Osteoporosis Prescreening and Bone Mineral Density Prediction using Dental Panoramic Radiographs

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***Abstract*— Recent studies have shown that Dental Panoramic Radiograph (DPR) images have great potential for prescreening of osteoporosis given the high degree of correlation between the bone density and trabecular bone structure. Most of the research works in these area had used pretrained models for feature extraction and classification with good success. However, when the size of the data set is limited it becomes difficult to use these pretrained networks and gain high confidence scores. In this paper, we evaluated the diagnostic performance of deep convolutional neural networks (DCNN)-based computer-assisted diagnosis (CAD) system in the detection of osteoporosis on panoramic radiographs, through a comparison with diagnoses made by oral and maxillofacial radiologists. With the available labelled dataset of 70 images, results were reproduced for the preliminary study model. Furthermore, the model performance was enhanced using different computer vision techniques. Specifically, the age meta data available for each patient was leveraged to obtain more accurate predictions. Lastly, we tried to leverage these images, ages and osteoporotic labels to create a neural network based regression model and predict the Bone Mineral Density (BMD) value for each patient. Experimental results showed that the proposed CAD system was in high accord with experienced oral and maxillofacial radiologists in detecting osteoporosis and achieved 87.86% accuracy.**

***Clinical relevance*— This paper presents a method to detect osteoporosis using DPR images and age data with multi-column DCNN and then leverage this data to predict Bone Mineral Density for each patient.**

I. INTRODUCTION

One of the most common bone diseases is osteoporosis. It develops asymptomatically in early stages among patients above the age of forty. It affects the bone mineral density and causes micro-architectural deterioration of bone tissue leading to risks of bone fracture [3]. In the US, it has affected at least 3 million patients every year [10]. Dual-energy X-ray Absorptiometry (DXA) is an effective measure to identify bone mineral density (BMD) and is used to diagnose osteoporosis but the cost of a DXA scan is relatively high [4], [7]. Due to the paucity of resources in detecting and controlling its spread and given the unprecedented number of cases coming up each day, it becomes essential to devise some Computer Aided Mechanism that can help in detection of this bone quality deterioration even without the intervention of a Medical Practitioner.

The area of osteoporosis prescreening using DPR is relatively new but is still largely probed by various computer vision researchers. The texture in the DPR images serve as a rich source of information about the bone mineral density. Yu *et al*. [11] in 2019 used the pretrained network like AlexNet for feature extraction and then built an Octuplet Siamese Network on the top of the features. Finally they had this Network trained on the eight regions of interest (ROIs) for each DPR image to predict osteoporosis condition. Kavitha *et al*. [5] in 2012 had used kernel based Support Vector Machine (SVM) for continuous measurement of cortical width of the mandible on DPRs to identify women with low BMD or osteoporosis. Ren *et al*. [8] in 2020 developed a statistic shape model (SSM) for trabecular landmark detection so as to eliminate the expensive process of landmark annotation by the dentists. Bo *et al*. [2] used a two stage SVM based fine tuning scheme over an augmented texture enhanced DPR ROIs dataset for osteoporosis classification. Roberts *et al*. [9] showed that the additional image texture features extracted from the DPR images correlated with osteoporosis detection and used the combined features as the potential biomarker for osteoporosis evaluation. In the paper by Lee *et al*. [6] the diagnostic performance of the DCNN-based CAD system for the detection of osteoporosis in panoramic radiographs was evaluated and it was found such a system was capable of early detection of osteoporosis for asymptomatic patients.

Inspired by the success of Lee *et al*. [6], we have tried to reproduce their results on an even smaller dataset of 70 subjects and evaluated if such a system could produce promising classification results on our images as well. In this study, considering BMD is one of the key index for osteoporosis evaluation, we were interested in predicting BMD value using DPR image for each patient. Note that our method does not rely on manual annotation of the RoIs in the trabecular bone image. We only considered the area of the mandibular bone region of the image when created our dataset. We then worked with three kinds of neural networks developed from scratch. These were single-column deep convolutional neural network (SC-DCNN), multi-column deep convolutional neural network (MC-DCNN), and multi-column deep convolutional neural network with VGG16 net as the feature extractor.

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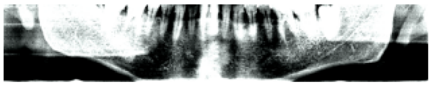

Fig. 1: Input image for SC-DCNN.

