Building a deep learning model to detect osteoporosis from dental panoramic X-Ray image

Farah Brangakgi

Submitted to: JMIR Bioinformatics and Biotechnology
on: July 19, 2024

Table of Contents

Original Manuscript.. 5

Building a deep learning model to detect osteoporosis from dental panoramic X-Ray image

Farah Brangakgi[1]

[1]Damascus University Damascus SY

Corresponding Author:
Farah Brangakgi
Damascus University
Damascus, Syria
Damascus
SY

Abstract

Background: The project discusses the development of a deep learning model to detect osteoporosis from dental panoramic X-Ray images. It provides an in-depth understanding of human bone structure, osteoporosis, its symptoms, causes, prevalence, and risk factors. The project also explains bone density measurement using dual-energy X-ray absorptiometry (DEXA) and the application of artificial intelligence (AI) and machine learning (ML) in medical imaging. The study uses panoramic dental X-rays to evaluate AI technology in dental imaging and classification of mandible inferior cortical based on Klemetti and Kolmakow criteria. The model architecture consists of convolutional, pooling, fully connected, ReLU, and Softmax layers. Dropout and earlystop is added to the model. The training process uses the train-test approach with 100 epochs and a batch size of 32, and performance evaluation measures such as accuracy, sensitivity, specificity, and F1-score are used to assess the classifier's performance. The findings and methodology provide a comprehensive understanding of the application of deep learning in the detection of osteoporosis from dental panoramic X-Ray images, and the study demonstrates a robust approach to implementing AI in medical imaging for osteoporosis detection.

Objective: • A tool for assisting dentists was developed in this study in identifying signs of osteoporosis for future patient care or aiding orthopedic physicians in taking actions upon diagnosing panoramic dental images.
• This tool can also facilitate individuals in recognizing indicators in their own dental panoramic images, promoting increased attention to their health or consulting a doctor to mitigate the progression of osteoporosis.
• This tool holds significant medical and economic importance, as doctors can diagnose osteoporosis from panoramic images, saving costs and time for patients.

Methods: The Python model utilizes several essential libraries for various tasks. NumPy facilitates numerical operations and efficient handling of data arrays. The OS module interacts with the operating system, aiding in file and directory manipulation. The Glob module searches for pathnames matching specified patterns. OpenCV and PIL assist in image processing tasks, such as resizing and manipulation. TensorFlow's Keras module offers utilities for preparing images for deep learning models. Provided code snippets illustrate functions for renaming images to numerical formats, resizing images, and constructing a model with MobileNet architecture. Early stopping is implemented during training to prevent overfitting, monitoring the model's performance on a validation set to halt training if no improvement is observed after a set number of epochs. Training results shows duration, loss, and accuracy metrics for each epoch.

Results: Fig. 2 presents a segment of the training outcomes, exhibiting information for every epoch, encompassing the duration, training loss, validation loss, and both training and validation accuracy. Fig. 3 depicts a graph illustrating the accuracy throughout training and validation across epochs.
The model demonstrates an overall improvement in accuracy over the epochs. Fluctuations in validation accuracy suggest some sensitivity to the dataset or potential overfitting.
Table 1 shows the overall experimental results achieved by the proposed method on the proposed features using MobileNet classifier. In summary, the model demonstrates good performance with high precision, recall, and F1-score, resulting in an overall accuracy of 85%.
A separate set of data, which was not used during the model building process, was introduced to evaluate the performance of the model. This evaluation dataset consisted of dental panoramic X-ray images from patients who had undergone both DXA scan

and DBR(26). The labeling of the evaluation dataset was based on the DXA scan results. Specifically, the dataset included 10 normal images and 19 osteoporosis images. The model was then tested on this evaluation dataset, and the results shows that the overall count of true incidences is 23 out of 29. Consequently, the accuracy is 79.3%, which is really close to the model evaluation.

