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Osteoporosis Detection Using Deep Learning

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ABSTRACT

Osteoporosis is a bone disorder which occurs due to low bone mass, degradation of bone micro-architecture and high susceptibility to fracture. It is a major health concern across the world, especially in elderly people. Osteoporosis can cause spinal or hip fractures that may lead to socio-economic burden and high morbidity. Therefore, there is a need for the early diagnosis of osteoporosis and predicting the presence of the fracture. We introduce a Convolutional Neural Network model to effectively diagnose osteoporosis in bone radiography data. Automated diagnosis from digital radiographs is very challenging since the scans of healthy and osteoporotic subjects show little or no visual differences. In this paper, we have proposed a model to separate healthy from osteoporotic subjects using high dimensional textural feature representations computed from radiography images. CNN can help us bring the use of structural MRI measurements of bone quality into clinical practice for the detection of Osteoporosis as it gives high accuracy.

KEYWORDS: *CNN, MRI, CT Scan, Osteoporosis*

I. INTRODUCTION

Osteoporosis is a bone condition caused by a reduction in bone mass and degeneration of bone structure, that leads to high susceptibility to fragility fractures. Osteoporosis-related fracture is a major global health risk, affecting one in three women and one in five men over the age of 50. According to the Asia-Pacific Regional Audit in 2013, osteoporosis accounts for more hospitalization than diabetes, myocardial infarction, and breast cancer, in women above the age of 45 years. It is more prevalent among the elderly population, especially postmenopausal women. With a rise in the aging population, there will be a substantial rise in the incidence of fractures. It is projected that by 2050, at least one-third of the world population will be aged over 50 years and in Asia alone, a 7.6-fold increase in aging population is expected, that may result in more than 50% of the global fractures to occur in Asia.

Bones are the rigid organs in the human body which protect important organs such as brain, heart, lungs and other internal organs. The human body has 206 bones with various shapes, size, and structures. There are varied types of medical imaging tools that are available to detect different types of abnormalities such as Computed Tomography (CT), X-ray and Magnetic Resonance Imaging (MRI). CT and X-rays are most frequently used for fracture diagnosis because it is the easiest and fastest way for the doctors to study the injuries of joints and bones.

Texture Characterization of Bone radiograph images is a challenge in the osteoporosis diagnosis. Osteoporosis can be defined as a skeletal disorder characterized by a compromise on bone strength predisposing to an increase in the occurrence of fracture. The most common method for osteoporosis diagnosis is to estimate Bone Mineral Density (BMD) by dual-energy X-ray absorptiometry. However, BMD alone represents only 60% of fracture prediction. The characterization of trabecular bone microarchitecture has been recognized as an important factor and completes the osteoporosis diagnosis using BMD, but it cannot be routinely obtained by noninvasive methods and requires a bone biopsy with histomorphometric analysis. 2-D texture analysis offers an easy way to evaluate bone structure on conventional radiography images. The evaluation of osteoporotic disease from bone radiograph images presents a major challenge for pattern recognition and medical applications. Textured images from the bone micro-architecture of healthy and osteoporotic subjects show a high degree of similarity, thus drastically increasing the difficulty of classifying such textures. Fig. 1 & 2 shows the bone texture similarities of control and osteoporotic images.

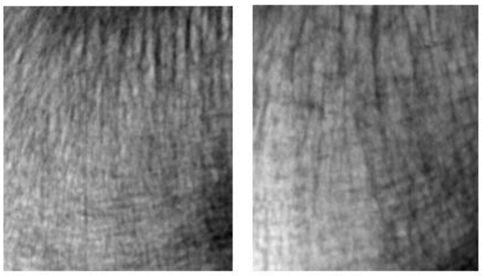


Fig. 1: Osteoporotic Patient X Ray Image

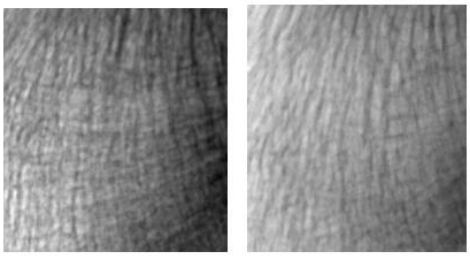


Fig. 2: Control Patient X Ray Image

II. RELATED WORKS

A variety of these techniques, including Artificial neural networks (ANNs), Bayesian Networks (BNs), SupportVector Machines (SVMs) and Decision Trees (DTs) have been widely implemented in medical research for the design and development of predictive models, resulting in accurate and effective decision making. Even though it is evident that the use of Machine Learning methods can improve our understanding of Osteoporosis detection, an appropriate level of validation is needed in order for these methods to be considered in everyday clinical practice.