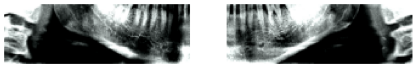

Fig. 2: Input image for MC-DCNN.

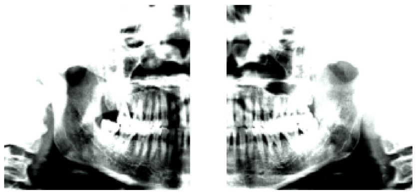

Fig. 3: Input image for MC-DCNN with VGG16 as feature extractors.

II. METHODOLOGY

A. Problem Formulation

We utilized a dataset of 70 DPR images from different subjects for osteoporosis classification and detection. The images come from 49 subjects with osteoporosis and 21 normal. For the BMD prediction task, we introduced a two-branch network to predict the BMD value based on DPR image. We deemed the predicted value to be correct if it was within the range of 15 percent of the actual BMD value. The BMD values were missing for a set of 10 subjects and therefore we only use the samples with the BMD records. The BMD values were unique without showing a general trend or pattern.

SC-DCNN was restricted to the region of interest (ROI), which was the mandible below the teeth-containing alveolar bone, for an image size of 1000 $\times$ 200 pixels. A simple preprocessing approach of zero-centring the data was used and the mean of the training data was calculated and subtracted from all the image pixels. For the both MC-DCNNs, the two ROIs, the right and left mandibular body areas, were extracted on each panoramic radiograph, resulting in two 400 $\times$ 200 pixel ROIs. We duplicated the grayscale images into three channels to fit for the input of feature extractor. A simple preprocessing approach of zero-centring the data was initially used. Besides, we also introduced some techniques to improve the performance above the baseline model. Firstly, the data was augmented by doubling the training and testing images using mirrored images. Secondly, we used Deep Conv2D layers rather than the shallow ones. Thirdly, we used the complete resized images instead of just lower jaw part. And finally, we performed normalization in all three channels of the inputs.

B. Network Architecture

In MC-DCNN, each column in this network consisted of a stack of five convolutional layers, where each convolutional layer (Conv) was followed by a max-pooling layer (Pool) and a ReLU activation layer. The feature maps of the fifth convolutional layers from the left and right columns of the network were concatenated and fed through two fully connected layers with a Softmax classifier at the output. The multi-column structure allowed for the learning of the left and right halves of image features separately, and the classifier on the top used features from both halves to make the final interpretation. We employed back-propagation to train the networks and used Adam as optimizer.

C. Deep Learning Approach: using Age Metadata

The metadata of age for each subject is available in the dataset of 70 DPR, which was in the range of 50 to 60 years of age. For DPR images based osteoporosis classification using DCNNs, the age information could be leveraged to check for variation in our model performance with or without it. The initial step was to scale the age data using Min-Max scaler, which could bring age data in a range comparable to the pixel values in the normalized image. Then we experimented with three different approaches to concatenate age data in the classifier layers, with the features extracted from the feature layers. The first approach was to simply concatenate the scaled age data to the features passed to the first layer in the classifier. The second approach was to concatenate the scaled age data to the features passed to the last layer in the classifier. In the third approach we concatenated the scaled age data to the features passed to both layers in the classifier, so that the age feature would gain more weight and influence model classification. As we will see in Section III, the third approach provided better results compared to the others. Therefore in our following design we concatenated the age to the features passed to every classification layer.

D. Approach for BMD Regression using DNNs

The goal of a regression problem is to predict a single numeric value which in our case is the BMD. We formulated the task as building a DNN model with one main branch and one auxiliary branch. Specifically, the main branch is designed for predicting the numerical BMD value while the auxiliary branch for the classification of osteoporosis condition. We introduced the classification auxiliary branch to incorporate more information which benefited training and feature extraction. Both branch losses were differentiable so the end-to-end back-propagation could be employed to train the model. The loss_1 and loss_2 were from two sub modules and the final-loss was the sum of loss_1 and loss_2. Two branches shared the same backbone for feature extraction. The classification branch had the age data concatenated in each of the final classification layers. The logits layer had two nodes in one-hot encoding scheme. Osteoporosis label classification used Adam optimizer (initial learning rate as 0.001) while BMD regression used SGD optimizer. The corresponding loss functions were cross entropy loss and mean absolute error (MAE) and were summed up and back propagated in the network as shown in the Figure 5. This is valid because gradients are automatically accumulated in *pytorch*. This means unless we call *optim.zero-grad()* to set gradients to zero, gradients will keep accumulating. So, the