Conclusions: The project discusses the development of a deep learning model to detect osteoporosis from dental panoramic X-ray images. The project highlights the importance of early detection and treatment of osteoporosis and the potential of artificial intelligence (AI) and deep learning models in improving diagnostic accuracy. The findings contribute to the advancement of AI in healthcare. The project explains the working principles of convolutional neural networks (CNNs) in image processing and sequence prediction tasks. It uses precision, recall, F1-score and accuracy in the evaluation of the proposed deep learning model. The results section presents the performance evaluation of the CNN model using dental panoramic X-ray images. It also shows the experimental results achieved by the proposed method. The project also mentions the calculation of accuracy, sensitivity, and specificity scores for evaluating the model's performance. In terms of the procedure, the project briefly describes the process of obtaining dental panoramic X-ray images and the positioning of the patient during the scan. It also mentions the signs observed in the dental panoramic X-ray images that indicate osteoporosis, such as thinning of the bone cortical and reduced definition of the cortical bone. For future research, future research is needed, using different deep CNN architectures, more validated and qualified labeled image dataset, the appropriate number of datasets, since the method has shown a great potential for assessing a large number of images.

(JMIR Preprints 19/07/2024:64546)
DOI: https://doi.org/10.2196/preprints.64546

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Title Page

Building a deep learning model to detect osteoporosis from dental panoramic X-Ray image

Farah Hassan Brangakgi[1]
Prof. Yasser Khadra[2]

1. Bachelor degree in Biology, Damascus University, Damascus, Syria master's in Bioinformatics, Syrian Virtual University, Damascus, Syria
2. postgraduate diploma in medical engineering from Damascus University in 2001. master degree in signals and imaging and Ph.D in medical digital image processing and pattern recognition from University of Lyon in 2008.

Corresponding Author
Farah Hassan Brangakgi
Bioinformatics, Syrian Virtual University, Damascus, Syria
Email: Farah.brenjikji@gmail.com
Mobile no.: +963-991-320544

Key points

- A tool for assisting dentists was developed in this study in identifying signs of osteoporosis for future patient care or aiding orthopedic physicians in taking actions upon diagnosing panoramic dental images.
- This tool can also facilitate individuals in recognizing indicators in their own dental panoramic images, promoting increased attention to their health or consulting a doctor to mitigate the progression of osteoporosis.
- This tool holds significant medical and economic importance, as doctors can diagnose osteoporosis from panoramic images, saving costs and time for patients.

Building a deep learning model to detect osteoporosis from dental panoramic X-Ray image

ABSTRACT

The project discusses the development of a deep learning model to detect osteoporosis from dental panoramic X-Ray images. It provides an in-depth understanding of human bone structure, osteoporosis, its symptoms, causes, prevalence, and risk factors. The project also explains bone density measurement using dual-energy X-ray absorptiometry (DEXA) and the application of artificial intelligence (AI) and machine learning (ML) in medical imaging. The study uses panoramic dental X-rays to evaluate AI technology in dental imaging and classification of mandible inferior cortical based on Klemetti and Kolmakow criteria. The model architecture consists of convolutional, pooling, fully connected, ReLU, and Softmax layers. Dropout and earlystop is added to the model. The training process uses the train-test approach with 100 epochs and a batch size of 32, and performance evaluation measures such as accuracy, sensitivity, specificity, and F1-score are used to assess the classifier's performance. The findings and methodology provide a comprehensive understanding of the application of deep learning in the detection of osteoporosis from dental panoramic X-Ray images, and the study demonstrates a robust approach to implementing AI in medical imaging for osteoporosis detection.

INTRODUCTION

Osteoporosis is a systemic skeletal disease that develops when bone mineral density and bone mass decreases, making them fragile and more likely to break, or when the structure and strength of bone changes. It develops slowly over several years and is often only diagnosed when a fall or sudden impact causes a bone to break (fracture). Symptoms of vertebral (spine) fracture include severe back pain and loss of height. According to the World Health Organization (WHO), osteoporosis is a major global health concern that can lead to increased morbidity, mortality and socio-economic burden. Osteoporosis is reported to cause more hospitalization than myocardial infarction, diabetes and breast cancer, in women above 45 years of age (International Osteoporosis Foundation 2013). Approximately 50% of women and 20% of men will experience osteoporotic fractures in their lifetime (Insider 2013). According to the World Health Organization (WHO), measurement of BMD using DXA is considered as the gold standard method for the identification of osteoporosis (Kaniset al. 2008).

