

# Artificial Intelligence-Powered System for Identifying Bone Deterioration in Radiological Imaging

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**Abstract** — The aim of this research was to investigate the potential of deep convolutional neural networks (DCNN) for developing a reliable osteoporosis diagnostic tool using cone-beam computed tomography (CBCT) scans of the mandible. The study utilized CBCT scans of patients' mandibular bone tissue and incorporated two pre-existing DCNN architectures derived from the ResNet-101 model. Findings from the study suggest that employing transfer learning methodologies can produce satisfactory outcomes in the creation of deep learning models for osteoporosis detection, even when the availability of mandibular CBCT image datasets is restricted.

**Keywords** — osteoporosis; radiology; medicine; artificial intelligence.

## I. INTRODUCTION

Artificial Intelligence (AI) holds immense promise in revolutionizing the sphere of medical diagnostics by amplifying accuracy, operational efficiency, and scale of diagnostic decisions. Its major implementation can be witnessed in the interpretation of medical imagery like X-rays, MRI, and CT scans. Deep learning algorithms, trained on extensive medical image data, can automatically discern patterns and characteristics suggestive of particular diseases or conditions, thus facilitating early detection and diagnosis. For example, deep learning algorithms have shown efficacy in correctly detecting certain cancer forms, such as lung cancer. [1]

Osteoporosis, a disease of the skeletal system marked by reduced bone mineral density (BMD) and microarchitectural deterioration leading to compromised bone strength and increased fracture risk, is the second most prevalent medical disorder after cardiovascular disease per the World Health Organization. It affects one in three women and one in five men over 50 years old. [2] Approximately 62% of all cases are due to postmenopausal osteoporosis. [3]

Osteoporotic fractures often dramatically impair quality of life or can be fatal. Early detection and the commencement of prevention or treatment are of paramount importance. However, dual-energy x-ray absorptiometry (DEXA) - the most widely used diagnostic method - isn't universally accessible and isn't appropriate as a screening method.

Dental x-rays could potentially identify the risk of osteoporosis, thereby adding value to this relatively ubiquitous examination method. Our prior study established that postmenopausal women with reduced BMD demonstrate altered mandibular cortical bone structure and thickness, which can be easily and accurately detected on digital orthopantomogram (OPG) radiographs, indicating a high likelihood of osteoporosis. [4]

With the rising availability of cone-beam computed tomography (CBCT) as a cost-efficient, radiation-proportional 3D examination method, OPG X-ray examinations are becoming less popular. CBCT is now the predominant examination method in dental implantology and is also commonly used in other dental specialties. [5] The three-dimensional nature of CBCT and its superior resolution of the jaw structure makes it more informative, suggesting that changes in mandibular cortical bone quantity and quality detected by CBCT could provide more accurate identification of women at increased risk of osteoporosis. [6]

To ensure the clinical application of this method without necessitating additional training for dentists, it is imperative to develop an AI-powered tool for automated detection of osteoporosis in CBCT scans. The objective of this study is to develop a deep neural network that can assess the risk of osteoporosis in maxillofacial CBCT examinations and evaluate its performance.

## II. MATERIALS AND METHODS

This study engaged postmenopausal women who had undergone cone-beam computed tomography (CBCT) scans at the Institute of Stomatology at Riga Stradiņš University for implantation planning. The CBCT scans were conducted using a single device with defined parameters, and dual-energy x-ray absorptiometry (DEXA) was employed for the evaluation of bone mineral density. The model was trained using a total of 188 CBCT scans.

The analysis and processing of the data from the CBCT scans were performed using OnDemand3DTM software. The focus of the study was on the quantification of the computed tomography cortical index (CTCI) to examine the condition of the cortical bone structure. Further, a panoramic reconstructed image was utilized for the determination of CTCI.

The AI segment of the study encompassed the design and execution of a deep neural network based on the ResNet-101 architecture to detect and analyse the mandibular bone in the CBCT imagery. The primary network was initially trained using the ImageNet dataset. The network was divided into three stages:

**Slice classification:** In the initial classification network, the correct slice from the CBCT where both mandibular canals were visible was identified. This stage used a neural network based on the ResNet-101 architecture, with output probabilities reflecting the certainty level in identifying a slice with mandibular bone. The ResNet-101 deep learning network was trained employing the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.001. [7] The dataset was randomly partitioned into training and validation subsets following a 70:30 ratio.

Regression for pinpointing crucial points: The second regression network was designed to detect seven key points (five for the mandibular bone line and two for the mandibular nerve canals) that signified the mandibular cortical bone and mandibular nerve canals on the slice as accurately as feasible. The previously labelled data was employed in the training process, and the identified points were used to establish the mandibular bone line and compute the perpendicular intersection area of the mandibular bone. In this phase, the ResNet-101 deep learning network was trained using the Adam optimizer with a learning rate of 0.001.

Estimating the thickness of the mandibular cortical bone: In the final stage, the thickness of the mandibular cortical bone was calculated and juxtaposed with the ground truth. The findings from the earlier stages were used to assess the thickness of the mandible. A deterministic function was used to calculate perpendicular bone intersections and to estimate bone thickness based on density differentiation.

The choice of the ResNet-101 architecture was due to its deep residual learning approach which mitigates the problem of vanishing gradients and facilitates more effective optimization. The network also incorporated average pooling layers instead of fully connected layers, reducing the number of parameters and enabling the learning of deeper representations with a fewer number of parameters.

### III. RESULTS

All the CBCT scans were carefully annotated semantically, forming the basis for model training. In the initial phase, a classification network based on the ResNet-101 architecture was established, targeting the identification of the correct slice from the CBCT where the entirety of the mandibular canal could be observed. The model achieved an accuracy of roughly 94% on the validation set.

During the second phase, a regression network was developed using the ResNet-101 architecture, trained to draw a line across the mandibular bone following five points and subsequently draw another line between two points intersecting the canal. Pixel to millimetre conversion can be achieved by multiplying the pixel value by a conversion factor of 0.3. It achieved approximately 1 px accuracy in terms of Mean Absolute Error (MAE) for the validation set.

In the final phase, an algorithm was developed to calculate the thickness of the mandibular bone cortical layer from a specific CBCT slice, which was used to ascertain the existence or non-existence of osteoporotic changes. The algorithm managed to estimate mandible bone thickness with a deviation of roughly 1 mm.

### IV. DISCUSSION & CONCLUSIONS

In this paper, we introduce a methodology for classifying CBCT images of mandibular bone tissue for osteoporotic changes using a deep convolutional neural network model. Well-structured and trained convolutional neural networks have the potential to lay the foundation for an effective diagnostic method for osteoporosis through the classification of CBCT images of mandibular bone tissue. Our future research plan involves developing a comprehensive osteoporosis diagnostic system grounded on CBCT images of the mandible and other bones impacted by the disease. For actualizing this proposed diagnostic system prototype, tests on an expanded patient cohort, along with the development of an algorithm boasting superior classification accuracy and sensitivity, are imperative.

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