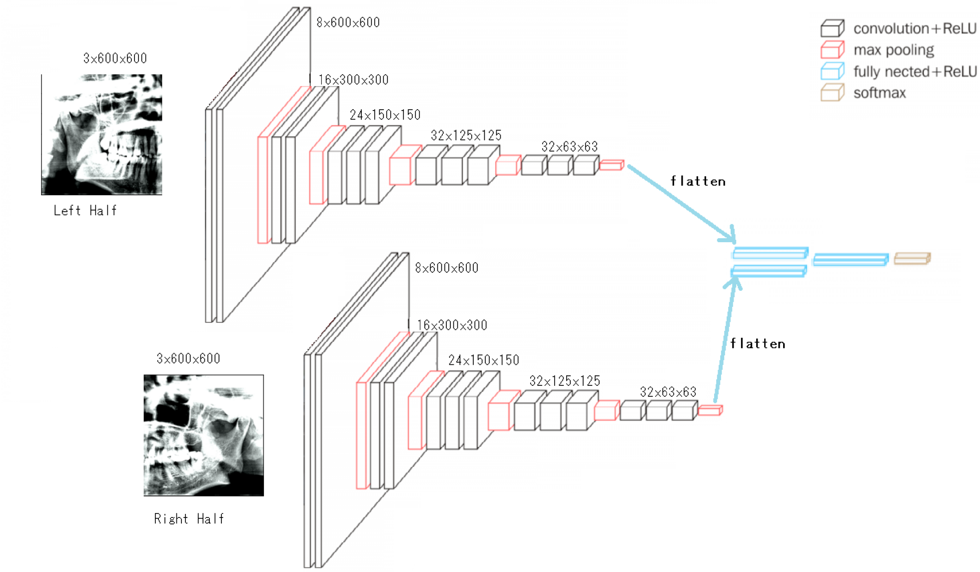

Fig. 4: Multi-column deep convolutional neural network (MC-DCNN)

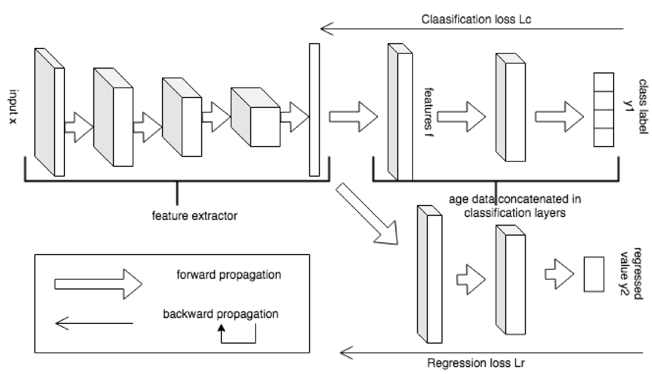

Fig. 5: Neural network architecture for BMD regression by using DPR images as input and leveraging age data and osteoporosis label.

tails of the model will use the appropriate gradients, while the common part uses the accumulated gradient.

III. EXPERIMENTS AND RESULTS

A. Environmental Settings

There were 80% samples that were used as training samples and 20% data that were used as test samples. For the osteoporosis classification task we used 5-fold cross validation as the evaluation criteria over 25 epochs. For regressing the BMD values, we used 61 available DPR sampels and 3-fold validation with 50 epochs each was performed. The final accuracy was calculated by averaging over all the folds cross validation results. The program was running on Colab [1] with one NVIDIA Tesla K80 GPU. We do not have access to the dataset in [6] so the proposed methods are evaluated on a dataset of 70 subjects.

B. Osteoporosis Classification Results

Table I illustrates the accuracy for different age concatenation settings of SC-DCNN. There were four observations for this experiment. First, the approach in which age parameters were fed in the first fully connected (FC) layer performed better than no age concatenated approach by a large margin 4.25%. Second, the approach in which age parameters were fed in the last fully connected (FC) layers performed better than age when only fed in the first FC layer by 2.81%. Third, the approach in which age parameters were fed in both the FC layers outperformed only feeding in the last FC layer by 3.57%. Fourth, on giving more weight to age, the performance of the deep learning model improved. We were consequently able to conclude that age factor actually helped improving the DCNN model performance.