Over a number of years researchers have reported associations between osteoporosis or low bone mineral density and signs that can be detected on dental radiographs, particularly in the width of the inferior mandibular cortex and the texture of the trabecular bone. The goal of dental radiography is to obtain diagnostic information while keeping the exposure to the patient and dental staff at minimum levels. This is the principle for the “As Low As Reasonably Achievable” (ALARA) to reduce health risks from ionizing radiation. The signs that can be found in radiographs that indicate osteoporosis are as follows: generalized osteopenia, more evident in the column, thinning of the bone cortical, and enhanced primary trabeculation associated with loss of secondary trabeculation[22]. The radiological sings for osteoporosis are radiolucency of the upper and lower jaws and reduced definition of the cortical bone associated with bone erosion (Fig. 1).

During the early stages of osteoporosis, the oblique line of the mandible presents more contrast, especially because the loss of the trabecular bone mass, leading to a more radiolucent mandible body, enhancing the contrast compared to the oblique line.

Deep learning is a type of machine learning that can process a wider range of data resources (images, for instance, in addition to text), requires even less human intervention, and can often produce more accurate results than traditional machine learning. Deep learning uses neural networks -based on the ways neurons interact in the human brain- to ingest data and process it through multiple iterations that learn increasingly complex features of the data. The neural network can then make determinations about the data, learn whether a determination is correct, and use what it has learned to make determinations about new data.

Developing a tool to assist dentists in identifying signs of osteoporosis for future patient care or aiding orthopedic physicians in taking actions upon diagnosing panoramic dental images. It can also facilitate individuals in recognizing indicators in their own dental panoramic images, promoting increased attention to their health or consulting a doctor to mitigate the progression of osteoporosis. This tool holds significant medical and economic importance, as doctors can diagnose osteoporosis from panoramic images, saving costs and time for patients.

MATERIALS AND METHODS

The Python model utilizes several essential libraries for various tasks. NumPy facilitates numerical operations and efficient handling of data arrays. The OS module interacts with the operating system, aiding in file and directory manipulation. The Glob module searches for pathnames matching specified patterns. OpenCV and PIL assist in image processing tasks, such as resizing and manipulation. TensorFlow's Keras module offers utilities for preparing images for deep learning models. Provided code snippets illustrate functions for renaming images to numerical formats, resizing images, and constructing a model with MobileNet architecture. Early stopping is implemented during training to prevent overfitting, monitoring the model's performance on a validation set to halt training if no improvement is observed after a set number of epochs. Training results shows duration, loss, and accuracy metrics for each epoch.

DATASET

The data were conducted on panoramic dental radiographs to evaluate the application of the AI technology in dental imaging. A panoramic radiograph is a panoramic scanning dental X-ray of the upper and lower jaws. The subjects of this study were collected from multiple sources, repository data open source, Kaggle is one of the sources and figshare is another (links to both sites are provided at the end of this project). Data were also conducted from privet dental clinic by consumption of the doctor while commitment to keep the privacy of the patients. section of the data was collected from master's project in Damascus university faculty of dentistry, 29 dental X-ray images (10 normal and 19 osteoporosis) patient went under panoramic dental X-ray and DXA scan for hip and lumbar (L2-L4). This section kept apart from the data to test the algorithm accuracy. 400 patients were involved in this project, the patients included male and female, aged from 20 to 66 years old. Extraction of features that can characterize the properties of bones of normal and osteoporotic people is an important step in the diagnosis of osteoporosis. Feature extraction may be broadly categorized as radiogrammetric measurement, bone density measurement and texture analysis Due to the difficulty in acquiring a substantial amount of data from patients who underwent both panoramic dental X-ray and DXA scan, the data were categorized using the Klemetti and Kolmakow method.

