values exceed the threshold value, it shall be intimated as the foreground image, and if it is below the onset value then intimated as a background image. Thresholding is said to be a non-linear process that converts the image from grayscale to a binary image. Here conversion has two levels that are considered to pixels using the threshold value. Here the process, the selection of the initial threshold value, is purely based on the histogram and grayscale of an image.

Feature extraction

Here, an algorithm is used for feature extraction which is based on the LBP operator [1]. In this LBP operator, the features of all images are extracted then images are partitioned into tiny blocks and lastly, the binary pattern histograms are extracted as shown in Figure 2. Binary code is generated for each neighboring pixel [12]. The LBP operators are used for describing image texture. By selecting the neighboring region of each pixel as 3 x 3, whose central value is a threshold value and taking the results in terms of binary number into account, and accordingly, the pixels are named. Further, the histograms of the names are used as an image descriptor shown in Figure 3. LBP is extended to operate on the circular regions with variable sizes.

The produced histograms have different in order associated with all regions of the input image. The below equation redefines the histogram of the image as,

$$H_i = \sum_{x,y} I\{f(x,y) = i\} \qquad i = 0,1,\dots,n-1$$

"n" is the no. of the different names generated by LBP, based on below equation as,

$$I(A) = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases}$$

Histogram contains detailed information about tiny patterns like borders, flat regions, spots and a lot more. To get an appropriate representation of the image and to achieve image spatial, information is also saved. Therefore, the input image is partitioned into bins (blocks) and the extended histogram is based on the below equation,

$$H_{i,j} = \sum_{x,y} I\{f(x,y) = i\}\, I\{(x,y) \in R_j\},$$
$$i = 0,1,\dots,n-1 \text{ and } j = 0,1,\dots,m-1$$

Table 1. Calcium value Estimation.

Types of images	Calcium value (g/cm^2) without binning technique	Calcium value (g/cm^2) with binning technique
Normal	6.7143	8.6711
Osteopenia	6.5614	8.2554
Osteoporosis	5.9459	7.2035

Table 2. Specificity and sensitivity measurement references.

Specificity and sensitivity measurement references			
TP (true positives)	TN (true negatives)	FP (false positives)	FN (false negatives)

Table 3. Performance comparison.

Technique	Accuracy	Sensitivity	Specificity
Multi-class SVM with binning technique	97.4%	98.3%	91.8%
Multi-class SVM without binning technique	95.1%	96.15%	89.00%
Probabilistic Neural Network (PNN)	94.3%	88.2%	94.2%

Table 4. Calcium values for the validation images.

S. No.	Image	Calcium values with binning	Bone disorder prediction
1	(a) Image	8.6414	Osteopenia
2	(b) Image	8.8764	Osteopenia
3	(c) Image	6.3439	Osteoporosis

Table 5. Calcium value estimation.

S. No.	Calcium values from subject's reports	Calcium values estimated from proposed method	Bone disorder prediction based on report	Prediction based on proposed method
1	8.5	8.6414	Osteopenia	Osteopenia
2.	8.9	8.6235	normal	Osteopenia
3	8.3	8.6336	Osteopenia	Osteopenia
4	8	8.2300	Osteopenia	Osteopenia
5	6.5	6.812	Osteoporosis	Osteoporosis
6	9.6	9.5258	normal	normal

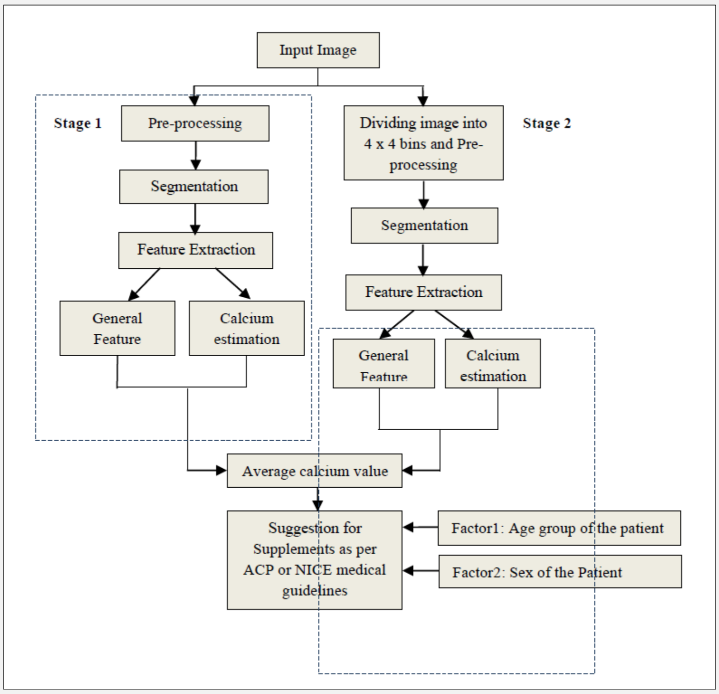

Figure 1. Block diagram of proposed Methodology.