Michel Kocher [1] has discussed recent and state-of-the-art advances in imaging techniques for the diagnosis of osteoporosis and fracture risk assessment. The author has also talked about segmentation methods used to segment the region of interest and texture analysis methods used for classification of osteoporotic and healthy subjects. Also, challenges posed by the current diagnostic tools have been studied and feasible solutions to circumvent the limitations are discussed.

Costin Florian Ciu·del [2] has discussed physics-based models, employing finite element analysis (FEA) which have shown great promise in being able to non-invasively estimate biomechanical quantities of interest in the context of osteoporosis. The limitation is that these models have high computational demand which limits their clinical adoption. The paper discusses a deep learning model based on a convolutional neural network (CNN) for predicting average strain as an alternative to physics-based approaches. The model is trained on a large database of synthetically generated cancellous bone anatomies, where the target values are computed using the physics-based FEA model. The performance of the trained model was assessed by comparing the predictions against physics-based computations on a separate test data set. Correlation between deep learning and physics-based predictions was very good (0.895, $p < 0.001$), and no systematic bias were found in BlandAltman analysis. The CNN model also performed better than the previously introduced Support Vector Machine (SVM) model which relied on handcrafted features (correlation 0.847, $p < 0.001$). Compared to the physics-based computation, average execution time was reduced by more than 1000 times, leading to a real-time assessment of average strain.

Kazuhiro Hatano [3] has discussed visual screening using Computed Radiography (CR) images is an effective method for osteoporosis, however, there are many similar diseases that exhibit a state of low bone mass. In this paper, we propose an automatic identification method of osteoporosis from phalanges CR images. In the proposed method, we implement a classifier based on Deep Convolutional Neural Network (DCNN), and identify unknown CR images as normal or abnormal. For training and evaluating of CNN, we use pseudocolor images.

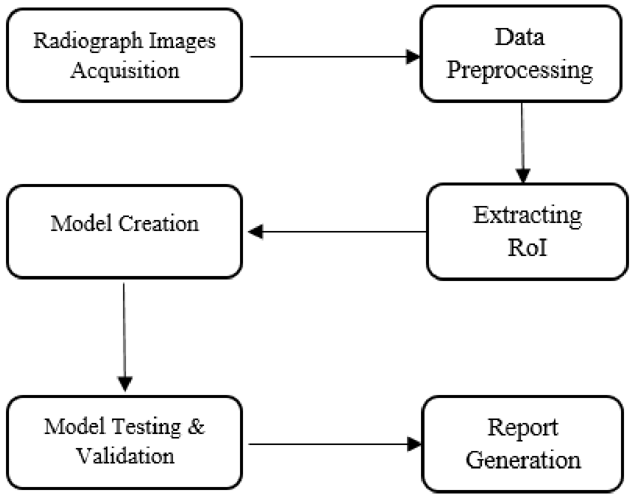
MS Kavitha [5] has discussed the diagnostic efficacies achieved by the application of an RBF kernel-SVM showed that CAD system was accurate and effective for identifying women with low BMD. The author claims the SVM method can be a reliable choice for the proposed system because it is fast and specific for classification, using dental panoramic radiographs, of postmenopausal women with low BMD. Based on highly satisfactory sensitivity and specificity results, the proposed system is expected to be a helpful tool for classifying women with low BMD and is also expected to provide a second diagnosis that may reduce misdiagnoses.