DATA PREPROCESSING

For consistency of image preprocessing, the images were resized to a uniform size of 224 × 224 pixels. Transform a set of Images that were taken and processed under varying condition into a set where each has the same brightness and contrast.

BASIC ARCHITECTURE

The model consists of five convolutional layers, with the initial layers handled by the base_model serving as the input processing. Additionally, there is one pooling layer, three dropout layers, two fully connected layers, and one output layer. A Rectified Linear Unit (ReLU) activation layer is positioned next to each convolutional layer. The fifth convolutional layer is connected to a Softmax classifier through a fully connected layer. The Softmax output provides the probabilities associated with normal or osteoporosis conditions. The model is compiled using the Adam optimizer with a learning rate of 0.0002, employing categorical cross entropy as the loss function and accuracy as the evaluation metric. Additionally, early stopping is implemented with a patience of 10 epochs to monitor validation loss and restore the best weights. The scikit-learn `train_test_split` function was employed to randomly partition the dataset into training, validation, and testing sets in a ratio of 50:25:25. The image dataset underwent the train-test approach, ensuring that the splitting process maintained accurate label percentages for the training, validation, and testing data. The training process spanned 100 epochs with a batch size of 32, utilizing the provided training and validation datasets.

RESULTS

Fig. 2 presents a segment of the training outcomes, exhibiting information for every epoch, encompassing the duration, training loss, validation loss, and both training and validation accuracy. Fig. 3 depicts a graph illustrating the accuracy

throughout training and validation across epochs.
The model demonstrates an overall improvement in accuracy over the epochs. Fluctuations in validation accuracy suggest some sensitivity to the dataset or potential overfitting.
Table 1 shows the overall experimental results achieved by the proposed method on the proposed features using MobileNet classifier. In summary, the model demonstrates good performance with high precision, recall, and F1-score, resulting in an overall accuracy of 85%.
A separate set of data, which was not used during the model building process, was introduced to evaluate the performance of the model. This evaluation dataset consisted of dental panoramic X-ray images from patients who had undergone both DXA scan and DBR[26]. The labeling of the evaluation dataset was based on the DXA scan results. Specifically, the dataset included 10 normal images and 19 osteoporosis images. The model was then tested on this evaluation dataset, and the results shows that the overall count of true incidences is 23 out of 29. Consequently, the accuracy is 79.3%, which is really close to the model evaluation.

DISCUSSION

Although DPRs are commonly performed for the evaluation of dentition and adjacent structures of the jaw, some clinical assistant diagnosis (CAD) systems based on DPRs have been suggested for screening systemic diseases, such as osteoporosis. The model training process involved the utilization of essential Python libraries such as NumPy, OS, and OpenCV for handling numerical operations, interacting with the operating system, and image processing, respectively. This facilitated efficient data manipulation and preparation for the subsequent steps in the deep learning pipeline. The model architecture was constructed with a Convolutional Neural Network (CNN) framework, leveraging the powerful MobileNet as the base model. This architecture incorporated multiple layers including convolutional layers, pooling layers, fully connected layers with a softmax layer for output prediction, and activation functions. The model is trained using the collected dataset, with data preprocessing techniques such as resizing and normalization applied to enhance performance. The model was trained for 29 epochs, revealing a dynamic learning process as depicted in Fig. 42. The initial epochs demonstrated moderate accuracy, suggesting room for improvement. As training progressed, fluctuations in validation accuracy were observed, indicating potential sensitivity to the dataset or signs of overfitting. The model's overall accuracy improved over time, reaching a commendable level. The training duration, indicated that each epoch took approximately 16 seconds, resulting in a total training time of 8 minutes.

