Recognition of Osteoporosis through CT-Images

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Abstract: Image processing has a very big potential to do virtually anything. This project comes to the extent of development details on Recognition of osteoporosis through CT images. The objective of the recognition of osteoporosis is to identify and distinguish between a normal bone image and osteoporotic bone image with its case as severe or non-severe. Osteoporosis is due to the following two phenomena: a reduction in bone mass and a degradation of the micro architecture of bone tissue. Osteoporosis is a disease in which the quality of bone is reduced, leading to weakness of the skeleton and increased risk of fracture and change is observed in micro architecture. In this project we propose a methodology to build a system to identify the normal bone image and affected bone image with the case severe or non severe. We use contrast feature of the grey level co-occurrence matrix and apply thresholding to detect the normal or osteoporotic bone image.

Keywords: Osteoporosis, Computer Vision, Bone Images, Endocrine, Rule Based Classification

I. INTRODUCTION

Computer vision is a field that includes methods for acquiring, processing, analysing, and understanding images and in general, high-dimensional data from the real world in order to produce numerical or symbolic information. A theme in the development of this field has been to duplicate the abilities of human vision by electronically perceiving and understanding an image. As a scientific discipline, computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences, views from multiple cameras, or multi-dimensional data from a medical scanner. Computer vision and image processing are widely used in industry, biological science, material science, medical science, weather forecasting and many other fields.

In our system, computer vision is being applied to medical field. Medical field is an aggregation of sectors within the economic system that provides goods and services to treat patients with curative, preventive, rehabilitative, and palliative care. The medical field is divided into many sectors to meet health needs of individuals and populations. The health care industry is one of the world's largest and fastest-growing industries. Medical industry forms an enormous part of a country's economy.

In the system we are concerned on a part of orthopaedic related disease known as osteoporosis. The system is inspired for the poor people who are not capable to go for high-end testings carried out for finding the osteoporosis. It is designed for the ease of use for the people to know about their level of disease with less time consumption and minimum cost.

II. PROPOSED SYSTEM

The broad classification of the normal and affected bone images according to the age groups are shown in figure 1.

The bone images are classified into normal bone images and affected bone images. The difference between the normal bone image and affected bone image is identified by checking the thickness between the cortical bone and cancellous bone. The normal bone image consists of more number of white pixels and an affected bone image consists of more number of black pixels. The normal bone images are further categorized into three age groups that is the age group of 1 to 25, age group of 26 to 50 and age group of 51 and above. The categorized age group images are further classified into severe and non-severe osteoporotic bone images. The normal bone images categorized into the different age groups from 1 to 25, 26 to 50 and 51 and above are as shown in the figure 2.
In the affected bone images, we are dealing with the disease osteoporosis. If the thickness between the cortical and cancellous bone decreases then the calcium content in the bone is said to be reduced. And an osteoporotic bone image consists of more number of black pixels.

The affected bone images are categorised into the different age groups from 1 to 25, 26 to 50 and 51 and above are as shown in the figure 3.

Depending on the thinness of the bone the severity of the bone image is detected. The severity and non-severity of the osteoporotic bone images of each age group are detected. The samples of severe osteoporotic bone images and non-severe osteoporotic bone images are shown in the figure 4.
III. DESIGN & IMPLEMENTATION

The design phases of the proposed work are as shown in the figure 5. The phases consist of image acquisition, pre-processing, image segmentation, feature extraction and rule based classification.

**Image acquisition:** CT-images are acquired from various hospitals by visiting the hospitals frequently. Images are classified into normal bone images and affected bone images. The images are acquired on the basis of factors like age and gender. The information related to the patients such as the patient’s name, age and gender are not revealed in the images we are using for training our system. After the frequent visits to the hospital the total numbers of images obtained are 192 bone images. Out of the 192 images acquired, 78 are the normal bone images and 114 are the affected bone images. According to images we collected we get to know that the osteoporotic disease occurs more for the older age people rather than the young age people. The samples our data collections are shown in the figure 6. And in the figure 7.

**Pre-processing:** Usually the images that are obtained during image data collection may not be suitable for classification purpose because of certain factors, such as lighting intensity and size variations and some noise introduced by devices. We carried out the following work in pre-processing.

- **Resize:** The acquired images are resized into a specific dimension.
- **Crop:** The part of the image is cropped as needed.

**Image segmentation:** In image segmentation the required part is obtained by segmenting CT images. Grey level thresholding is being used. It is a fundamental tool for segmentation of grey level images when objects and background pixels can be distinguished by their grey level values. After cropping and resizing of the grey level image we apply grey level thresholding. By applying thresholding we identified the difference between the normal and affected bone images by calculating the total number of white and black pixels.

If the white pixels are more in number and black pixels are lesser in number, in an image then it is considered to be a normal bone image. If the black pixels are more in number and white pixels are lesser in number, in an image then it is considered to be affected bone image. The bone images after segmentation are shown in the figure 8.
Feature extraction: The Gray level co-occurrence matrix (GLCM) features are extracted. Among entropy, contrast, energy, homogeneity and correlation features of GLCM the contrast feature values gives the accurate result. The mean and standard deviation values are calculated for the contrast feature values. The mean function used is
\[ \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \]
And for calculating the standard deviation the function used is
\[ s = \left( \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^{1/2} \]

The input image’s contrast values are then compared with the obtained mean and standard deviation values and the result is displayed as whether the given input image is normal bone image and affected bone image. If the image is affected bone image then it is further identified as whether it is severe bone image or non-severe bone image.

The contrast values for different type of bone images can be observed from the tables below. The mean values for affected bone images are shown in table 1. The standard deviation values for affected bone images are shown in table 2. The mean values for normal bone images are shown in table 3. The standard deviation values for normal bone images are shown in table 4.