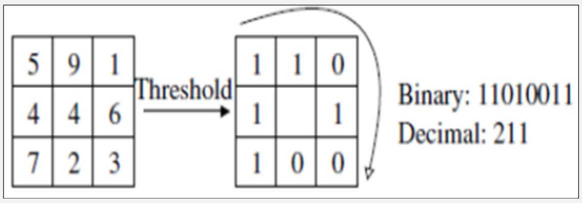

Figure 2. LBP operator.

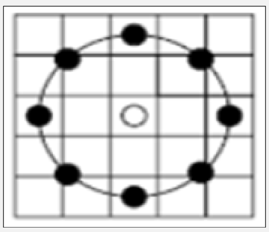

Figure 3. Circular neighborhood blocks.

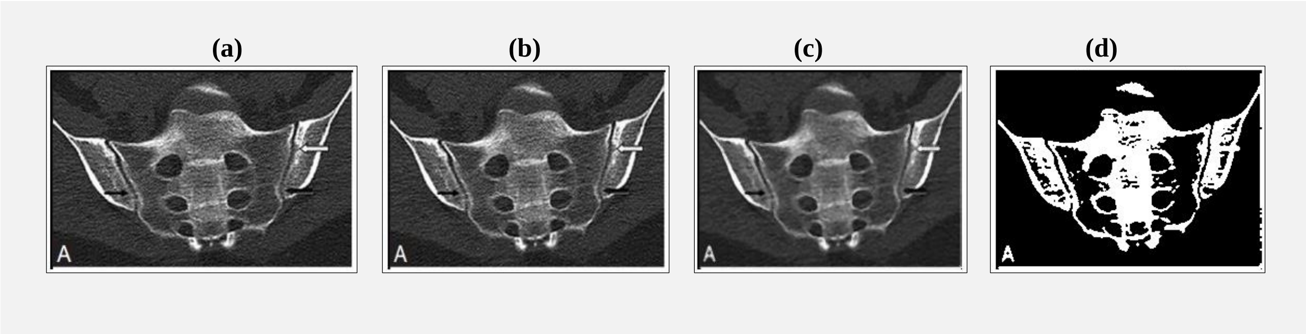

Figure 4. Results of stage 1 (a) Input Image, (b) Resized Image, (c) Noise removed Image, (d) Segmented image.

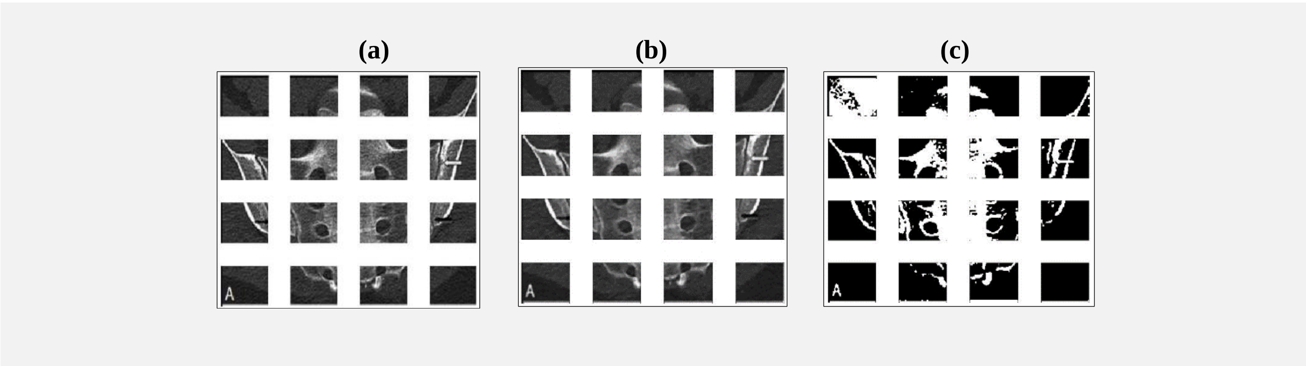

Figure 5. Results of stage 2, (a) resized image (b) Noise removed image (c) Segmented image.