This efficient training process was crucial for optimizing computational resources and achieving faster model convergence. The model's performance is evaluated using metrics like precision, recall, and F1-score. These metrics collectively provide a comprehensive evaluation, as illustrated in Table 1, of the classifier's performance for both individual classes and overall. Overall accuracy is 0.85, indicating that 85% of the predictions across both classes were correct. In the medical context, an accuracy exceeding 80% is deemed satisfactory. However, determining 80% as the sole target accuracy for considering a system useful is not a straightforward decision. To further assess the model's generalization capability, a separate evaluation dataset, not used during the model building, was introduced. This dataset consisted of dental panoramic X-ray images from patients who had undergone both DXA scan and DBR. The model's predictions on this dataset, revealed a high accuracy of 79.3%. This alignment between the evaluation dataset results and the model's overall accuracy underscores the robustness and reliability of the model.

The outcome of the model demonstrates favorable results when applied to unseen data, confirming that the model accuracy stands at 85%, surpassing the threshold of 80%.

CONCLUSION

The project discusses the development of a deep learning model to detect osteoporosis from dental panoramic X-ray images. The project highlights the importance of early detection and treatment of osteoporosis and the potential of artificial intelligence (AI) and deep learning models in improving diagnostic accuracy. The findings contribute to the advancement of AI in healthcare. The project explains the working principles of convolutional neural networks (CNNs) in image processing and sequence prediction tasks. It uses precision, recall, F1-score and accuracy in the evaluation of the proposed deep learning model. The results section presents the performance evaluation of the CNN model using dental panoramic X-ray images. It also shows the experimental results achieved by the proposed method. The project also mentions the calculation of accuracy, sensitivity, and specificity scores for evaluating the model's performance. In terms of the procedure, the project briefly describes the process of obtaining dental panoramic X-ray images and the positioning of the patient during the scan. It also mentions the signs observed in the dental panoramic X-ray images that indicate osteoporosis, such as thinning of the bone cortical and reduced definition of the cortical bone. For future research, future research is needed, using different deep CNN architectures, more validated and qualified labeled image dataset, the appropriate number of datasets, since the method has shown a great potential for assessing a large number of images.

REFERENCES

1. Yu Y 2016 Machine Learning for Dental Image Analysis arXiv
2. Sharma S 2020 Osteoporosis: Detection Using Dental Radiography J. Dent. Oral Sci.
3. Kavitha M S, Asano A, Taguchi A, Kurita T and Sanada M 2012 Diagnosis of osteoporosis from dental panoramic radiographs using the support vector machine method in a computer-aided system BMC Méd.
4. Sam M, Areeckal A S and S S D 2017 Early Diagnosis of Osteoporosis Using Active Appearance Model and Metacarpal Radiogrammetry 2017 13th Int. Conf. Signal-Image Technol. Internet-Based