Peng Chu [6] has proposed an image-based osteoporosis classification method using dental panoramic radiography dataset. The method combines multiple ROI information by using a two-stage classification model, the first stage is a linear SVM model which is constructed with respect to a grouped region and given feature. The probability outputs of the first stage SVM models and the new SVM model are combined together. The experimental results show that the proposed method with the HOG feature achieves an accuracy of 72.5% with a low p-value (0.0164). The author concludes that the combination of image feature analysis and machine learning techniques on panoramic radiography images has the potential for osteoporosis detection.

III. METHODS AND MATERIALS

In Machine Learning, classification and object detection using Convolutional Neural Networks (CNNs) have shown better performance. Usage of Artificial Neural Networks (ANNs), which are inspired by the human brain, can also be used for classification and prediction. An ANN mainly has three input layers, an output and a hidden layer with activation function on hidden and output layers. These layers consist of a number of interconnected nodes, the number of weights in between the nodes will increase rapidly, which is an issue with the ANN. CNN a translational invariant of the neural networks which consists of some convolutional and fully connected layers. CNN uses several small filters on the input and then subsampling the space of filter activations until there is a good number of high-level features.

A Convolutional Neural Network is biologically influenced variants of multi-layer feed forward model that is currently widely using in image classification and recognition tasks. The layers of CNN are mainly classified into four layers or operations. The first layer is a convolutional layer, which is based on a mathematical approach called convolution, which takes a kernel and applied it to all over an input image to generate a filtered image. The second operation is Pooling or sub-sampling which reduces the dimensionality of the feature map although keep the most important information for the next convolution layer. The third layer is an activation function layer, which applies activation function elementwise and got the output by checking whether the neurons are fired or not. ReLU, sigmoid functions, tanh functions etc., are some of the common activations functions.



The last layer is a fully connected layer, where all the neurons from the previous layer are connected to all nodes in the adjacent layers which is the same as the fully connected multilayer perceptron. CNN must learn lots of weights and thus, we need a huge amount of data for training, but in the medical domain, we don’t get enough data to be used for training from scratch. To counter this problem for the training of CNN an alternative approach Transfer learning can be used. Transfer learning is an approach where knowledge leaned from the previous task can be applied to some new task domain. Here, we have used transfer learning concept, by using pre-trained CNN which is trained on ImageNet dataset. ImageNet is a popular database for images which consists of more than 13 million images of 1000 distinct object classes.

We have used a pre-trained CNN architecture (VGG16) as described in as one of Chatfield’s [8] work. The CNN has five convolution layer and followed by three fully connected layers. We are using a pre-trained network to extract features from the last hidden layer after applying the activation function (post relu) [9]. The X-Ray images used in the experiment are different from the images in the ImageNet database, but we are hypothesizing some useful texture features might exist. The input image size is 224x224 for the CNN architectures so we use bicubic interpolation to resize the input images. The x-ray images are grayscale, so we modified the code and extracting features using only the R channel and ignoring B and G channel. The deep features that we are extracting are of 4096 dimensions.

IV.EXPERIMENT

The dataset used in this experiment consists of 174 bone texture X-Ray images obtained from IEEE-ISBI 2014 competition. In the given dataset, 58 images are using for testing and don't have any labels or class given and 116 images are equally subdivided into osteoporotic and control cases.

We have used a pre-trained CNN model in our experiment. The model required 224x224 input image, so using bi-cubic interpolation method we have resized the images. After resizing, the size of extracted deep features vector from each X-Ray images were 4096 and then classifying it using the features. The best result of 79.3% was obtained using post-relu features from the VGG.

V. CONCLUSION

Classifying Osteoporosis by just considering the x-ray images is very difficult as the images obtained from the osteoporotic patient looks very similar to that of the healthy patient. We have proposed CNN for classification and extracting features. However, training a CNN requires a huge amount of data. But we had access to only a very small number of training data, which is insufficient to train a CNN. To solve this problem, we have used a transfer learning approach – pre-trained CNN model. The pre-trained CNNs are trained on ImageNet data and we are using it to extract features from the last hidden layer after applying the activation function. On the training set, the best result of 79.3% was achieved. The future scope of the project is to work more on deep feature to generate a better classification result on blind test data and tune the CNN to give better results.

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