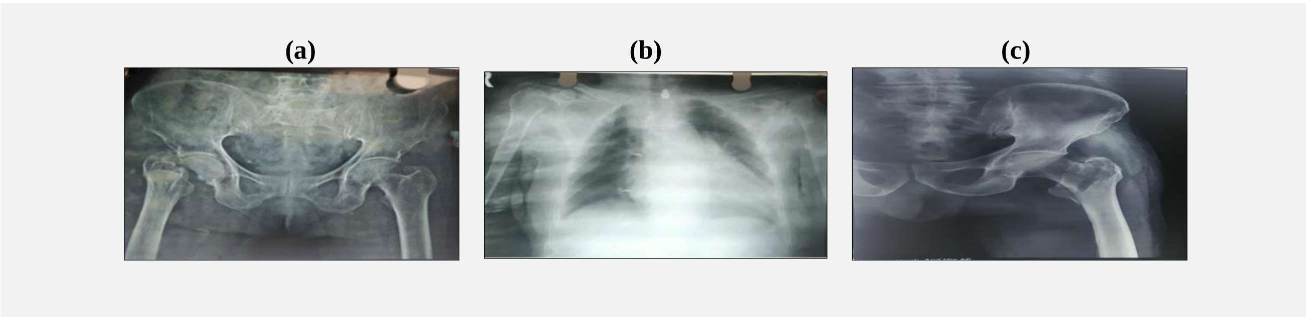

Figure 6. Radiology images of osteoporosis and osteopenia for systematic validation for clustering based on calcium estimation (a, b, & c).

Here, the description of the image is attained in three different levels. The names of the histogram have the details on some patterns at the pixel level in the image, and then the names are gathered in a tiny area in order to provide some details on the regional level. The regional histograms are connected to provide an optimal report on the image.

Calcium estimation

Once the region is converted to 0's and 1's using the segmentation technique, features are to be extracted from binary numbers. This number is used for further classification and analysis. From these, features like correlation, energy, contrast, homogeneity is extracted. The proposed methodology calculates the various features which include BMD and the calcium volume is

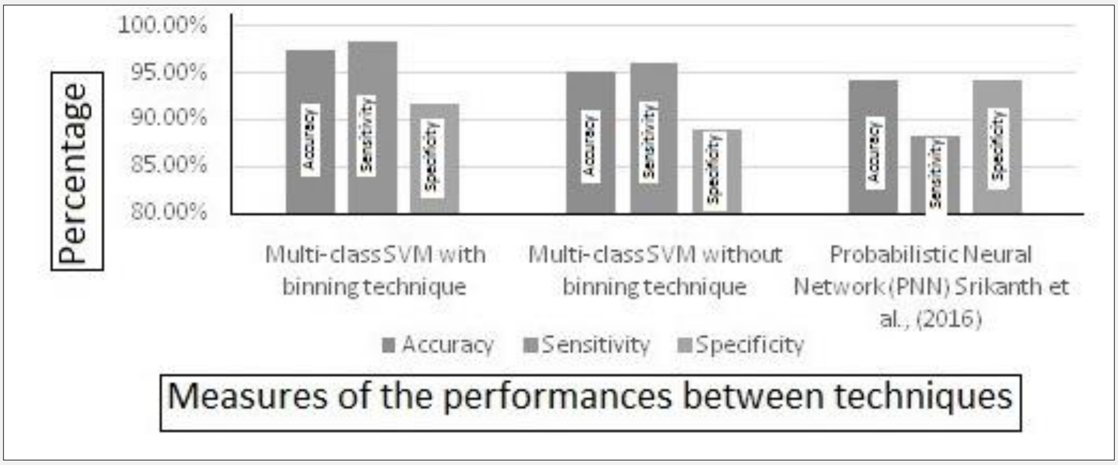

Figure 7. Performences Comparsion between Existing and Proposed Techinques.

calculated from the binary preprocessed region. The threshold value is identified by a method called Gaussian distribution for bone density values. BMD is meant as bone mineral content (BMC) which is divided by the predicted area of the input 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 hybrid feature vectors to obtain the final feature vector.