Syst. (SITIS) 173–8
5. Watanabe P C A, Watanabe M G de C and Tiossi R 2012 Osteoporosis
6. Sukegawa S, Fujimura A, Taguchi A, Yamamoto N, Kitamura A, Goto R, Nakano K, Takabatake K, Kawai H, Nagatsuka H and Furuki Y 2022 Identification of osteoporosis using ensemble deep learning model with panoramic radiographs and clinical covariates 12 6088
7. Yamamoto N, Sukegawa S, Kitamura A, Goto R, Noda T, Nakano K, Takabatake K, Kawai H, Nagatsuka H, Kawasaki K, Furuki Y and Ozaki T 2020 Deep Learning for Osteoporosis Classification Using Hip Radiographs and Patient Clinical Covariates Biomolecules 10
8. Krizhevsky A, Sutskever I and Hinton G E 2017 ImageNet classification with deep convolutional neural networks Commun. ACM 60 84–90
9. Kavitha M S, Asano A, Taguchi A, Kurita T and Sanada M 2012 Diagnosis of osteoporosis from dental panoramic radiographs using the support vector machine method in a computer-aided system BMC Méd. Imaging 12 1
10. Wang W, Li Y, Zou T, Wang X, You J and Luo Y 2020 A Novel Image Classification Approach via Dense-MobileNet Models Mobile Information Systems 2020 7602384
11. Çakur B, Şahin A, Dagistan S, Altun O, Çaglayan F, Miloglu Ö and Harorli A 2008 Dental Panoramic Radiography in the Diagnosis of Osteoporosis J. Int. Méd. Res. 36 792–9
12. Alourfi Z. (2019). Prevalence and Factors Associated with Low Bone Mass and Osteoporosis in Syrian Postmenopausal Women. Mathews J Case Rep 4(3): 58.
13. Hijazi N and Alourfi Z 2020 Association between Hypertension, Antihypertensive Drugs, and Osteoporosis in Postmenopausal Syrian Women: A Cross-Sectional Study Adv. Med. 2020 7014212
14. Kini, U. and Nandeesh, B.N. (2012) Physiology of Bone Formation, Remodelling, and Metabolism. In: Fogelman, I., Gnanasegaran, G. and Wall, H., Eds., Radionuclide and Hybrid Bone Imaging, Springer, Berlin, Heidelberg, 29-57.
15. Rock Creek Wellness (2018). Body composition analysis. https://www.rockcreekwellness.com/dxa-analysis/. (Accessed on April, 2018).
16. Adams, J. E. (2009). Quantitative computed tomography. European Journal of Radiology, 71(3), 415–424.
17. Foundation, I. O. Facts and statistics about osteoporosis and its impact. Lyon, France: International Osteoporosis Foundation; 2004 [cited 2011]; Available from: http://www.iofbonehealth.org/facts-and-statistics.html.
18. Adams JE. Quantitative computed tomography. Eur J Radiol. 2009 Sep;71(3):415-24. doi: 10.1016/j.ejrad.2009.04.074. Epub 2009 Aug 13. PMID: 19682815.
19. McCulloch, W. S., Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4), 115-133.
20. Hebb, D. O. (1949). The organization of behavior: A neuropsychological approach. New York: John Wiley & Sons.
21. Klemetti E, Kolmakov S, Heiskanen P, Vainio P, Lassila V. Panoramic mandibular index and bone mineral densities in postmenopausal women. Oral Surg Oral Med Oral Pathol. 1993;75(06):774–779.
22. Tiossi R, Costa PP, Plauto C.A Watanabe. The influence of osteoporosis in oral health. In: Osteoporosis: Risk Factors, Symptoms and Management. 2012. Nova Science Publishers, Inc.
23. Lee K-S, Jung S-K, Ryu J-J, Shin S-W and Choi J 2020 Evaluation of Transfer Learning with Deep Convolutional Neural Networks for Screening Osteoporosis in Dental Panoramic Radiographs J. Clin. Med. 9 392
24. World Health Organization: WHO scientific group on the assessment of osteoporosis at primary health care level. Summary Meeting Report, Brussels, Belgium, World Health Organization 2007:1-17.
25. Hijazi N and Alourfi Z 2019 Prevalence and Factors Associated with Low Bone Mass and Osteoporosis in Syrian Postmenopausal Women Mathews J. Case Rep. 4
26. Barngkgei I, Haffar I A and Khattab R 2014 Osteoporosis prediction from the mandible using cone-beam computed tomography 44 263–71
27. Christopher Aranha Watanabe, P., Antonio Rodrigues, G., Rodrigues Azenha, M., Campos Ribeiro, M., de Almeida Souza Filho, E., Angelo Soares Vieira, R., & Santos Bottacin, F. (2021). Bone Quality of the Dento-Maxillofacial Complex and Osteoporosis. Opportunistic Radiographic Interpretation.