Table II illustrates the accuracy for different networks over 5-fold cross-validation with data augmentation and other techniques mentioned in Section II. We can see that MC-DCNN outperformed all the other models and achieved 87.8571% classification accuracy. The multi-column structure, which allows for the learning of the left and right half of image features separately, is more robust for the classification task.

TABLE I: Accuracy of different age concatenating approaches for SC-DCNN classification model.

Age concatenation	No age	In the first cls. layer	In the last cls. layer	In both cls. layer
SC-DCNN	70.800	75.0473	77.8571	**81.4285**

C. BMD Prediction Results

The results have been produced on the Multi-channel deep neural network. The train losses dropped down from 0.13 to 0.001. For our regression metric, we deemed the predicted value to be correct if it was within the range of

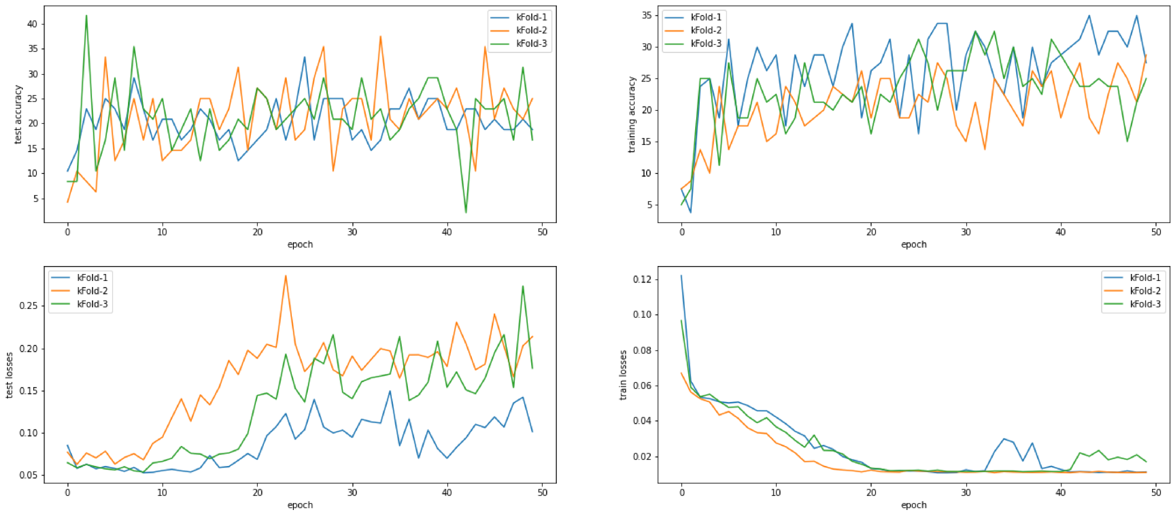

Fig. 6: Multi-column deep convolutional neural network (MC-DCNN)

TABLE II: Accuracy scores for age concatenation for different networks over 5-fold cross-validation.

	SC-DCNN	MC-DCNN VGG16	MC-DCNN
5-fold CV accuracy	85.7143	83.1250	**87.8571**

15 percent of the actual BMD value. For values outside this range the network would be penalized using ℓ_1 regression loss. We obtained the mean accuracy of 37.5% in cross validation setting which implied that the network could correctly regress the BMD values for 37.5 out of 100.

IV. CONCLUSIONS

In this paper, leveraging different computer vision techniques, we re-evaluated and improved the performance of DCNN-based CAD system in the detection of osteoporosis on DPR images. In the first part of our study we manifested that exposing age data to each of the classification layer in the multi-column based deep network could improve the results of osteoporosis label prediction. It implied that age and trabecular bone structure had some level of correlation and could be used together for osteoporosis prescreening. In the second part of our study, we manifested that the BMD was correlated with the DPR image and it was possible to predict the BMD value for a patient along with osteoporosis prescreening. To achieve the aforementioned system, we designed a two-branches network. The main branch was for the BMD regression while the auxiliary branch was for osteoporosis classification which benefited the training. The current methods takes the whole or specific areas of DPR image as input, which is sub-optimal to extract discriminative features. A more adaptive and flexible sampling approach should lead to better performance for this task. Future study may also focus on involving other related features to improve the BMD prediction performance.

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