Stage 2: Processes

Here, the input bone image has been processed to estimate its calcium value in two stages. In both stages, the image undergoes all the above-mentioned image processing techniques with binning in the first stage and without binning in the second stage. Binning is the procedure of combining a cluster of pixels into a single pixel and it is a way a group a number of more or less continuous values into a smaller number of bins. Binning, also known as quantization, is used for transforming continuous numeric features into discrete ones. To construct a histogram, the first step is to “bin or bucket” the range of values that is, divide the entire range of values into a series of intervals and then count how many values fall into each interval. Windowing is another process that is similar to binning process but it varies in the procedure as it is the process of selecting some image segment of the total pixel value range and then displaying the pixel values within that segment over the full brightness. The bins are usually specified as consecutive non-overlapping intervals of a variable. The main advantage of binning process as follows, i) Faster readout speeds, ii) Improves signal to noise ratio (SNR), iii) Ability to convert continuous values into discrete values and iv) Ability to increase frame rate. The entire input is divided into 4 x 4 bins [21] and applied to preprocess, segmentation, feature extraction, and calcium estimation process to each bin separately and the calcium values of all bins are added together. Finally, stage 1 and stage 2 calcium values are summed up to obtain more precise calcium estimation. This makes the difference between the two stages and estimated calcium values were averaged from both stages.

RESULTS AND DISCUSSION

The simulation of the automatic bone disorder classification system is carried out using MATLAB R2016, 4GB RAM system. It is widely used software for abnormal detection from various human part images obtained from various tools. The process consists of pre-processing of the image, image segmentation and finally feature extraction technique. Results of each stage were demonstrated for three types such as normal, osteoporosis, and osteopenia of images. The Figure 4 demonstrates different preprocessing stages of an osteopenia bone image. Figure 4(a) is the raw input image and then the image are resized to 384 x 256 fixed image size and converted into a grayscale image from RGB image which are publicized in Figure 4(b). Figure 4(c) demonstrates that the noise removed images using median images which improve the contrast and quality of the images. These noise-removed images are fed to the Otsu-based segmentation which segments the abnormal area of the images. Figure 4(d) publicized the segmentation results of the image.

In stage 2, the entire input is divided into 4 x 4 bins and applied to preprocessing, segmentation, feature extraction and calcium estimation process to each bin. Then, the calcium values of all bins are added. Finally, stage 1 and stage 2 calcium values are summed to obtain a more precise calcium estimation (Figure 5).
The volume of calcium values is estimated for the three types of segmented bone images. These values are one of the parameters which are concatenated with the features set for both training and testing phases. Table 1 demonstrates that the estimated calcium values (g/cm^2) for three categories of images.
The performance of the automatic bone disorder classification is evaluated using accuracy, sensitivity and specificity. Accuracy is described as the quality of the classification algorithm which considers four items as false positives, true positives, and false negatives, true negative. Specificity and sensitivity measure only positive and negative cases, respectively (Table 2).
In Figure 6, the graphical representation shows the individual performances such accuracy, sensitivity and specificity of multi-class SVM with binning technique, multi-class SVM without binning technique and probabilistic neural network (PNN). 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 95.1% of accuracy, 96.15% sensitivity and 89% of specificity. These results verified the best performance of the proposed method. The classification and validation are illustrated in Table 3. Calcium values were estimated for the images shown in Figure 6 using the multi-threading stages method, and these images were declared by the physician as bone disorder patients. The calcium values were tabulated in Table 4 for all three bone images (a, b, & c) displayed in Figure 6.
The result listed in Table 4 as image "a" and image "b" is affected with osteopenia condition and image "c" is affected with osteoporosis condition and the same was accepted by the physician. Table 5 displays the overall validation report and the values were compared with the original subject's calcium values and predicted reports provided by the practitioner and proposed method's calcium values and predicted conclusions. The bone disorder prediction ratio attained 80% for the proposed research methodology and the remaining 20% de-prediction was due to image capture position and low clarity (less feature extraction affected). Aiming to reduce the de-prediction ratio considerably by improving the feature extraction from processed input images, therefore estimating the calcium values can improve and hence the success rate can be improved.
The Figure 7 shows the graphical representation of the performences different techniques with respect to bar chart and the proposed system has high impact on the expected outcomes when compared with other techniques. This added more weightage to proposed system. Table 5 displays the overall validation finding of the calcium values of the subjects of the proposed system and original finding and prediction from the practitioner.

CONCLUSION

The calcium (Ca) element was estimated for the classification of bone disorders by averaging the calcium values with and without binning techniques and further processed with image processing techniques for classification. The results are improved in terms of accuracy (97.4%), and sensitivity (98.3%). Validation of the results was performed with bone images and these bone images were declared by the physician as bone disorder affected images. The success rate of the bone disorders prediction is 80% and the remaining 20% was de-predicted due to image capture position and low clarity (less feature extraction affected). Thereby this study provides a valid recommendation for patients on their bone disorder conditions and based on the NICE guidelines, few suggestions on medication have been provided for different age groups of bone disorder patients.

Declaration of Interest:
None of the authors have any conflict of interest to declare.

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