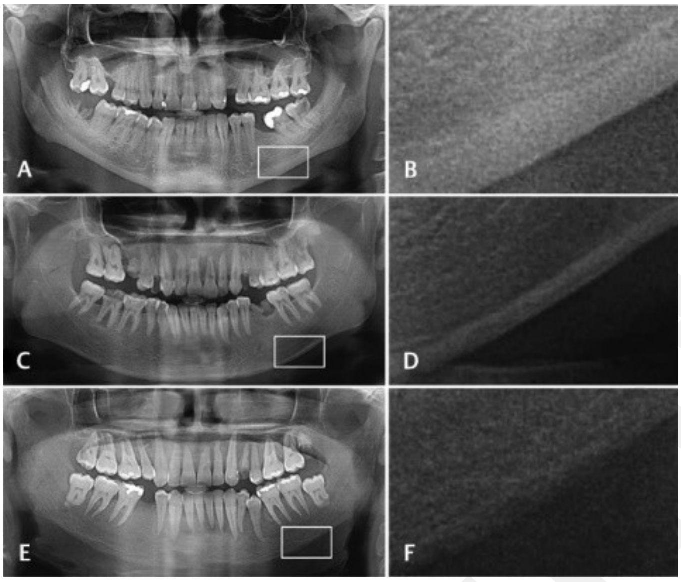

Fig. 1 Normal cortex—the endosteal margin of the cortex was even and sharp on both sides (A and B). C2: Mildly-to-moderately eroded cortex—The endosteal margin showed semilunar defects (lacunar resorption) or it appeared to form endosteal cortical residues (C and D). C3: severely eroded cortex—The cortical layer formed heavy endosteal cortical residues and it was clearly porous (E and F).

```
Epoch 1/100
10/10 [==============================] - 19s 2s/step - loss: 1.1262 - accuracy: 0.5127 - val_loss: 0.5030 - val_accuracy: 0.7722
Epoch 2/100
10/10 [==============================] - 16s 2s/step - loss: 0.8574 - accuracy: 0.6044 - val_loss: 0.4358 - val_accuracy: 0.8481
Epoch 3/100
10/10 [==============================] - 16s 2s/step - loss: 0.7662 - accuracy: 0.6677 - val_loss: 0.4179 - val_accuracy: 0.8354
Epoch 4/100
10/10 [==============================] - 16s 2s/step - loss: 0.7486 - accuracy: 0.6930 - val_loss: 0.4267 - val_accuracy: 0.8228
Epoch 5/100
10/10 [==============================] - 16s 2s/step - loss: 0.7922 - accuracy: 0.6835 - val_loss: 0.4270 - val_accuracy: 0.8228
Epoch 6/100
10/10 [==============================] - 16s 2s/step - loss: 0.5756 - accuracy: 0.7437 - val_loss: 0.3971 - val_accuracy: 0.8228
```

Fig. 2 Section of the training results

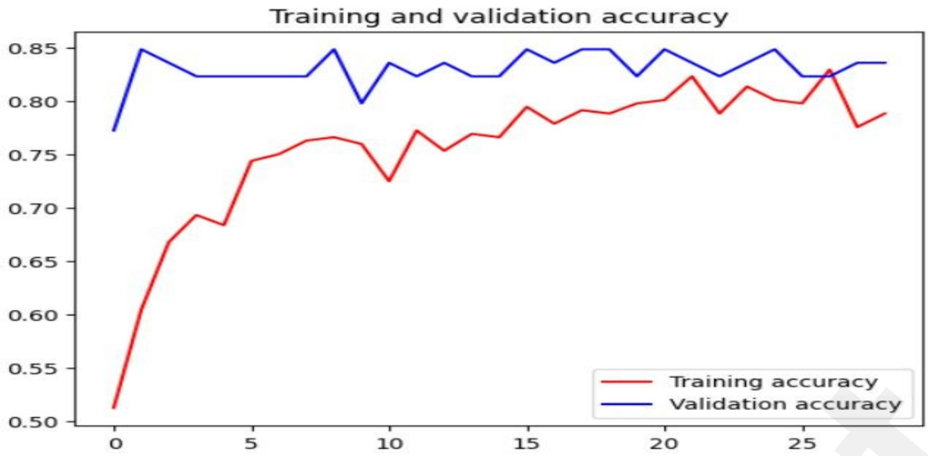

Fig. 3 Plot code and displaying

	Precision	Recall	F1-score	accuracy
Normal	0.87	0.87	0.87	0.85
Osteoporosis	0.81	0.81	0.81	

Table 1 table of the result

Keywords: deep learning, CNN, convolutional neural network, python, osteoporosis, dental panoramic x-ray