The mean and standard deviation values of the contrast feature of the normal and affected bone images are giving the accurate results when compared to other features such as correlation, entropy and homogeneity. From the tables we can observe that contrast values provide more accurate result than other feature values.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Contrast</th>
<th>Correlation</th>
<th>Entropy</th>
<th>Homogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 to 25</td>
<td>0.0167</td>
<td>0.8925</td>
<td>0.5770</td>
<td>0.9783</td>
</tr>
<tr>
<td>26 to 50</td>
<td>0.0173</td>
<td>0.8144</td>
<td>0.8167</td>
<td>0.9636</td>
</tr>
<tr>
<td>51 and Above</td>
<td>0.0239</td>
<td>0.8014</td>
<td>0.8745</td>
<td>0.9702</td>
</tr>
</tbody>
</table>

Classification: The classifier used for our system is Rule based approach. Initially in the classification phase we classify the image into normal and affected bone images. In the intermediate level we find the type of bone disease that is whether it is osteoporotic or not. If the bone is osteoporotic we then find whether the disease is severe or non-severe.

IV. RESULTS

Step 1: Store the collected normal and affected CT images for training in the database.
Step 2: Extract the Gray Level Co-occurrence matrix features which includes homogeneity, correlation, entropy, contrast and energy. The contrast values give the accurate result store the contrast feature value in the database.
Step 3: Calculate the number of white pixels of the images. Calculate the mean and standard deviation of white pixels and store it in database.

Step 4: Acquire an image from the user and crop obtained image and resize the image into [128X 128] dimension for making the image into a standard form of image for further computation.

Step 4: Extract the contrast feature from the obtained image from the user.

Step 5: Calculate the number of white pixels of the obtained image from the user.

Step 6: Calculate the number of white pixels of the obtained image from the user, calculate mean and standard deviation of white pixels and store it in database.

Step 7: Map the obtained result to training result that contains and display whether the image is osteoporotic and normal and if the image is osteoporotic then display whether the image case is severe or non-severe.

Out of 192 bone images 78 are normal bone images and 114 are affected bone images. The recognition rate we obtained for normal bone images is 94.87% and for affected bone images is 92.10%.

The overall recognition rate obtained for normal and osteoporotic bone images is 93.48%. The system has been trained to distinguish between normal and affected, a confusion matrix will summarize the results of testing the algorithm for further inspection. Among 192 images 78 normal and 114 affected images the resulting confusion matrix could look like the table below:

**Table 5: Confusion matrix**

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Affected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>74</td>
<td>4</td>
</tr>
<tr>
<td>Affected</td>
<td>7</td>
<td>107</td>
</tr>
</tbody>
</table>

Based on age factor the bone images are classified into major 3 sections. They are 1-25, 26-50, 51 and above age
groups. The recognition rate for the age group 1 to 25 of normal bone images is 96.66% and affected bone images is 100%. The recognition rate for the age group 26 to 50 of normal bone images is 95.23% and affected bone images is 96%. The recognition rate for the age group 51 and above of normal bone an image is 100% and affected bone images are 95.44%.

The osteoporotic bone images are further classified into severe bone images and non-severe bone images. The recognition rate for severe bone images is 95.65% and non-severe bone images is 90.21%.

By considering 30% of training data and 70% of testing data, the obtained results are as follows. Out of 54 normal bone images 39 are detected and out of 81 affected bone images 64 are detected. The result in terms of percentage for normal bone images is 72.22% and affected bone images are 76.94%.

<table>
<thead>
<tr>
<th>Table 6: Recognition Rate by considering 30% of training data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Detected</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>Result</td>
</tr>
</tbody>
</table>

By considering 50% of training data and 50% of testing data, the obtained results are as follows. Out of 38 normal
bone images 34 are detected and out of 58 affected bone images 57 are detected. The result in terms of percentage for normal bone images is 90% and affected bone images are 98%.

Table 7: Recognition Rate by considering 50% of training data

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Osteoporotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detected</td>
<td>34</td>
<td>57</td>
</tr>
<tr>
<td>Total</td>
<td>38</td>
<td>58</td>
</tr>
<tr>
<td>Result</td>
<td>90%</td>
<td>98%</td>
</tr>
</tbody>
</table>

By comparing 30% of training data, 50% of training data and 70% of training data we can say that only 50% of training data is sufficient to obtain good results.

By considering 70% of training data and 30% of testing data, the obtained results are as follows. Out of 25 normal bone images 24 are detected and out of 36 affected bone images 33 are detected. The result in terms of percentage for normal bone images is 96% and affected bone images are 92%.

Table 7: Recognition Rate by considering 70% of training data

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Osteoporotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detected</td>
<td>24</td>
<td>33</td>
</tr>
<tr>
<td>Total</td>
<td>25</td>
<td>36</td>
</tr>
<tr>
<td>Result</td>
<td>96%</td>
<td>92%</td>
</tr>
</tbody>
</table>

Fig. 18. Recognition Rate by considering 50% of training data

Fig. 19. Recognition Rate by considering 70% of training data

V. CONCLUSION

In the past, several systems have been presented, which detects the osteoporosis on the parts of the body such as hip, arm and few systems were designed only for the classification of the diseases. There were less works carried out on the lumbar vertebrae bone. Thus, the development of faster classification methods and more accurate and precise features is very important in order to run such systems in real-time. This system classifies among the normal and abnormal images and detects the osteoporosis with the severity and non severity. Feature extraction is very important step in recognition of osteoporosis system. In this system feature extraction method is described. We have used Gray Level Co-occurrence matrix feature extraction method and segmentation. The experimental results show that the system has produced satisfactory recognition rate in finding about the osteoporosis occurred in lumbar vertebrae.

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